MODELING AND EXPERIMENTAL STUDY ON DRILLING RIG ANTI-JAMMING VALVE WITH BP NEURAL NETWORK

Wei Ma* – Fei Ma

School of Mechanical Engineering, University of Science and Technology Beijing, Beijing 100083, China

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Abstract:

An effective anti-jamming system is significant in improving the working reliability of hydraulic drilling rigs. An anti-jamming valve is a core component of an anti-jamming system. A back-propagation (BP) neural network model was established for an anti-jamming valve by analyzing the structure and working principle of an anti-jamming valve on a drilling rig and by utilizing the theory of neural network. The established model was employed and applied with the raw information to a stone pit to perform structural topology optimization and obtain the optimal model. The theoretical feed pressure was determined through calculation and analysis after the rock drill became completely jammed. A comparison between the relative error of computed results and the experimental values shows that the forecast data obtained with the BP model (8%) are closer to the experimental values than those obtained with the theoretical formula (14%). The highly nonlinear characteristic of a BP neural network provides a fresh insight into the intellectualization of a drilling rig anti-jamming system.

1 Introduction

Drilling rigs often encounter jamming accidents during high-speed drilling. Jamming is an important factor that influences both drilling efficiency and quality. An effective anti-jamming device is significant in hydraulic drilling rigs. Some scholars have studied the anti-jamming system of drilling rigs. Wu et al. [1] established an unbalanced loading model of drill bit, revealed the deviation mechanism, and provided a plan to control the feed force. For the three different jamming phenomena, Luo et al. [2] proposed a method for determining jamming that involves two parameters, namely, the “rate of change” and “absolute variation.” Zhao et al. [3] adopted AMESim and Simulink joint simulation and used a fuzzy control theory to validate the feasibility of rotation pressure signal by automatically controlling the feed force.

In conclusion, some research into anti-jamming systems is currently focused on the entire dynamic response characteristics of this system. This approach has to some extent solved the drill jamming problem. However, the anti-jamming valve, which refers to mechanism, hydrodynamics, and automation, is a complex physical system. The

* Corresponding author. Tel.: +8613241904343
E-mail address: maweiustb@163.com

reliability of the anti-jamming valve largely depends on several field couplings. Obviously, it has strong nonlinearity. Thus, to establish the model and to determine the key factors that affect performance and influencing rules are of utmost importance in the design of anti-jamming valves.

The research object of this paper is a new anti-jamming valve of a drilling rig. Curves of rotation and feed pressure are directly measured. Jamming phenomena in complex changing conditions of rocks are also captured, and the corresponding pressure signals are obtained.Thus, an anti-jamming valve model with back-propagation (BP) neural network is established. The influencing factors of anti-jamming valve performance are analyzed through simulation and experiments.

2 Anti-jamming system and anti-jamming valve

The schematic diagram of an anti-jamming system [4] is shown in Fig. 1. The sketch and schematic diagram of an anti-jamming valve are shown in Fig. 2.

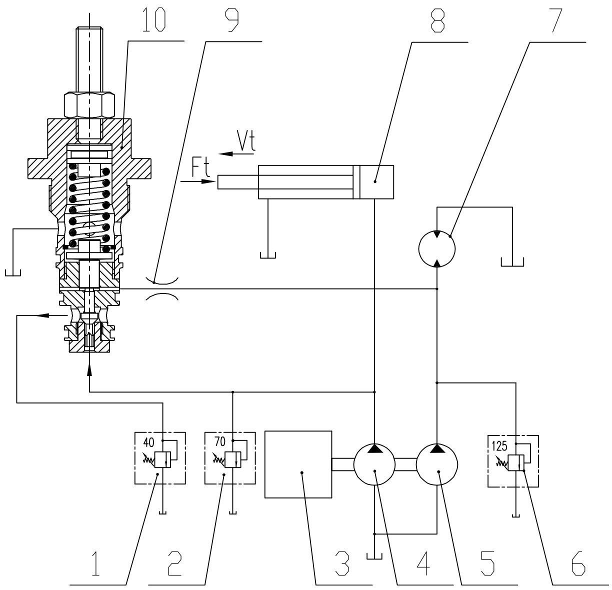

Figure 1. Schematic diagram of anti-jamming system. 1-low feed pressure relief valve; 2-high feed pressure relief valve; 3-engine; 4-feed pump; 5- rotation pump; 6-rotation relief valve; 7-rotary motor; 8-feed cylinder;9-damper orifice; 10-anti-jamming valve.

