energies

Article

A New Method for Intelligent Prediction of Drilling Overflow and Leakage Based on Multi-Parameter Fusion

Mu Li [1,2], Hengrui Zhang [1,2,*], Qing Zhao [1], Wei Liu [1], Xianzhi Song [2], Yangyang Ji [1,2] and Jiangshuai Wang [3]

1 CNPC Engineering Technology R & D Company Limited, Beijing 102206, China
2 School of Petroleum Engineering, China University of Petroleum, Beijing 102249, China
3 School of Petroleum and Natural Gas Engineering, Changzhou University, Changzhou 213000, China
* Correspondence: zhang15009183937@163.com; Tel.: +86-15009183937

Abstract: The technical focus of drilling operations is changing to oil and gas reservoirs with higher difficulty factors such as low permeability and fracture. During the drilling process, drilling operations in deep complex formations are prone to overflow and leakage complications. Leakage and overflow problems will change the performance of the drilling fluid in the wellbore, impacting the wellbore pressure, and causing complex accidents such as stuck drilling and collapse. In order to improve the level of control over the risk of wellbore overflow and leakage, it is necessary to predict the mud overflow and leakage situation and to arrange and control the risk of leakage and overflow that may occur in advance to ensure the safety of drilling. By using a genetic algorithm to optimize the multi-layer feedforward neural network, this paper establishes a GA-BP Neural Network Drilling overflow and leakage prediction model based on multi-parameter fusion. Through the optimization training of 14 parameters that may affect the occurrence of complex downhole accidents, the mud overflow and leakage are predicted. The prediction results of the model are compared with the prediction results of a conventional BP neural network, and verified by the real drilling data. The results show that the MAE, MSE, and RMSE of the GA-BP neural network model are improved by 2.91%, 4.48%, and 10.93%, respectively, compared with the BP neural network model, and the prediction quality is higher. Moreover, the amount of mud overflow and leakage predicted by using the GA-BP neural network matches well with the pattern of mud overflow and leakage data in real drilling, which proves the effectiveness and accuracy of the GA-BP neural network in overflow and leakage prediction.

Keywords: neural network; genetic algorithm; multi-parameter fusion; mud overflow and leakage

Citation: Li, M.; Zhang, H.; Zhao, Q.; Liu, W.; Song, X.; Ji, Y.; Wang, J. A New Method for Intelligent Prediction of Drilling Overflow and Leakage Based on Multi-Parameter Fusion. *Energies* **2022**, *15*, 5988. https://doi.org/10.3390/en15165988

Academic Editor: Hossein Hamidi

Received: 12 July 2022
Accepted: 15 August 2022
Published: 18 August 2022

1. Introduction

Drilling is a very complex subsurface operation with a large number of repetitive and uncertain influences, making it difficult to describe the actual drilling process with accurate modeling [1]. Especially when drilling in deep and complex formations, downhole complications such as overflow and leakage are prone to occur, which will lead to great harm to drilling operations. If an overflow and leakage condition is detected too late, time will be lost for primary well control, resulting in increased difficulty for secondary well control. By monitoring downhole measurements and establishing early detection methods for complex conditions, it is possible to detect downhole complexity in time, prevent its further development and deterioration, and reduce processing difficulties, thereby significantly reducing non-productive time and improving drilling efficiency [2].

The traditional source of drilling condition interpretation data is the surface mud logging data, and most of the field downhole condition interpretation methods mainly rely on the field operator's experience, and lack of reliable theoretical model guidance, interpretation speed, and accuracy can be improved. The causes of downhole overflow and leakage are complex and influenced by a variety of factors, and the downhole environment is variable, making it difficult to describe the causes of overflow and leakage conditions. Aiming at the complex problems such as overflow and leakage, Mengbo Li and Miao He et al. [3,4] first proposed the downhole dual lateral point measurement method, and established a real-time interpretation model of downhole dual-point pressure based on the inversion theory of unscented Kalman filter, taking the position of complex points and the amount of leakage as the inversion parameters, and realizing accurate quantitative interpretation and analysis for downhole gas leakage conditions. Stokka et al. [5] conducted a study of gas intrusion alarms to detect overflow by measuring the transfer time of pressure pulses in the wellbore mud system. Bryant et al. [6] used MWD pulse signals in the annulus and downhole sensors to measure mud resistivity to achieve early warning of bottomhole gas intrusion. Orban et al. [7] developed a new flowmeter measurement system that can identify any inlet and outlet flow differences exceeding 1.9 L/s for both water-based and oil-based muds. Schubert et al. [8] installed an acoustic measurement device at the casing suspension valve to monitor the annular fluid level in real time to determine if a malignant leak was occurring.

From the above research, scholars have focused on the use of downhole measurement tools and rely on the intrinsic mechanism of the drilling system to determine and warn of spill conditions after they occur; however, there is no research on the early prediction of overflow and leakage. Therefore, it is crucial to develop a self-learning mud overflow and leakage prediction model in an effort to diagnose and detect mud overflow and leakage in a timely and accurate manner. The authors use a Genetic Algorithm to optimize the multilayer Back Propagation Neural Network, fuse several influencing factors that may cause the occurrence of downhole overflow and leakage conditions, and establish a GA-BP neural network drilling overflow and leakage prediction model based on multi-parameter fusion through the learning of a large number of training set data, effectively guiding the actual engineering situation.

