Study on the Early Warning of Fracturing Sand plugging Based on Improved BP Neural Network

He Zhang [a], Mingzhu Chen [b] and Guoliang Li [c]

School of Mechanical and Electrical Engineering, Southwest Petroleum University, Chengdu, 610500, China

[a]11413843@qq.com,[b]4250519152qq.com,[c]7814186542qq.com

Abstract

China's low permeability oil and gas distribution is wide, large reserves, hydraulic fracturing is to transform oil and gas, oil and gas wells to improve production and increase the injection of important measures. An improved conjugate gradient algorithm is proposed by studying the fracturing mechanism, fracturing construction risk analysis and the mechanism of sand plugging and its characterization. Through the network training and generalization ability of the model, the risk of sand plug can be correctly identified and accurately predicted, which can guarantee the safety of fracturing construction. Through the field application, the warning accuracy is high, can accurately calculate the crack direction, can meet the needs of the scene.

Keywords

drilling,fracturing, conjugate gradient, BP neural network.

1. Introduction

With the development of oil and gas exploration in deep and deep strata, hydraulic fracturing has become an effective method to transform oil and gas reservoirs[1,2], which is an important measure to increase oil and gas wells and increase oil and gas recovery. China's low-permeability oil and gas layers are widely distributed and large reserves, and this objective resource condition determines the preferred measures and methods for hydraulic fracturing as a low-permeability oil and gas field. It plays an irreplaceable role in the exploration and development of stable and low-permeability new oil and gas fields The important role [3] . At present, the domestic hydraulic fracturing in theory, equipment and technology and other aspects have a lot of development, but there are still many problems. Such as weak fracturing monitoring and construction quality management, as well as lack of cost-effective measurement and fracturing assessment at the site. With the development and application of hydraulic fracturing technology, there is an urgent need to measure and evaluate the method of groundwater fractures. Currently, the methods of on-site measurement and evaluation of groundwater fractures are mainly indirect monitoring such as direct monitoring of microseismic monitoring and well test analysis and production history fitting. But relatively speaking, fracturing pressure analysis is recognized as the most powerful and economically viable technique for assessing fracturing processes and hydraulic fractures [4-7] .

Based on this, the evaluation and analysis of monitoring parameters and the optimization of sand plugging algorithm are carried out, BP neural network algorithm is selected. And the basic BP training algorithm for BP neural network is slow and easy to fall into the local minimum. Based on the analysis of previous research results, an improved conjugate gradient algorithm is proposed, Which can effectively improve the convergence performance and training speed of the network, and establish a real-time early warning model of fracturing sand plugging based on improved BP neural network.

2. Study on the Mechanism and Characterization of Fracture

The key to the construction of hydraulic fracturing is whether the formation of fractures can be consistent with the crack extension of fracturing construction design. The formation and extension of fractures is a kind of mechanical behavior, and its form and extension orientation are closely related to the fracturing site construction. Adjust the fracturing in the construction of controllable factors to control the extension of fracturing cracks, related to the success or failure of fracturing construction[8]. Figure 1 shows the growth of hydraulic fractures:

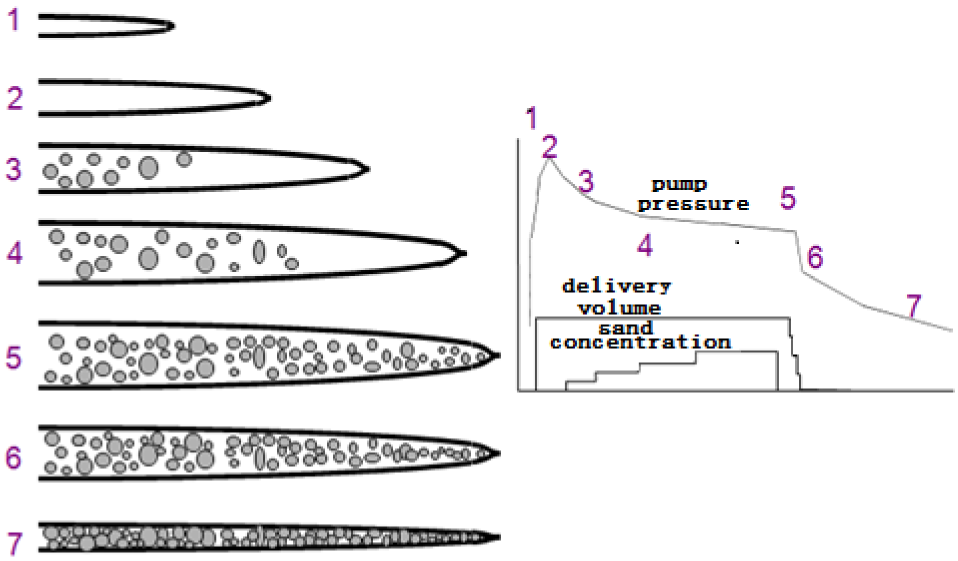

Fig. 1 Hydraulics growth

2.1 Sand plugging mechanism

2.1.1 Sand plug type

In the process of fracturing construction, the sand plugging accident is mainly manifested as the sand plug and the sand plug in the near-well area[9,10], and there are different trends in the pressure of the pump ,as shown in figure 2.

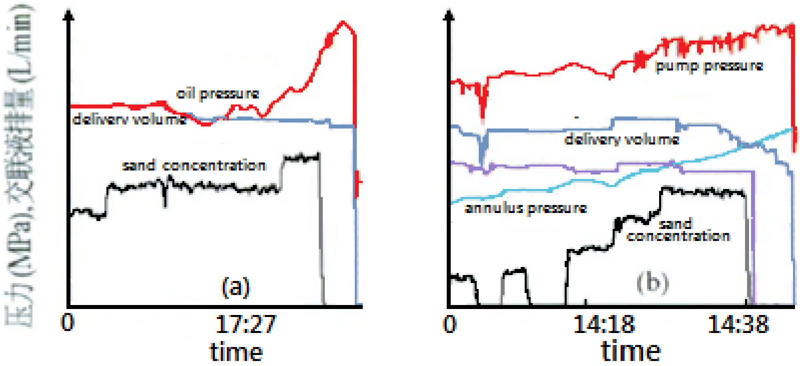

Fig. 2 near the well formation of the sand plugging map

2.1.2 The impact of Sand plug [11]

If the occurrence of sand plugging the accident will cause the following main inpact:

（1）Resulting in fracturing construction failure, can not form a high diversion capacity of the cracks;

（2）Construction pressure will rise sharply, the fracturing of the construction of the column and the sink caused serious damage and even lead to pipe scrapped;

（3）Resulting in waste of fracturing fluid and proppant;

（4）If you want to re-fracturing or open well production must be carried out sand work, increase the cost of fracturing construction.

2.2 Characterization of phenomena and laws of sand plug

The risk of sand plug occurs mainly in the late stage of the sand and the stage of replacement. In the normal fracturing process can be identified by the following characteristics and risk factors abnormalities to identify the situation.

（1）During the normal fracturing process, sand plugging occurs in the later stage of the sand loading stage. At this point the proppant concentration is high, with sand discharge capacity must be due to the formation of clogging, carrying sand in the bottom of the hole into the formation, the most direct performance is the bottom of the pressure rise, and the ground surface is the phenomenon of oil pressure rise, casing pressure rise;

（2）During the normal fracturing process, after the end of the sanding stage, at the end of the stage to replace sand stage. At this time to carry sand liquid displacement is zero, the proppant concentration is zero, in the wellbore carrying sand liquid continue to enter the formation. If sand plugging occurs, the bottom hole pressure rises, and the ground surface is characterized by a rise in tubing pressure and a rise in casing pressure.

In summary, in the fracturing construction process occurs sand plug, the bottom of the pressure rise, tubing pressure, casing pressure rise. The parameters of the sand plug are the discharge displacement, the proppant concentration, the bottom pressure, the tubing pressure and the casing pressure.