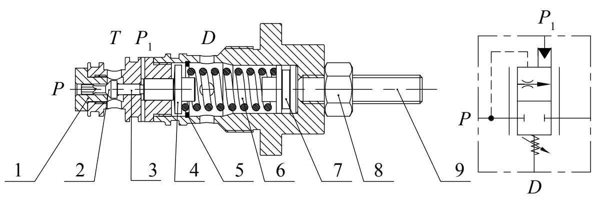

Figure 2. Sketch and schematic diagram of anti-jamming valve. 1-seat; 2-spool; 3- mandrel; 4- spring seat; 5- retaining ring; 6-spring; 7- adjusting plug; 8- lock screw; 9- adjusting screw.

If rotation pressure P_1 exceeds the setting value, the spool, mandrel, and spring seat overcome spring pretight strength, thereby causing the anti-jamming valve to open. The maximum movement distance of the spool is limited with the retaining ring. The oil of the controlling feed partially flows from the low feed pressure relief valve though the restriction chamber. Feed pressure and feed speed are then reduced. Under normal circumstances, the rotation pressure is reduced and kept at a relatively stable value. The spool changes its position from fully open to fully closed depending on the severity of the rotation pressure that exceeds the setting value. Feed pressure then varies steadily from high to low.

The adjusting screw compresses the spring and sets the critical rotation pressure when turned clockwise.

3 Model of anti-jamming with BP neural network

Factors that affect jamming and the jamming feedback parameters are assigned as input layer nodes and output layer nodes, respectively. The anti-jamming valve model with BP neural network is established by determining reasonable hidden layer node numbers and link weight coefficients between the input and output layers.

A BP neural network is the abbreviation of an erroneous reverse transmission neural network, which is one of the most successful and widely applied neural network models. A neural network system is a highly complicated nonlinear kinetics system [5]. This system functions through the extremely abundant and perfect connections and formations of a large number of neurons. A neural network cannot be established accurately with a mathematical model. A neural network summarizes the implicit relationship in the systematic input–output by studying input–output training sample data.

If P input samples exist, then the input vector is X^k (k = 1, 2, … P), and the expected output vector is T^k (k = 1, 2, … P). The arithmetic of a BP network is described as follows [6–8]:

(1) The model is initialized and the initial values are given to all weights and thresholds.

(2) During the process of model initialization, the study samples are inputted/entered, and the input and output of each layer are calculated according to the following equations:

$$u_j^k = \sum_i W_{ij} o_i^k - \theta_j \tag{1}$$

$$o_j^k = f(u_j^k) = f(\sum_i W_{ij} o_i^k - \theta_j) \tag{2}$$

where W_{ij} is the weight of node i and node j. θ_j is the threshold of node j; $f(\cdot)$ is the node function, which can be linear or S-type nonlinear.

(3) The model error is calculated according to Equation (3).

$$E = \sum_{k=1}^{P} E_k = \frac{1}{2}\sum_{k=1}^{P}\sum_{i=1}^{n}(t_i^k - y_i^k)^2 \tag{3}$$

If the model error is $E \geq e$ or the individual error is $\left|t_i^k - y_i^k\right| \geq e$, Step 4 follows. Otherwise, the model results meet the requirements.

(4) The modified GrADS errors δ_j^k of each layer are calculated according to Equation (4). Then, the weights are modified through Equation (5).

$$\frac{\partial E_k}{\partial W_{ij}} = \frac{\partial E_k}{\partial u_j^k}\frac{\partial u_j^k}{\partial W_{ij}^k} \tag{4}$$

$$W_{ij}^{(c+1)} = W_{ij}^{(c)} + \eta\frac{\partial E}{\partial W_{ij}} = W_{ij}^{(c)} + \eta\sum_{k=1}^{P}\delta_j^k o_i^k \tag{5}$$

where η is the study step pace; δ_j^k is the modified GrADS error, $\delta_j^k = \partial E_k / \partial u_j^k$; and c is the coefficient iteration.