2. Commonly Used Overflow and Leakage Monitoring Methods

Downhole complications such as overflow and leakage that occur during drilling are closely related to changes in pressure and flow rate. For example, drilling fluid leakage will reduce the upward flow rate of drilling fluid above the annulus leakage point, leading to a reduction in annulus pressure consumption; formation fluid intrusion will increase the flow rate in the upper annulus, triggering an increase in pressure consumption, but such downhole incidents are reflected in a slower rate of change in wellhead parameters. Therefore, engineers consider extracting features from multi-parameter signals such as bottom-hole pressure data to reflect the actual downhole conditions and identify complex downhole conditions. Through the analysis of the judgment results, it can be judged whether there is overflow or leakage in the well. Corresponding measures can be taken in time to prevent the further expansion of the overflow condition, such as controlling the wellbore pressure by means of managed pressure drilling (MPD). The earlier a leak is detected, the better the wellbore pressure can be controlled.

To summarize the early overflow and leakage monitoring methods, they mainly include the drilling fluid flowmeter monitoring method, wellhead conduit liquid level monitoring method, improved flow monitoring method, drilling with annular pressure monitoring method, stand pressure and case pressure monitoring method, and acoustic gas intrusion monitoring method [9,10]. The advantages and disadvantages of the above six methods are summarized as shown in Table 1.

Table 1. Summary of early overflow and leakage detection methods.

Monitoring Location	Monitoring Methods	Monitoring Principle	Advantages and Disadvantages	Calculate the Amount of Overflow and Leakage
Ground	Drilling fluid flowmeter monitoring	Flow conservation	Simple operation, easy to install, overflow and leakage can be monitored simultaneously, but cannot stop metering in time after shutting down the well, with general accuracy	Yes
	Wellhead conduit liquid level monitoring	Expansion principle	Low cost, easy to install, timely monitoring, but general accuracy	No
	improved flow monitoring	Flow conservation	High accuracy, applicable to the conditions of tripping and inserting a drill pipe	Yes
	Stand pressure and case pressure monitoring	Pressure balance principle of U-shaped pipe	Timely monitoring, high accuracy, able to cope with a variety of complex downhole conditions, but its system requires repeated testing and calibration	Yes
Underground	Drilling with annular pressure monitoring	Measurement with drilling (MWD)	Timely and intuitive monitoring, high accuracy, but high cost, can only be used in open pump conditions	Yes
	Acoustic gas intrusion monitoring	Sound wave propagation theory	Timely monitoring and high accuracy can calculate the overflow and leakage, but the acoustic signal processing is complex and susceptible to interference, and may be judged distorted	Yes

3. GA-BP Neural Network Drilling Overflow and Leakage Prediction Model

3.1. BP Neural Network Algorithm

A BP neural network consists of an input layer, hidden layer, and output layer, which is a typical multi-layer feed-forward neural network with good nonlinear mapping ability by learning training through error backpropagation. In BP neural networks, each layer of neurons only affects the state of the neurons in the next layer, and the output error is calculated if the output of the output layer does not match the desired output of the given sample. The error returns along the original connection path, and the weights between the neurons in each layer are adjusted so that the error decreases along the gradient to the minimum [11,12].

During training, the selected samples cannot be directly input into the BP neural network for training, and need to be normalized. The normalization formula is as follows.

$$k' = \frac{(k - k_{\min})}{(k_{\max} - k_{\min})} \tag{1}$$

where k' is the normalized value of k; $k_{\min}$ and $k_{\max}$ are the minimum and maximum values in the sample.

After a large number of learning samples in the training set are trained, the weights between the neurons in each layer are fixed, and the analysis of the data in the test set begins. At this stage, there is only forward propagation of input information, and the forward propagation follows the forward propagation process of input information in the training stage of the BP neural network. Therefore, when using a BP neural network for the prediction of wellbore mud overflow and leakage, the main work is to find out and adjust the relationship between the weights of neurons in each layer to reduce the prediction error and achieve the function of reasonable guidance for engineering practice [13,14].

A BP neural network for prediction should provide a large number of input data samples for the neural network to learn; set the input layer nodes in the three-layer neural network as x_i, the hidden layer nodes as y_i, the output layer nodes as o_k, the desired output as d_k, the weight relationship between the input layer to the hidden layer as w_{ij}, and the weight between the hidden layer to the output layer as v_{jk}. The basic calculation formula of the BP neural network is as follows:

$$\begin{aligned} y_j &= f(\text{ net }_j) = f\left(\sum_{i=0}^{n} w_{ij} x_i\right) \\ o_k &= f(net_k) = f\left(\sum_{i=0}^{m} v_{jk} y_j\right) \end{aligned} \tag{2}$$

The activation function of neurons in the BP neural network adopts Sigmoid function [13], as shown below:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

When the output is not equal to the desired output, calculate the output error E.

$$E = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2 = \frac{1}{2}\sum_{k=1}^{l}\left\{d_k - f\left[\sum_{j=0}^{m} w_{ij} f\left(\sum_{i=0}^{n} v_{jk} x_i\right)\right]\right\}^2 \tag{4}$$

As can be seen from the above equation, the BP neural network output error is a function of the weights w_{ij}, v_{jk}, and the error can be changed by adjusting the weights. When the error reaches a minimum, the size of the weights of each layer is determined so as to achieve the final accurate prediction.

