Safety evaluation of casing string based on BP artificial neural network

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Abstract. In the traditional safety assessment of casing string, some influencing factors are ignored for modelling convenience, which makes the casing string safety assessment effect of oil and gas well not very ideal. For complexity and randomness of casing load and its properties parameters in complex well conditions, BP artificial neural network is created in MATLAB based on the analysis of the influencing factors of casing string security. Casing string section whose safety assessment is more mature is taken as a sample to train the BP neural network. The trained network is applied to make case assessment. At the same time, GUI interface is applied to implement the visualization. The results show that safety evaluation of the casing string can be achieved by using BP neural network. The accuracy of the casing string network safety evaluation is high. It will realize the visualization of safety evaluation and provide more accurate and effective reference for the design of casing string.

1. Introduction
In recent years, the growing global demand for oil makes the trend that drilling of oil become deeper and more complex. High temperature, high pressure and high stress in complex deep wells have becoming the main factors which influence the strength of the casing[1-3]. Complex petroleum exploitation environment make the downhole casing more prone to damage. With the increase of the number of deep wells, casing damage has become a problem that can not be ignored. How to effectively analyze casing damage in a variety of complex factors and how to provide scientific design basis and to provide effective protection for the stable development of oil and gas field have become an arduous task of workers on petroleum science and technology[4-6].

For complexity and randomness of casing load and its properties parameters in complex well conditions, BP artificial neural network method is created for safety assessment of casing string. MATLAB GUI interface is applied to implement the visualization based on the analysis of the influencing factors of casing string security, which lay the foundation of in-depth development of the security and reliability of casing under complex well conditions.

2. Basic principle of BP neural network and its algorithm
2.1. Basic principle
Artificial neural networks[7,8] is a kind of information processing system which imitates biological brain structure and function. Artificial neural network has better approximation ability for nonlinear function, which has now become a kind of technology for nonlinear system modeling, identification and control, and is increasingly widely used around the world.

The BP Neural Network[9,10] is a one-way transmission of multi-layer forward Neural Network, it refers to the algorithm of error back propagation. BP network is a typical multi-layer network, composed of input layer, hidden layer and output layer. Layer to layer is adopted full connection and there is no connection between each neuron in the same layer. Figure 1 is a BP network topology structure containing a hidden layer. In the Figure 1, "O" represents the neurons, and a straight line segment represents connecting the two layers of neurons represents the connection weights between them.

Figure 1. BP neural network model.

2.2. The general theory of BP algorithm
The general theory of BP algorithm can be summarized as forward propagating mode and backward propagating mode[11-13], which are shown below:
(1) Forward propagating mode
The input pattern vector is set as \( A_k = (a^k_1, a^k_2, \ldots, a^k_n) \) and the desired output vector is \( Y_k = (y^k_1, y^k_2, \ldots, y^k_m) \), \( k = 1, 2, \ldots, m \), in which \( n \) is the number of input layer units; \( q \) is the number of output layer units; \( m \) is the number of learning mode.
① Calculating the input of each hidden layer unit:
\[
S^k_j = \sum_{i=1}^{n} w_{ij} a^k_i - \theta_j; j = 1, 2, \ldots, p \tag{1}
\]
In the equation (1), \( w_{ij} \) is the connection weight from input layer to hidden layer; \( \theta_j \) is threshold value of the hidden layer unit; \( p \) is number of the hidden layer unit
② Calculating the output of the each hidden layer unit \( b^k_j \):
\[
b^k_j = f(x) = f(s^k_j); j = 1, 2, \ldots, p \tag{2}
\]
In the equation (2): \( f(x) = \frac{1}{1 + e^{-x}}; b^k_j \) is the activation value of the hidden layer.
③ Calculating the input and output of output layer of each unit:
\[
L^k_t = \sum_{j=1}^{q} v_{jt} b^k_j - \gamma_t; t = 1, 2, \ldots, q, \tag{3}
\]
\[
c^k_t = f(L^k_t); t = 1, 2, \ldots, q \tag{4}
\]
In the equation: \( v_{jt} \) is connection weight from hidden layer to output layer, \( \gamma_t \) is threshold value of the output layer unit.
(2) Backward Propagation

① Calculating the correction error of output layer $d^e_i$:

$$d^e_i = (y^e_i - c^e_i)\frac{1}{2}\sum_{j=1}^{p} d^e_j$$ (5)

② Calculating the correction error of each element of the hidden layer $e^h_j$:

$$e^h_j = \sum_{i=1}^{N} d^e_i b^h_j (1-b^h_j) j = 1,2,\ldots,p$$ (6)

③ Fixing the weights between hidden layer and output layer $v_{ji}$ and various units of the output layer threshold $\gamma_j$:

$$v_{ji}(N+1) = v_{ji}(N) + \alpha d^e_i b^h_j$$ (7)

$$\gamma_j(N+1) = \gamma_j(N) + \alpha d^e_i$$ (8)

In the equation: $j = 1,2,\ldots;p; t = 1,2,\ldots,q; 0 < \alpha < 1$

④ Fixing the weights between input layer and hidden layer $w_{ij}$ and threshold of hidden units $\theta_j$:

$$w_{ij}(N+1) = w_{ij}(N) + \beta e^h_i c^h_j$$ (9)

$$\theta_j(N+1) = \theta_j(N) + \beta e^h_i$$ (10)

In the equation: $i = 1,2,\ldots,n; j = 1,2,\ldots,p; 0 < \beta < 1$

In the equations (7)-(10): $\alpha$, $\beta$ are the learning rate.