3.1 Input nodes

Rotation pressure is selected as the input node by analyzing the anti-jamming system and valve.

3.2 Output nodes

Modern drilling rigs have several types of anti-jamming devices:

DPCI: damper pressure control impact

FPCI: feed pressure control impact

IPCF: impact pressure control feed

RPCF: rotation pressure control feed

According to the analysis of the structure and function principles of an anti-jamming valve, the type of the anti-jamming device in this study is RPCF. The factors that affect jamming are highly complex ones because of a large drilling hole diameter. Moreover, the objective factors mostly indicate that drill bit feed pressure, rock qualities, and structures change through drilling. Thus, this study focuses on the research and analysis of drill bit feed pressure when establishing a BP neural network model. In other words, the output nodes of the model are feed pressures.

3.3 Hidden nodes

A BP network with one hidden layer can describe any mapping of n × m dimensions. Thus, a BP network with one hidden layer is selected to establish the model.

There is no existing theoretical formula that can be used to calculate the number of hidden cells. Thus, the number of hidden cells is selected by the following experiential equation:

$$n = \sqrt{m+l} + a \tag{6}$$

$$n = 2m + 1 \tag{7}$$

where n is the number of hidden cells, m and l are the number of input cells and output cells, respectively, and a is constant between 1 and 10.

Based on experience, the higher the number of hidden nodes, the better the prediction effect of networks. However, these methods lead to increased calculation when the numbers of hidden nodes are excessive; this result influences the convergence rate [9]. Prediction performance must be guaranteed while minimizing the number of hidden node. In general, there are not fewer (numbers of) hidden nodes than those of input and output nodes. The experiment is conducted at different hidden node numbers of 1, 3, and 5.

3.4 Transfer function and training function

To guarantee a nonlinear model, the network uses S-type transfer function "tansig" from input layer to hidden layer and S-type transfer function "logsig" from hidden layer to output layer. The training function is "trainlm".

4 Experiment

4.1 Data acquisition

The experiment has explored the reflecting characteristics of rock drill feed pressure with different hole factors. The precision of model is based on the analysis of abundant training samples. The training samples should be large enough to allow conclusions to be drawn from. Pressure sensors were mounted on the oil inlet and outlet of a feed cylinder and rock drill rotary motor. Data collection modules were connected to testing software on a notebook. The pressures in each part were tested during drilling.

The experiment was operated at a rock quarry in Hubei Province, China, as shown in Fig. 3. The measured data are presented in this paper. The sensors captured two jamming phenomena, as shown in Fig. 4 and 5. These moderately enlarged drawings show that feed pressure is decreased by increasing the rotation pressure. The feed and rotation pressures values return to normal after discharge of jamming phenomena.

Figure 3. Experiment field.

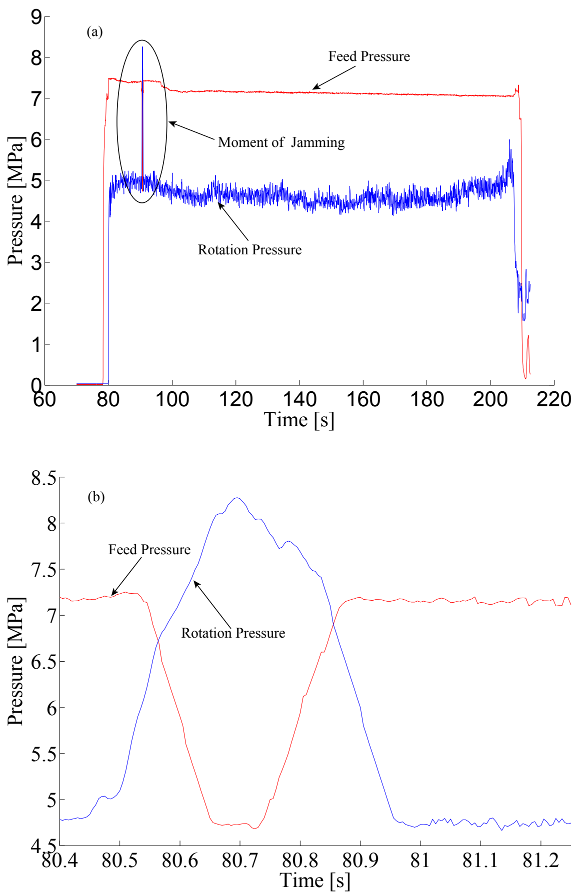

Figure 4. Curves of feed and rotation pressure:
(a) Drilling process;
(b) Moment of jamming.