3.2. Genetic Algorithm

3.2.1. Working Principle

A Genetic Algorithm was first proposed by Holland in the 1970s, and is a search algorithm based on the principles of natural inheritance and natural selection, combining the rule of survival of the fittest in biological evolution with the mechanism of random information exchange of chromosomes within the population [15,16]. The core elements of genetic search include selection, hybridization, and mutation. It works by first encoding the input data, then performing selection, crossover, and mutation operations with a certain probability until the individual with the greatest fitness is selected as the target value for output, and then stopping the operation [17].

3.2.2. Select Fitness Function

The fitness function is used as a measure of the size of the adaptive capacity of individuals in the population, and the training objective function is generally used as the fitness function of the genetic algorithm [18]. The inverse of the squared error is used as the fitness function in this paper, as shown below.

$$F = \frac{1}{E} = \frac{1}{\frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2} \tag{5}$$

3.2.3. BP Neural Network Model Optimized by Genetic Algorithm

The initial weights and threshold values in the BP neural network possess a large impact on the training results and are prone to local optimums during the training process. To solve the above problems, this paper introduces a genetic algorithm to improve the BP neural network and optimizes the weights and threshold values of the BP neural network. The obtained prediction model is able to adjust the input multiple downhole parameters to reach the optimal state and form a mud overflow and leakage prediction model based on multi-parameter fusion with a genetic algorithm optimized BP (GA-BP) neural network.

In this GA-BP neural network prediction model, the specific operation process is as follows:

(1) Acquisition of downhole parameters required for input;
(2) Pre-processing the collected data to remove the maximum and minimum values from the data to avoid possible erroneous data from interfering with the prediction results;
(3) Splitting the pre-processed data into two groups, one as the training set data and the other as the test set data;
(4) Import the training set data into the prediction model for training, and then import the test set data into the prediction model for prediction evaluation after the training is completed.

The design framework of the BP neural network optimization by the genetic algorithm is shown in Figure 1.

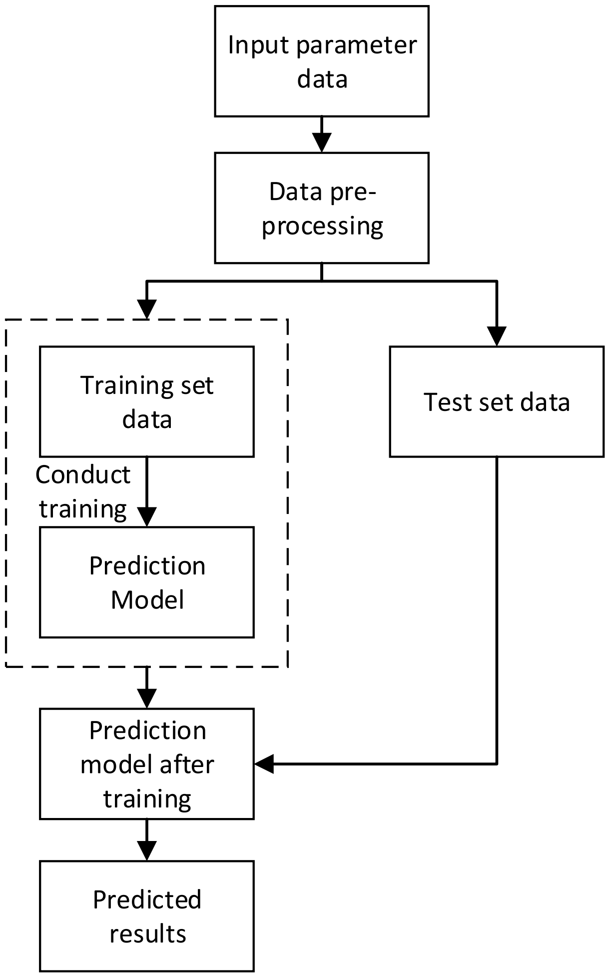

Figure 1. BP Neural Network Design Framework for Genetic Algorithm Optimization.

3.2.4. Prediction Model Design Process

In this paper, the parameters that may affect the mud overflow and leakage are fused, and the BP neural network structure used is shown in Figure 2. The input layer contains a total of 14 nodes, representing bit depth, hook position, hook speed, total pool volume, lag time, outlet flow rate, inlet temperature, outlet temperature, stand pressure, measured back pressure, outlet flow rate, outlet density, back pressure pump flow rate and bit ECD, respectively; the output layer has one node, representing mud overflow and leakage; the hidden layer refers to the principle of $n_1 = \sqrt{n+m} + a$ [19]. Where n is the number of output layer nodes, m is the number of output layer nodes, and a is a constant between [1, 10]. In the specified range, the speed and accuracy of the neural network model can be changed by changing the number of hidden layer nodes. Then, by repeatedly training the neural network model with a different number of hidden layer nodes, the results are as follows: when the number of hidden layer nodes is eight, the error sum of squares of the training results in the neural network model is the smallest, so the number of hidden layer nodes is set to eight. The training samples are normalized and then brought into the neural network model to make the results converge to the target vector.