3. Establishment of Fracture Early Warning Model

The fracturing warning model mainly includes the sand suspension early warning model and the crack expansion model based on the BP neural network. It is mainly used to prevent the occurrence of sand plugging and to determine whether the fracture direction conforms to the fracturing construction design. Based on the study of sand plugging mechanism and crack propagation model, the influencing factors and characterization parameters of sand plug are determined, and the fracturing pressure and fracture calculation are evaluated and analyzed. The BP neural network algorithm is used to establish the dynamic prediction model of fracturing. Through the comprehensive analysis of the monitoring parameters, the purpose of real-time warning of sand plugging is realized.

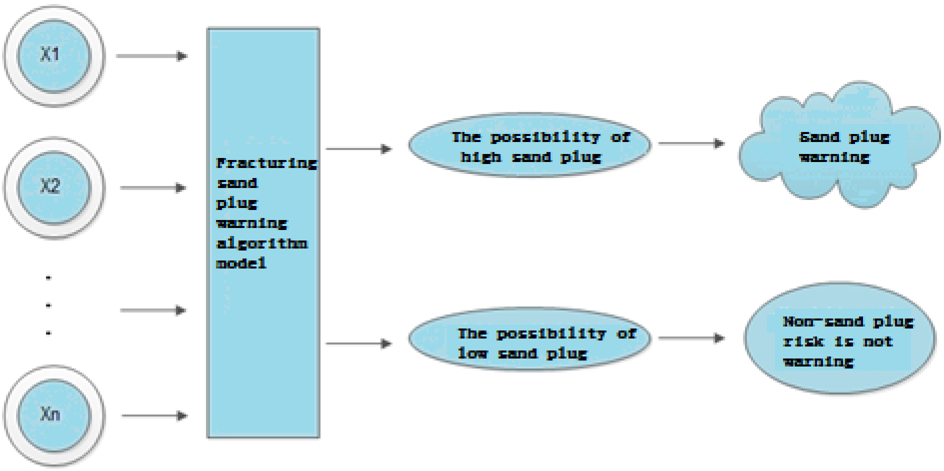

Fig.3 the warning process of fracturing sand plugging

3.1 Analysis of early warning flow of fracturing sand plug

Based on the BP neural network of the early warning process of fracturing sand plugging is a complex system engineering, Only follow the BP neural network mapping rules of the establishment of the principle and the network function to achieve the operational process, targeted analysis of fracturing sand blocking alarm parameters in order to obtain an ideal early warning results. Combined with BP neural network algorithm running process and engineering application practice, based on BP neural network fracturing sand blocking the alarm process is established as shown in Figure 4.