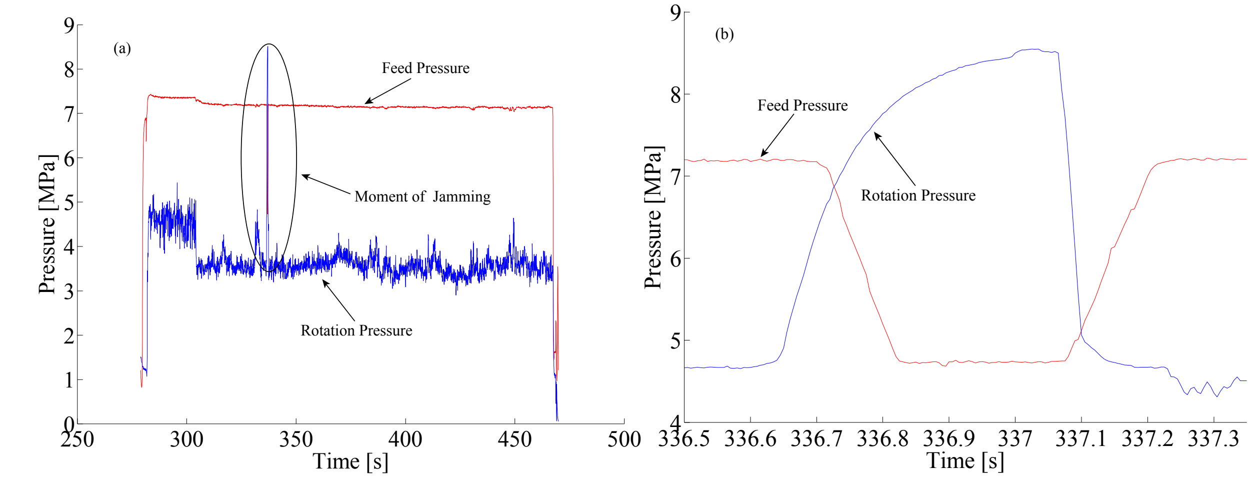

Figure 5. Curves of feed and rotation pressure (a) Drilling process; (b) Moment of jamming.

4.2 Model training and prediction

Table 1 shows two measured samples. The training precision of the model is 0.01 at study step pace 0.05. After 1070 iterations, precision meets the requirement and the training is terminated, as shown in Figure 6.
The predicted feed pressures were subtracted from the measured feed pressures in Fig. 7 to 9. Thus, the error curves were plotted, as shown in Figure 10.
The results show that regardless of the number of hidden nodes, the model can predict the working and releasing processes of an anti-jamming valve. When the number of hidden nodes is 3, the predicted feed pressures obtained are considerably close to the measured feed pressure. This result is consistent with the value calculated using Equation (7).

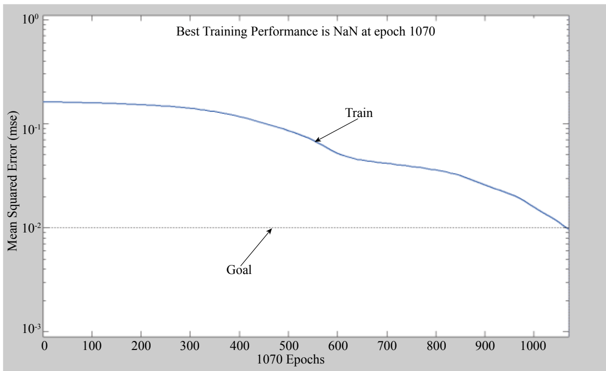

Figure 6. Best Training Performance is NaN at epoch 1070.