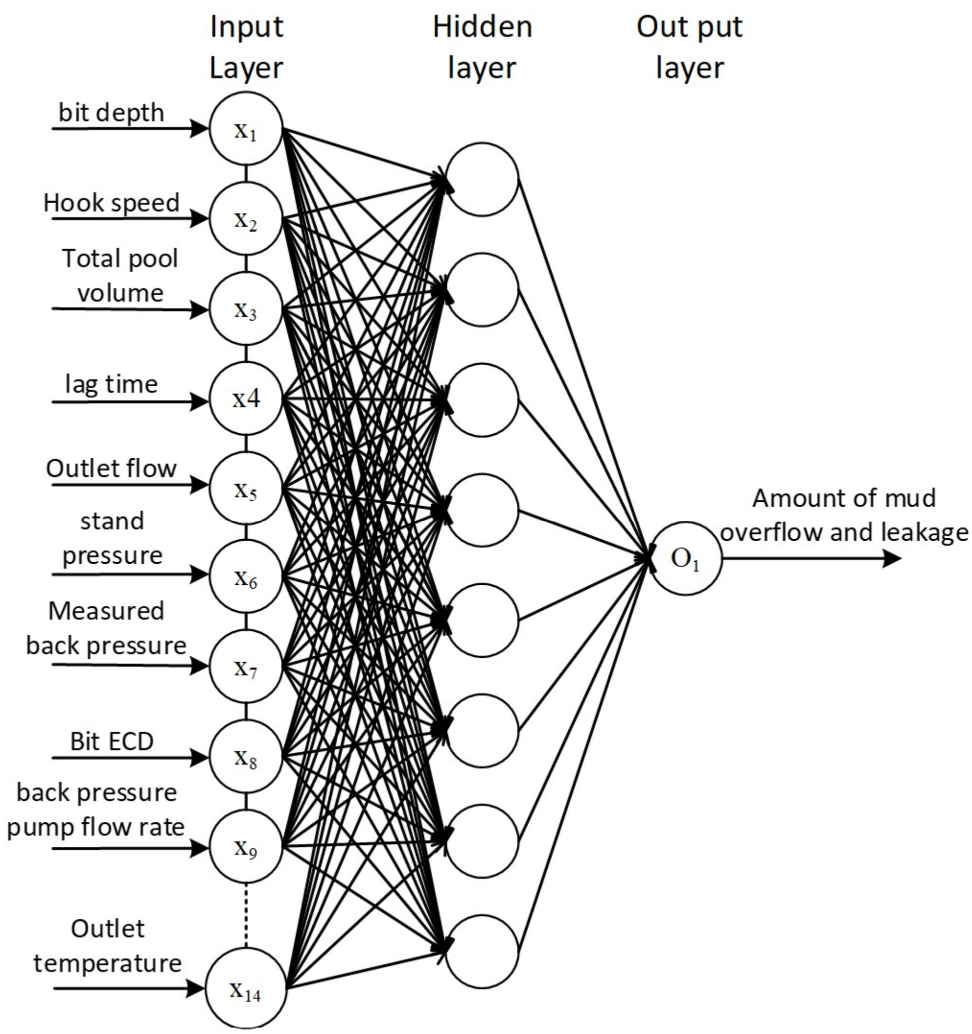

Figure 2. BP neural network topology for mud overflow and leakage prediction.

By combining the genetic algorithm with a BP neural network, the GA-BP neural network based on multi-parameter fusion is established to predict the downhole mud overflow and leakage situation by adjusting the processing of multiple downhole influence parameter data, which improves the prediction accuracy of the prediction model. The GA-BP neural network process is shown in Figure 3.