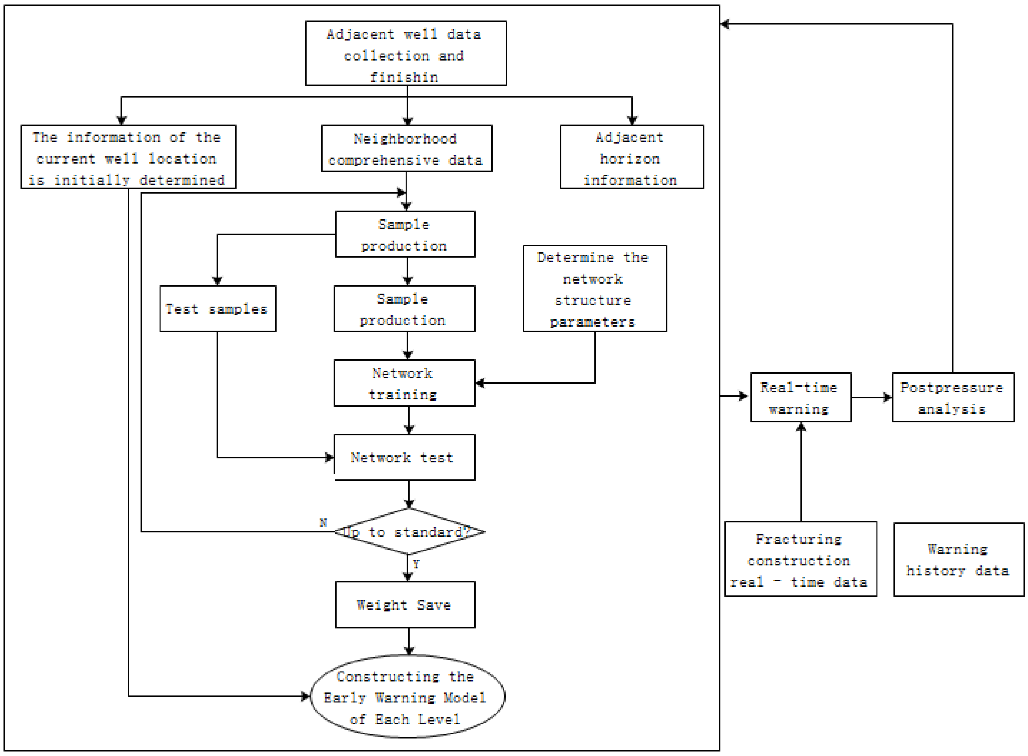

Fig. 4 Real-time warning process of fracturing sand plugging risk based on BP neural network

3.2 Theoretical basis of BP neural network

BP neural network is a multilayer feed forward neural network with input signal forward transmission and error back propagation. Figure 5 shows the most commonly used three-tier BP neural network structure.

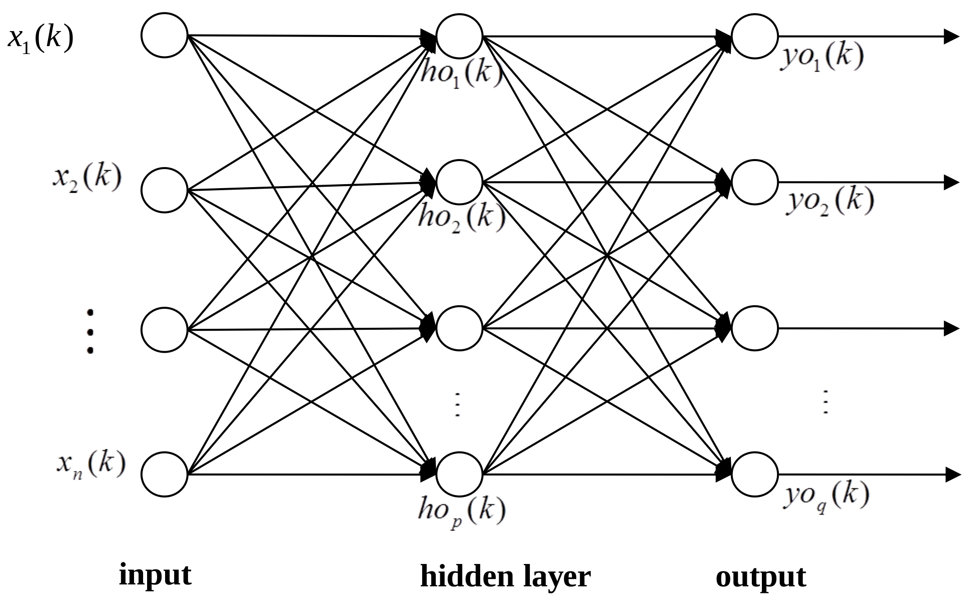

Fig. 5 Three-layer BP neural network model

BP neural network learning process is as follows:

（1）Network initialization。Before the network to learn, the weights w_{ih} 、 w_{ho} and the thresholds b_h 、 b_o of the nodes are connected to each layer. The random number is in the interval [-1,1]. At the same time, the calculation accuracy ε and the maximum number of training times M are determined, and the sample training count counter is set to 1, and the global error is set to 0.

(2) Randomly select the k sample input vector $x(k)=(x_1(k),x_2(k),\cdots,x_n(k))$, in the sample and its corresponding expected output vector $d(k)=(d_1(k),d_2(k),\cdots,d_q(k))$.