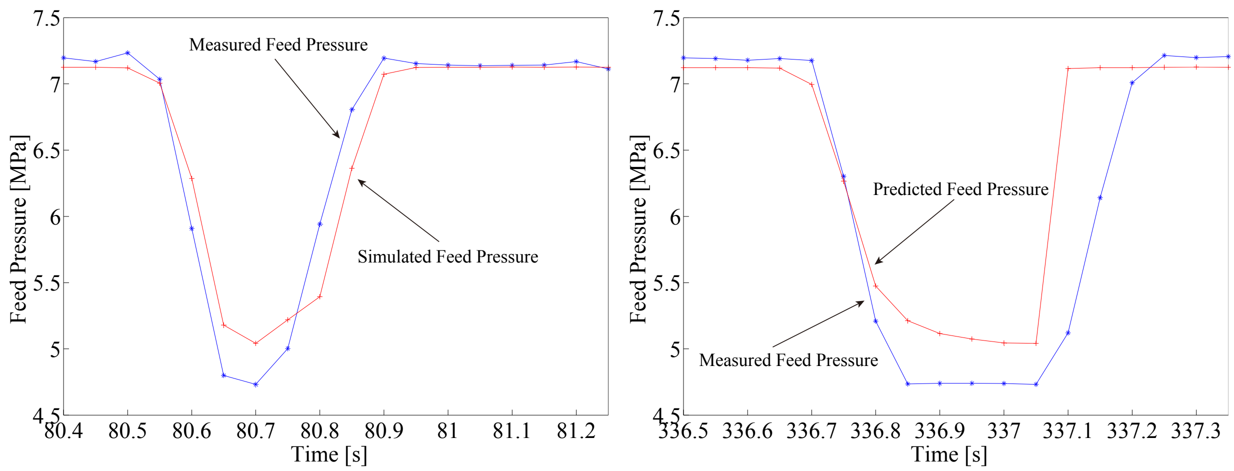

Figure 7. Simulation and prediction of feed pressure (1 hidden node).

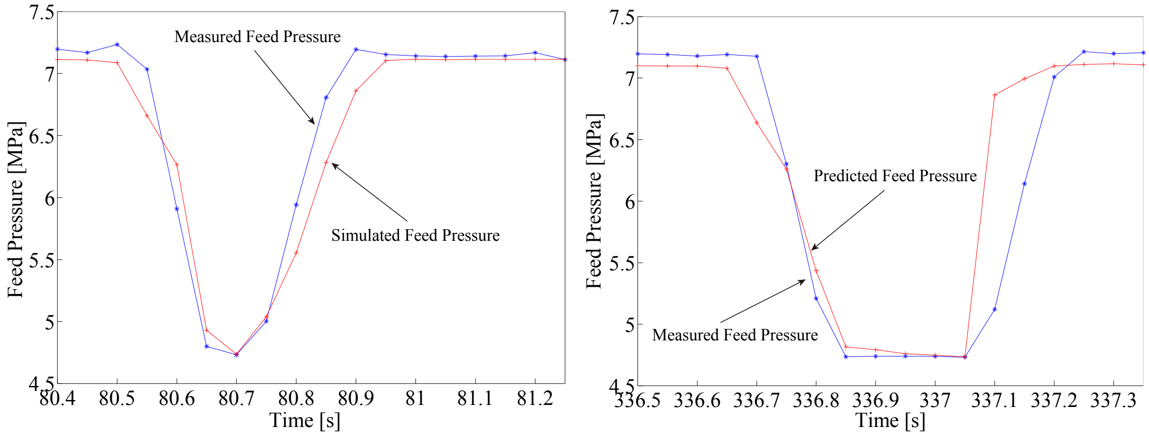

Figure 8. Simulation and prediction of feed pressure (3 hidden nodes).