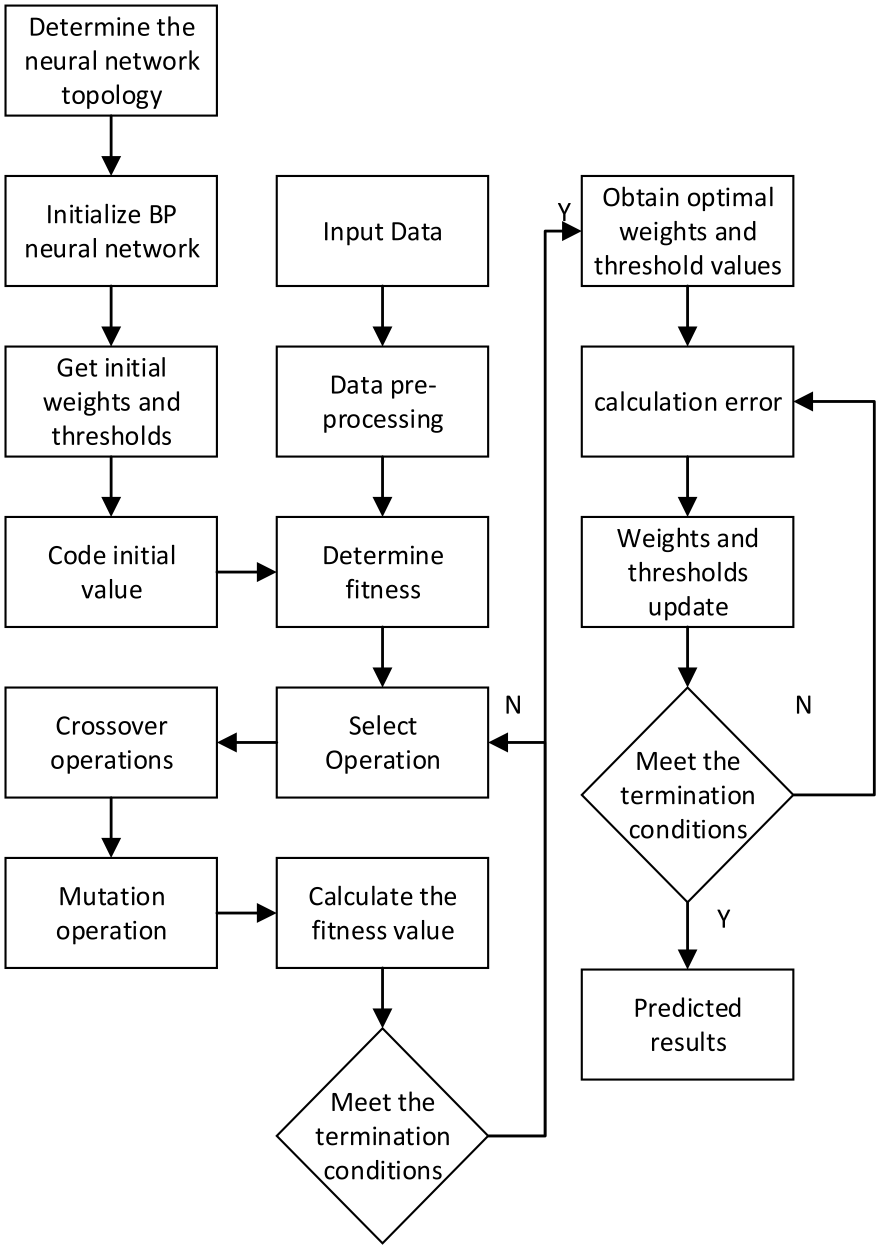

Figure 3. Flow chart of GA-BP neural network based on multi-parameter fusion for mud overflow and leakage prediction.

For the output results of the output layer, the positive and negative output values can be used to determine whether the downhole conditions are overflow or leakage. The criteria for judgment are as follows: a positive output value indicates overflow, and the larger the value, the more serious the overflow; a negative output value indicates leakage, the smaller the value, the more serious the leakage.

4. Case Study and Field Application

4.1. Prediction Model Parameter Settings

Based on the well-site data, 14 parameters that may impact mud overflow and leakage in the well section from 7353 to 7370 m, with a total of 13,000 sets of data, were selected as the training set, and adaptive learning was performed after random distribution. Due to a large amount of recorded data, only a few sets of data that had a large impact on mud overflow and leakage are selected here, as shown in Table 2.

Table 2. Mud overflow and leakage and some influencing parameters.

Serial Number	Bit Depth (m)	Hook Speed (m/s)	Total Pool Volume (m^3)	Lag Time (min)	Outlet Flow Rate (L/s)	Stand Pressure (MPa)	Measured Back Pressure (MPa)	Bit ECD (g/cc)	Amount of Mud Overflow and Leakage (m^3)
1	7357.218	−7.90577	130.6053	1171.991	0.308443	2.582324	0.103547	1.194486	0.00583
2	7359.945	0.157718	129.7675	166.7977	0.65213	19.01798	0.202857	1.254109	−0.83214
3	7358.348	−0.00000224	130.0333	157.4996	0.700712	18.50629	0.191837	1.254788	−0.56667
4	7361.483	0.0789	129.0595	162.7799	0.6359367	18.92549	0.2116311	1.254612	−1.540223
5	7363.75	0.0789	128.2953	165.256	0.606788	19.48083	0.1884698	1.254103	−2.304578
6	7365.363	0.0736	124.2411	165.2879	0.5954524	19.23505	0.2127033	1.254432	−6.35863
7	7367.853	0.1103576	124.7853	166.9601	0.6035493	19.16029	0.2088668	1.254383	−5.814759
8	7363.297	0.8625321	131.034	1133.94	0.1417158	1.692577	0.1181593	1.23978	0.4341111
9	7368.765	0.0986	132.9345	166.9787	0.4321674	18.76371	0.1940234	1.253989	2.334592

As can be seen from the data in Table 2, when downhole overflow and leakage occurs, various parameters have a great difference in mud overflow and leakage, and it is difficult to establish a unified functional expression to accurately describe mud overflow and leakage. Therefore, the downhole impact parameters are pre-processed and the processed values are used as the input layer of the GA-BP neural network, which puts the mud overflow and leakage volume and several real-time parameters of the downhole in the same system for consideration, avoiding the influence of single-factor parameter changes on the prediction results, ensuring the accuracy and authenticity of the data in the input layer of the neural network.

During training, the 14 influencing factors of bit depth, hook position, hook speed, total pool volume, lag time, outlet flow rate, inlet temperature, outlet temperature, stand pressure, measured back pressure, outlet flow rate, outlet density, back pressure pump flow rate, and bit ECD are used as input layer samples, containing eight hidden layer neurons. When the training count reaches 100,000 or the training error reaches 0.00065, the training is stopped and the predicted mud overflow and leakage is output. The specific neural network training parameters are shown in Table 3.

Table 3. Specific parameters of network training.