(3) The input $hi_h(k)$ is calculated by using the input template, the network weight w_{ih} and the threshold b_h to calculate the input $hi_h(k)$ of the neurons of the hidden layer, and then the output $ho_h(k)$ of the neurons of the hidden layer is calculated by the transfer function.

$$hi_h(k)=\sum_{i=1}^{n} w_{ih}x_i(k)-b_h \qquad h=1,2,3,\cdots,p \tag{1}$$

$$ho_h(k)=f(hi_h(k)) \qquad h=1,2,3,\cdots,p \tag{2}$$

(4) Calculate the input $hi_h(k)$ and output $ho_h(k)$ of the hidden layer nerve nodes.

$$hi_h(k)=\sum_{i=1}^{n} w_{ih}x_i(k)-b_h \qquad h=1,2,3,\cdots,p \tag{3}$$

$$ho_h(k)=f(hi_h(k)) \qquad h=1,2,3,\cdots,p \tag{4}$$

(5) Calculate the input $yi_o(k)$ and output $yo_o(k)$ of the output node's nerve node.

$$yi_o(k)=\sum_{i=1}^{p} w_{ho}ho_h(k)-b_o \qquad o=1,2,3,\cdots,q \tag{5}$$

$$yo_o(k)=f(yi_o(k)) \qquad o=1,2,3,\cdots,q \tag{6}$$

(6) Using the network expected output $d_o(k)$ and the actual output $yo_o(k)$, calculate the error function of the output layer of the node partial derivative $\delta_o(k)$.

$$\delta_o(k)=(d_o(k)-yo_o(k))f^{'}(yo_o(k)) \qquad o=1,2,3,\cdots,q \tag{7}$$

(7) The partial derivative $\delta_h(k)$ of the error function to the hidden layer is calculated by using the connection weight w_{ho} of the hidden layer and the output layer, the output layer $\delta_o(k)$ and the hidden layer output ho^k.

$$\delta_h(k)=\left(\sum \delta_o(k)w_{ho}\right)f^{'}(ho_h(k)) \qquad h=1,2,3,\cdots,p;o=1,2,3,\cdots,q \tag{8}$$

(8) Using the output node $\delta_o(k)$ and hidden layer node output $ho_h(k)$ correction hidden layer, the output layer between the connection weight w_{ho} and the threshold b_o.

$$w_{ho}^{N+1}=w_{ho}^{N}+\eta\delta_o(k)ho_h(k) \qquad h=1,2,3,\cdots,p;o=1,2,3,\cdots,q \tag{9}$$

$$b_o^{N+1}=b_o^{N}+\eta\delta_o(k) \qquad o=1,2,3,\cdots,q \tag{10}$$

(9) Use the input $\delta_h(k)$ of the hidden layer node and the input $x(k)$ of the input layer to correct the connection weight w_{ih} and the threshold b_h between the input layer and the hidden layer.

$$w_{ih}^{N+1}=w_{ih}^{N}+\eta\delta_h(k)x_i(k) \qquad i=1,2,3,\cdots,n;h=1,2,3,\cdots,p \tag{11}$$

$$b_h^{N+1}=b_h^{N}+\eta\delta_h(k) \qquad h=1,2,3,\cdots,p \tag{12}$$

(10) Calculate the global error E.

$$E=\frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(d_o(k)-yo_o(k))^2 \tag{13}$$

(11) After solving each layer and the weight coefficient, to determine whether the error to meet the expected requirements. When the error reaches the preset accuracy or reaches the preset maximum number of learning times to complete the completion of learning. Otherwise select the next learning sample, return to step 3, enter the next round of learning.

3.3 Defects and improving methods of BP neural network

BP neural network is a feedforward nonlinear mapping network, which constantly adjusts its internal structure by constantly adjusting its own structure to gradually adapt to various external environmental factors, and finally establishes the rules to deal with the problem , Is currently the most widely used engineering. Nevertheless, it also has a lot of problems [12-15].