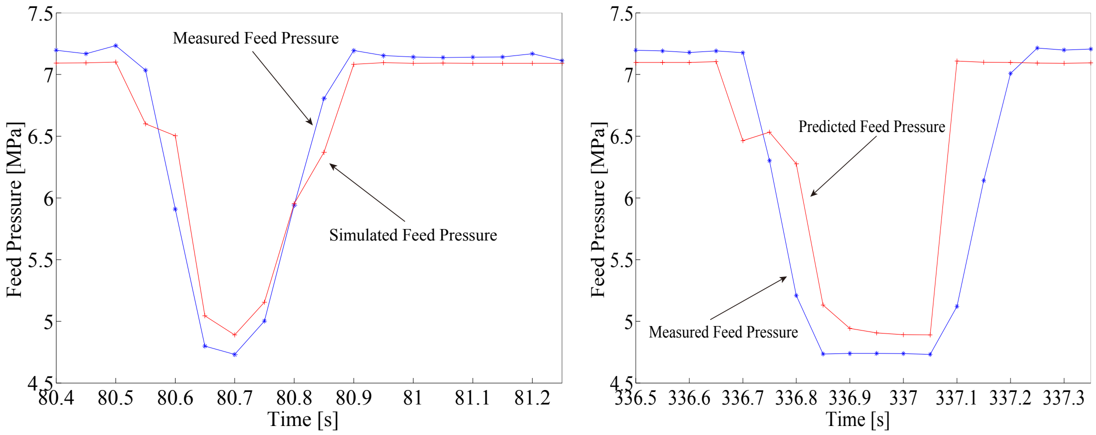

Figure 9. Simulation and prediction of feed pressure (5 hidden nodes).

Table 1. Simulation and prediction samples of BP neural network

Time/s	Feed pressure/ MPa	Rotation pressure/ MPa	Time/s	Feed pressure / MPa	Rotation pressure/ MPa
80.4	7.1973	4.7855	336.5	7.1973	4.6624
80.45	7.1689	4.8386	336.55	7.1905	4.6679
80.5	7.2331	5.0968	336.6	7.1792	4.6687
80.55	7.0342	6.3639	336.65	7.1909	4.9055
80.6	5.9087	7.1485	336.7	7.1763	6.3311
80.65	4.8002	7.9405	336.75	6.3024	7.2227
80.7	4.7321	8.2637	336.8	5.2096	7.7621
80.75	5.0032	7.8791	336.85	4.7356	8.0762
80.8	5.9412	7.6878	336.9	4.7397	8.2728
80.85	6.8056	7.1046	336.95	4.7406	8.3919
80.9	7.1939	6.0163	337	4.7388	8.5011
80.95	7.1526	4.9072	337.05	4.7324	8.5141
81	7.1416	4.7304	337.1	5.1211	5.0629
81.05	7.1374	4.7905	337.15	6.1405	4.7313
81.1	7.1404	4.7109	337.2	7.0086	4.6706
81.15	7.1414	4.7255	337.25	7.2141	4.4499
81.2	7.1686	4.7175	337.3	7.1985	4.3556
81.25	7.1117	4.7450	337.35	7.2067	4.5058

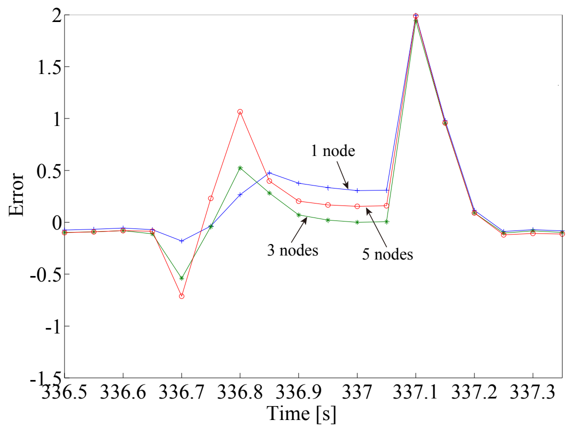

Figure 10. Error curves of prediction.