Parameters	Numerical Value
Maximum number of training sessions	10,000
Number of neurons in the hidden layer	8
Neural network learning rate	0.01
Training target error	0.00065
Whether to add a momentum factor	No

4.2. Error Assessment

To verify the accuracy of the prediction model, three error analysis methods, mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), are used in this paper to evaluate the accuracy of the prediction model, respectively. The three error formulas are shown below.

$$\begin{cases} \mathrm{MAE} = \frac{1}{N}\sum\limits_{i=1}^{N}\left|\hat{d}_i - d_i\right| \\ \mathrm{MSE} = \frac{1}{N}\sum\limits_{i=1}^{N}\left(\hat{d}_i - d_i\right)^2 \\ \mathrm{RMSE} = \sqrt{\sum\limits_{i=1}^{N}\left(\hat{d}_i - d_i\right)^2} \end{cases} \quad (6)$$

where $\hat{d}_i$ is the predicted value, $\hat{d}_i = \left\{\hat{d}_1, \hat{d}_2, \hat{d}_3, \ldots, \hat{d_N}\right\}$; d_i is the true value, $d_i = \{d_1, d_2, d_3, \ldots, d_N\}$.

The three error formulas are explained as follows.

(1) For MAE, the range is [0, +∞), MAE = 0 means the predicted value matches the true value perfectly, the larger the error, the larger the value of MAE;
(2) For MSE, the range is [0, +∞), MSE = 0 means the perfect model, the larger the error, the larger the value;
(3) For RMSE, the range is [0, +∞), which is more intuitive in order of magnitude compared to MSE, RMSE = 0 means that the predicted value matches the true value perfectly, and the larger the error, the larger the value.

4.3. Simulation of Prediction Results

Use the preprocessed training data to train the model, test the trained prediction model through the test set data, and compare the test results of the BP neural network with the GA-BP neural network The data prediction results are shown in Figures 4 and 5, respectively.

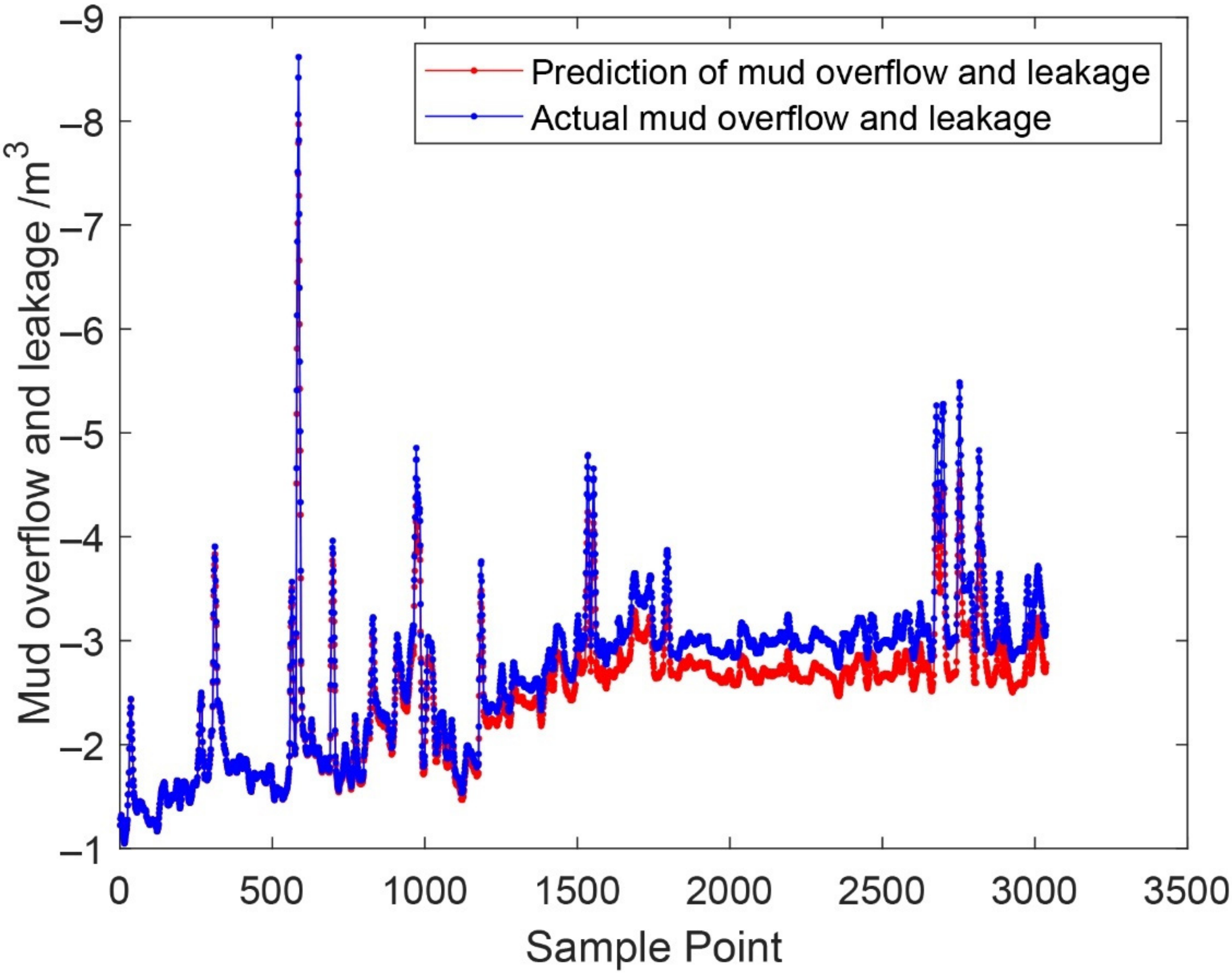

Figure 4. Mud overflow and leakage prediction results using BP neural network.