（1）BP algorithm is easy to make the neural network easy to fall into the local minimum, mainly because of its gradient in the gradient of the mean square error, and the gradient curve of the mean square error has many local and global minimum points;

（2）BP algorithm convergence speed is very slow, has learned good network generalization ability is poor;

（3）There is no reliable theory and method to accurately determine the number of neurons in the hidden layer;

3.4 An improved conjugate gradient BP algorithm

Aiming at the problems of BP algorithm mentioned above, this paper presents an improved algorithm for basic BP algorithm, and the improved algorithm can speed up the network convergence speed and optimize the neural network.BP neural network adopts negative gradient algorithm, this algorithm along the negative gradient direction of the neural network performance function continuously cumulative value and threshold value, due to the search direction orthogonal algorithm iterations, so near the extreme value point happens “sawtooth" form of oscillation [16].The fastest method of decreasing the value of the network performance function is the steepest descent method, but it is not the global convergence and the fastest local convergence. In this paper, we discuss the conjugate gradient algorithm of transformation gradient to speed up the convergence rate of network training, and use this algorithm to improve the convergence speed and convergence performance of the network.

3.4.1 Conjugate gradient method

The conjugate gradient method can be uniformly described as:

$$\begin{cases} f(X^{(k+1)}) = \min f(X^{(k)} + \alpha^{(k)} S(X^{(k)})) \\ X^{(k+1)} = X^{(k)} + \alpha^{(k)} S(X^{(k)}) \end{cases} \tag{14}$$

The formula(14), $X^{(k)}$ is A vector composed of network ownership value and threshold value, $S(X^{(k)})$ is the search direction of vector space composed of each component of X , and $\alpha^{(k)}$ makes $f(X^{(k+1)})$ to minutenessstep in $S(X^{(k)})$ direction. Therefore, it is possible to obtain the optimal search direction of the current iteration, and then seek the optimal iteration step in this direction.

According to the weights of network optimization steps to get optimization steps of the conjugate gradient method, first along the negative gradient direction search, then along the current search direction conjugate direction search, which quickly achieve optimal network performance function. Conjugate gradient method is better than most of the conventional gradient method, fast convergence speed, the basic idea is to conjugacy and steepest descent method, the steepest descent direction conjugate resistance, along the search direction, and the objective function extremum .The conjugate gradient vector is shown in figure 6. The direction vector is in the direction of the linear combination of the current direction vector and the previous direction vector. Gradient $g(k)$ is defined as the derivative of $f(x)$ with respect to x, namely $g(k) = \partial f(x)/\partial x$ .Due to conjugate direction vector of conjugate gradient method only depends on the initial direction of negative gradient, so the solution is likely to lose the advantages of the conjugate direction near, the drawback is that algorithm is global convergence of this algorithm but not the global optimal [17].

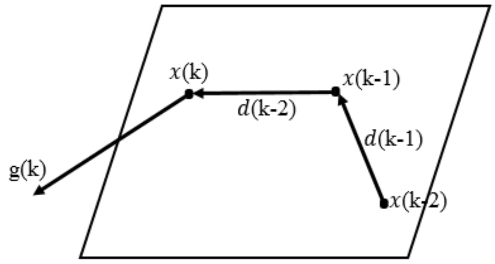

Fig. 6 conjugate direction vector diagram

3.4.2 Improved conjugate gradient method

The conjugate gradient method requires linear search in the process of the algorithm, and the linear search method is adopted to guarantee the convergence speed of the algorithm.

Gradient vector $g(k)$ and direction vector $d(0)$, $d(1)$,... $d(k-1)$ of subspace orthogonal, each iteration, the dimensions of the direction vector subspace plus 1, learning rate $\alpha(k)$ depends on Fletcher-Reeves linear search results, and along the search direction at each iteration $d(k)$ change.

If the learning rate $\alpha(k)$ of the conjugate gradient method is at the $k+1$ time, the target function value increases, then the search direction becomes non-decreasing, and the target function is no longer convergent, therefore, You need to set the $\alpha(k)$ learning rate k +1 for 0, and implement step by step, the gradient $g(k-1)=g(k)$, the direction vector $d(k-1)=d(k)$, and the conjugate gradient method will start again. After the completion of the above process iteration, the results will converge to the global minimum, which is equivalent to the most rapid descent of the conjugate gradient method.