3. Application of BP neural network on casing string safety evaluation

A safety evaluation model of casing string was established by using BP artificial neural network in 50 wells of an oil production plant in North China oil field.

3.1. Establishing the network topology structure

① Determining the number of nodes in the input layer

There are many factors which affect the safe operation of the casing string, such as geometry, mechanical properties and load of casing and cement ring. Among them, casing yield strength and equivalent stress will eventually affect casing reliability. They are associated with the safe operation of the casing string at different levels. In order to simplify the problem, only factors which have high correlation with the safe operation of the casing string are considered, while ignoring secondary factors. Therefore, correlation analysis is carried out on input variables. The optimized subset which is constituted by the significant variables is taken as the input variables of the network. In order to accurately extract the main factors, SAS system is used to analyze the significance of each factors. Research shows that the main factors which affect the safety operation of the casing string are as follows: in-situ stress $\sigma_x$, $\sigma_y$, pipe yield strength $S_0$, external extrusion pressure $P_0$, casing wall thickness $T$, casing diameter $D$, casing elastic modulus $E$. Thus the number of nodes which are determined are seven.

② Determining the number of nodes in the output layer

By setting different degrees of casing damage number of output layer neurons as the target amount, the operational safety of the casing string can be objectively characterized. While carrying out the casing string safety evaluation, weighted average of the objective data is rerunning after the sample data is normalized. The output layer nodes number is 4, which respectively are especially serious damage, serious damage, damage and minor damage.

③ Determining the number of layers of the network

The main reason that BP neural network can identify the nonlinear model is the hidden layer between the input layer and output layer, which is determined by the practical problems. The number of layers can be selected as 1, 2 or multiple. After many experiments the BP neural network which has a hidden layer is chosen as the best, and the node number is 15.
3.2. Establishing BP network learning samples
The data of 50 wells in an oil production plant in North China oil field is selected as the study sample of BP artificial neural network. Part of the data is in Table 1.

| Well number | \( \sigma_x \) | \( \sigma_y \) | \( S_0 \) | \( P_0 \) | \( t \) | \( D \) | \( E \) |
|-------------|----------------|----------------|--------|-------|-----|-----|-----|
| 1           | 31.25          | 37.29          | 758    | 21.5  | 10.2| 69.85| 2.11*10^5 |
| 2           | 32.31          | 42.03          | 758    | 22.3  | 10.4| 69.94| 2.11*10^5 |
| 3           | 35.74          | 47.90          | 758    | 23.1  | 11.5| 69.95| 2.11*10^5 |
| 4           | 36.84          | 52.31          | 758    | 23.5  | 11.3| 70.12| 2.11*10^5 |
| 5           | 39.45          | 49.31          | 758    | 23.8  | 11.6| 70.63| 2.11*10^5 |
| 6           | 40.21          | 53.42          | 758    | 24.2  | 11.7| 70.25| 2.11*10^5 |

3.3. Learning and testing of BP network
After the learning process is finished, the structure of the network is determined. A group of data is taken to test the trained network and the output of test vector is \( A = [0.3661, 0.1284, 12344, 0.1070] \). The error between the actual output and the target output is shown in Table 2. It is seen clearly that the error of output value of the test data is smaller, with an average error of 0.004. Under such a sample size, the precision is perfectly acceptable. Therefore BP neural network model can be used to evaluate casing string accurately.

| Target Output | Actual Output | Error |
|---------------|---------------|-------|
| 0.3656        | 0.3661        | 0.0013|
| 0.1274        | 0.1281        | 0.0055|
| 0.2334        | 0.2344        | 0.0043|
| 0.1065        | 0.1070        | 0.0047|

3.4. The predicted results evaluation of BP neural network
The input vector dimension of BP artificial neural network is 7 and the output vector is different degrees of casing damage, which are especially serious damage, respectively, serious damage, general damage and minor damage. Using a block of 20 Wells in North China oil field as the test data of BP neural network, the evaluation result which is carried out by commercial software Matlab is shown in Figure 2[14 -16]. The detailed method is illustrated by Sun[15]. As is shown in Figure 2, the maximum error between the predicting result and the actual value is 7.5%. Calculation speed of safety assessment is enhanced on complex deep well casing string by using the BP neural network.

![Figure 2. BP network predicting result of 20 wells compared with the actual value.](image)
4. Conclusions

(1) Through the analysis of casing loads, geometry and mechanical properties of casing, cement ring and stratum rocks, seven main factors are determined which are the in-situ stress σx, σy, pipe yield strength S0, external extrusion pressure P0, casing wall thickness t, outer diameter of the sleeve D and casing elastic modulus E. They are treated as evaluation index to carry on safety evaluation of the casing string.

(2) Through the analysis, I came to the following conclusions. Safety evaluation based on BP artificial neural network provides a convenient, effective way for casing safety evaluation. Compared with the traditional method, the evaluation results of calculation are more comprehensive and scientific. Calculation of the casing reliability has higher credibility, which can provide some calculation basis for the scientific and comprehensive analysis of casing.

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