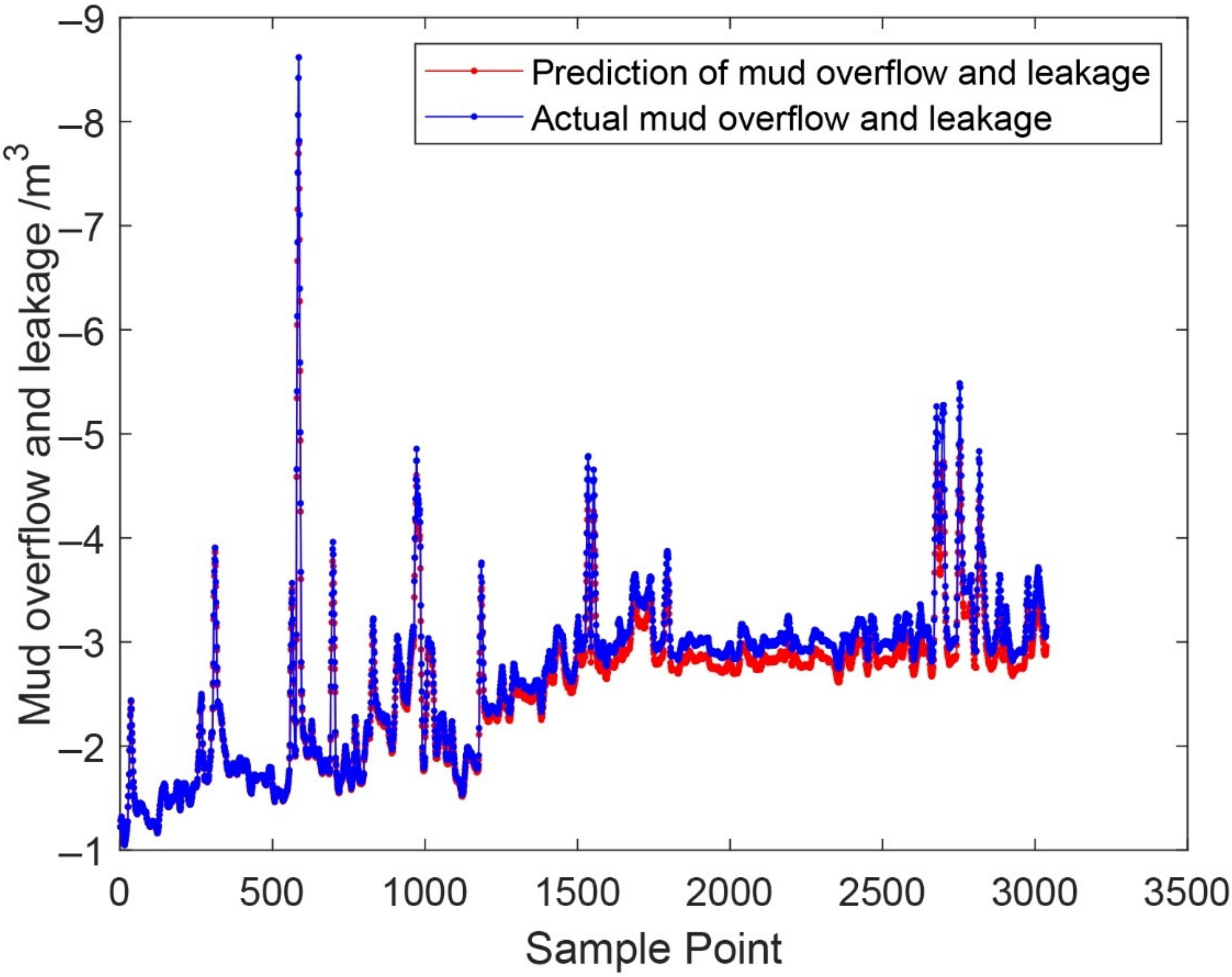

Figure 5. Mud overflow and leakage prediction results using GA-BP neural network.

After predicting the prediction models by using the test set data, the three errors of MAE, MSE, and RMSE of the two models are calculated separately according to the model prediction results as shown in Table 4. The MAE, MSE, and RMSE of the GA-BP neural network model in Table 4 are 2.91%, 4.48%, and 10.93% higher in prediction quality compared to the BP neural network model, respectively.

Table 4. Comparison of model prediction errors.

Prediction Models	MAE	MSE	RMSE
BP	0.06736	0.067281	0.25939
GA-BP	0.038279	0.022519	0.15006

Comparing the predicted values of the model with the downhole measured mud overflow and leakage, as shown in Figure 6, the difference between the predicted and true values is basically stable between ±0.4 except for some oscillation points. In addition, by analyzing the total downhole overflow and leakage, the calculation results show that the prediction error of the total predicted overflow and leakage is 7.75%, which proves that the GA-BP neural network drilling overflow and leakage prediction model based on multi-parameter fusion is able to accurately reflect the actual downhole overflow and leakage situation as a whole.