Improved conjugate gradient BP algorithm is as follows:

Select the initial point $w(0)$ and initial search direction $d(0)=-g(0)$;

k =0,1,2,..., $n-1$,The weight correction formula of BP network is

$$w(k+1)=w(k)-\alpha(k)d(k) \quad (15)$$

In formula (15), $\alpha(k)$ is the learning rate, which makes the upper form extremely small; $d(k)$ is the conjugate direction of the k iteration.

Calculate the new gradient vector $g(k+1)$

If $k=n-1$ Substitute $w(n)$ for $w(0)$ and return to step 1; Otherwise, step 5;

Calculate the conjugate direction $d(k+1)$ of the $k+1$ iteration,

$$d(k+1)=-g(k+1)+\beta(k)d(k) \quad (16)$$

$$\beta(k)=\frac{g^T(k)g(k)}{g^T(k-1)g(k-1)} \quad (17)$$

If $d^T(k+1)g(k+1)>0$,use $w(n)$ replaces $w(0)$ and returns step 1;Otherwise, step 2.

Thus, it can be seen that the improved conjugate gradient method can accelerate the convergence speed of the algorithm without increasing the function complexity and ensure global convergence.

4. Comparative analysis

A three-layer single-output BP neural network is created, which USES the basic BP neural network and the improved conjugate gradient BP algorithm to train the network and test it.The training sample is p = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10], t = [0, 0, 1, 0, 1, 0, 1, 0, 1].The selected BP network input layer neurons have 10, the hidden layer neurons 8, the output layer neuron 1.As the network input, t as the network output, and initializes the network, and trains the network with the basic BP algorithm and the improved conjugate gradient method respectively.Through a large number of simulation experiments, the error curve of network training (target error 0.001) is shown in fig. 7 and fig. 8.

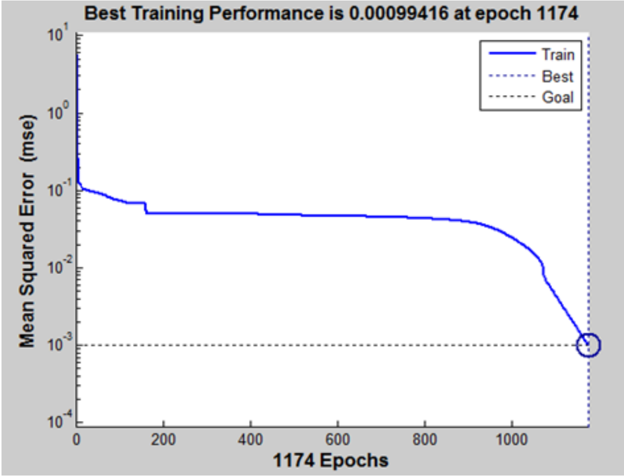

Fig.7 the training error curve based on BP algorithm

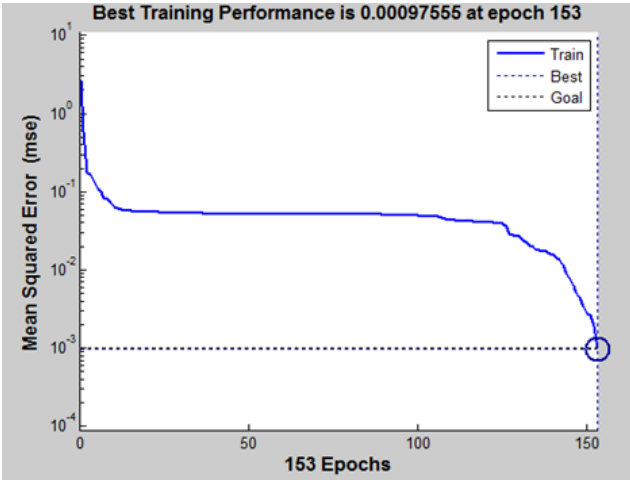

Fig.8 improved the training error curve of conjugate gradient BP algorithm

By comparing the simulation results of Fig. 7 and Fig. 8, the basic BP algorithm requires 1174 times of learning to complete the network training. The improved conjugate gradient BP algorithm has completed the training of the network only after 153 times. The improved conjugate gradient BP algorithm has better convergence performance.