5 Theoretical analyses

Feed cylinder does not work properly when the rock drill is jammed, and the spool of the anti-jamming valve is completely open at this time. The oil of the feed pump flows from the low feed pressure relief valve though the restriction chamber. The poppet valve flow formula [10] is:

$$q = n \cdot V = C_d A_0 \sqrt{\frac{2(P_{t1} - P_{t2})}{\rho}} \tag{8}$$

$$A_0 = \pi x \sin\theta (d_1 - x \sin\theta \cos\theta) \tag{9}$$

where q is the flow through the orifice of the poppet valve; n is the engine speed; V is the displacement of the feed pump; C_d is the flow coefficient; A_0 is the flow area; P_{t1} is the oil pressure flowing to the orifice; P_{t2} is the oil pressure flowing from orifice; ρ is the density of hydraulic oil; x is the poppet lift; θ is the poppet half angle; and d_1 is the hole diameter.
The parameters of an anti-jamming system are listed in Table 2.

Table 2. Parameters of anti-jamming system

Term	Meaning	Value
n	Engine speed	2200 $r \cdot min^{-1}$
V	Displacement of feed pump	10 $ml \cdot r^{-1}$
C_d	Flow coefficient	0.7
P_{t2}	pressure from orifice	4 MPa
ρ	Density of hydraulic oil	850 $kg \cdot m^{-3}$
x	Poppet lift	0.0015 m
θ	Poppet half angle	45°
d_1	Diameter of hole	0.0042 m

By adding the data listed in Table 2 into Formulas (8) and (9), we can obtain the rate of oil pressure flowing to the orifice P_{t1} = 4.88 MPa. After the rock drill is jammed, the theoretical feed pressure is 4.88 MPa.
The anti-jamming valve facilitates a stepless shift in feed pressure between high and low. The pressure is decreased when oil passes through the orifice. Feed pressure fails to reach the set value. Feed pressure remains high after the rock drill has been jammed, which is against the release of the jam.
The predicted results, calculation results, and measured results were compared and analyzed to estimate the effect of prediction. When the rock drill has been jammed, feed pressures are listed in Table 3. These feed pressures were calculated with the BP neural network model and theoretical formula. P_{t1}, P_{t3}, and P_{t5} are the predicted values obtained with the network model. The numbers of hidden nodes are 1, 3, and 5, whereas ε_1, ε_3, and ε_5, are the relative errors between the predicted and measured values. The numbers of hidden nodes are 1, 3, and 5.
Table 3 indicates that when the number of hidden layer nodes is 3, the relative errors between the predicted and measured values are less (i.e., there are fewer relative errors between the predicted and measured values) than those between the calculated and measured values. The feed pressures are also predictable when the spool is between fully open and fully closed. However, the theoretical formula can only be used when the spool is fully open.

6 Conclusion

(1) A BP neural network model was established for an anti-jamming valve. The factors that affect jamming are highly complex ones. This BP neural network model cannot be established adequately using a mathematical model. A model based on a BP neural network was presented to solve the problems of nonlinear feature.
(2) An appropriate topological network structure was presented to approach the measured values. The simulation and experimentation results showed that when the number of hidden layer nodes is 3, the relative errors of 8% between the predicted and measured values are obviously less than those of the 14% relative errors between the calculated and measured values.

(3) An anti-jamming system model with BP neural network provides a new approach into the design of a drilling rig intelligent control system. An intelligent anti-jamming system is characterized to obtain observational data by multiple sensors in connection with the complex working condition of a drilling rig. This system has the functions of self-perception, self-decision, and automation. In theory, the functions of an anti-jamming system can be realized by combining a high-reliability controller and a BP neural network model.

Table 3. Comparison of experiment, prediction and empirical formula

Serial number	Measured values	Predicted values						Calculated values	
	P_t/MPa	P_{t1}/MPa	ε_1/%	P_{t3}/MPa	ε_3/%	P_{t5}/MPa	ε_5/%	P_{t1}/MPa	ε/%
1	4.7356	5.2124	47.68	4.8162	8.06	5.1328	39.72	4.88	14.44
2	4.7397	5.1161	37.64	4.8024	6.27	4.9434	20.37	4.88	14.03
3	4.7406	5.0745	33.39	4.7593	1.87	4.9071	16.65	4.88	13.94
4	4.7388	5.0444	30.56	4.7481	0.93	4.8921	15.33	4.88	14.12
5	4.7324	5.0413	30.89	4.7357	0.33	4.891	15.86	4.88	14.76

Acknowledgments

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