5. Field application testing

5.1 Application of Fracturing Real - time Dynamic Early Warning System in Occurrence of Sand Plug in X Block A wells

X block B wells using conventional fracturing method, the wells in the target layer of 2981.2m-2994.3m fracturing due to sanding too fast sand plug situation. The well A is a fractured construction well, using conventional fracturing method, the well in the 2979.0m-2991.1m well fracturing. Therefore, the use of B wells in the well section 2981.2m-2994.3m fracturing construction data for the sample data (part of the sample data shown in Table 1), the real-time dynamic early warning system for field applications, A wells for real-time warning.

Before the system test, the sample data set and the test sample data set of the 2981.2m-2994.3m fracturing construction data are used in the well, and the weight and threshold matrix of the well are obtained. The fractured sand plugging the forensic knowledge base.

Table 1 sample data sheet of B well

Serial number	Relative time（min）	Tubing pressure（MPa）	Casing pressure（MPa）	Discharge volume（m³/min）	Proppant concentration（Kg/min）	…	Bottom pressure（MPa）	Pipe column friction（MPa）	Hole eye friction（MPa）
1	38.3	58.31	21.46	5.636	2.6	…	49.43	31.17	8.73
2	38.7	58.38	21.44	5.722	122.67	…	47.07	32.92	9.00
3	39.0	57.71	21.44	5.506	158.97	…	48.87	31.11	8.33
4	39.3	57.59	21.42	5.665	137.42	…	46.90	32.48	8.82
5	39.7	57.46	21.47	5.711	155.73	…	46.03	33.07	8.97
…		…	…	…	…	…	…	…	…
33	49.0	70.26	25.49	1.967	0	…	94.07	5.74	1.06
34	49.3	79.15	26.23	1.858	0	…	102.91	5.78	1.07
35	49.7	67.91	25.68	0.677	0	…	96.87	1.53	0.13
36	50.0	79.74	26.84	0.21	0	…	110.35	0	0

After establishing the knowledge base, the site real-time reading A wells fracturing data, sand blocking the risk of real-time warning. A wells at a relative time of 45.0 minutes due to the acceleration of the sand, the occurrence of sand plug risk. Select the time of A wells in the relative time of 44.3-46.0 minutes of real-time data, real-time data table in Table 2, the results of early warning analysis as shown in Table 3.

Table 2 real-time data table of A Well

Serial number	Relative time（min）	Tubing pressure（MPa）	Casing pressure（MPa）	Discharge volume（m³/min）	Proppant concentration（Kg/min）	…	Bottom pressure（MPa）	Pipe column friction（MPa）	Hole eye friction（MPa）
1	44.3	57.45	21.71	5.697	252.2	…	45.42	33.71	8.92
2	44.7	58.58	21.95	5.750	274.34	…	45.67	34.43	9.03
3	45.0	59.54	22.20	5.618	282.98	…	48.30	33.17	8.68
4	45.3	60.90	22.30	5.738	281.23	…	48.09	34.36	9.05
5	45.7	61.02	22.39	5.621	275.7	…	49.80	33.14	8.69
6	46.0	61.74	22.57	5.603	278.77	…	50.73	32.99	8.63

Table 3 real-time warning results output table of sand plugging risk of A well

Serial number	Relative time（min）	Output the result
1	44.3	Non-sand plug risk
2	44.7	Non-sand plug risk
3	45.0	Sand plug risk
4	45.3	Sand plug risk
5	45.7	Sand plug risk
6	46.0	Sand plug risk

After the field application statistics, based on the improved BP neural network sand plugging alarm accuracy rate of 89.35%, while the pressure-time double logarithmic curve slope prediction accuracy rate of 80.91%, so based on improved BP neural network sand blocking warning method early warning effect Better.

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