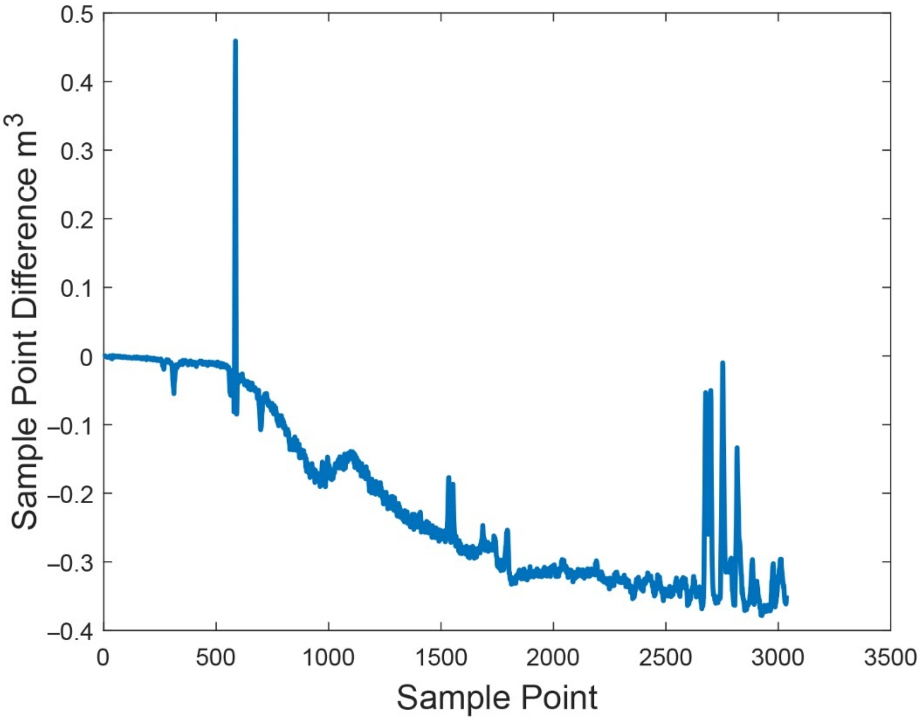

Figure 6. Difference between predicted and true values of sample points.

By analyzing the training results, it is found that the GA-BP neural network has better accuracy and a more precise prediction effect, which can predict the downhole overflow and leakage in real drilling, so as to make reasonable deployment and control in advance to ensure safe drilling operation.

5. Conclusions

(1) In this study, a genetic algorithm is introduced to optimize a BP neural network; combined with the relevant theories of drilling, a new downhole overflow and leakage prediction method is proposed. By selecting 14 kinds of parameters that may affect the occurrence of downhole overflow and leakage, a lot of training is carried out to obtain the optimal weight and threshold values of the model. Compared with the conventional BP neural network prediction results, it is found that the prediction accuracy of the new method is significantly improved.
(2) The GA-BP neural network prediction model established in this paper is different from the conventional monitoring methods of drilling mud overflow and leakage. The model does not involve the internal mechanism parameters of the drilling system, so as to avoid the influence of complex downhole parameters on the prediction accuracy.
(3) By comparing the prediction results with the actual measurements in the field, it is found that the model results predicted by the GA-BP neural network are in good agreement with the actual measured results, and the prediction quality is high. MAE, MSE, and RMSE are 0.038279, 0.022519, and 0.15006, respectively, and the prediction error of total overflow and leakage is 7.75%, which proves the effectiveness and accuracy of the GA-BP neural network in overflow prediction.
(4) The prediction of wellbore mud overflow and leakage using the GA-BP neural network can provide data support for actual drilling and technical support for engineering applications. After predicting the occurrence of overflow and leakage, the drilling engineers prevent the risk and ensured that the drilling operation is carried out safely by making early deployment of the well.

Author Contributions: Methodology, M.L. and X.S.; software, X.S.; validation, Q.Z.; formal analysis, H.Z.; investigation, Q.Z. and Y.J.; resources, J.W.; data curation, M.L.; Writing—original draft, H.Z.; Writing—review & editing, M.L., H.Z. and W.L.; visualization, H.Z. and J.W.; All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Forward looking fundamental major scientific and technological projects of CNPC (No. 2021DJ4106), the General Project of Jiangsu Province University Basic Science (NATURAL SCIENCE) Research (grant No. 22KJD430001), and the Startup Fund of Changzhou University Science Research (grant No. ZMF22020060).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Liao, M.Y. Neural network-based multi-parameter fusion for drilling process condition monitoring and fault diagnosis. *J. China Univ. Pet.* **2007**, *4*, 149–152. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=SYDX200704032&DbName=CJFQ2007 (accessed on 11 July 2022).
2. Wang, L. Research on Key Parameters of Drilling Leak Prevention and Plugging Based On BP Neural Network. Master's Thesis, Southwest Petroleum University, Chengdu, China, 2019. [CrossRef]
3. Li, M. Research on the Theory and Interpretation Method of Pressure Fluctuation in Pressure-Controlled Drilling Wellbore. Ph.D. Thesis, China University of Petroleum, Beijing, China, 2015.
4. He, M. Research on the Theory and Control Method of Real-Time Interpretation of Pressure-Controlled Drilling Overflow. Ph.D. Thesis, China University of Petroleum, Beijing, China, 2016.
5. Stokka, S.L.; Andersen, J.O.; Freyer, J.; Welde, J. Gas Kick Warner—An Early Gas Influx Detection Method. In Proceedings of the SPE/IADC Drilling Conference, Amsterdam, The Netherlands, 22–25 February 1993.
6. Bryant, T.M.; Grosso, D.S.; Wallace, S.N. Gas-Influx Detection with MWD Technology. *SPE Drill. Eng.* **1991**, *6*, 273–278. [CrossRef]
7. Orban, J.J.; Zanker, K.J. Accurate Flow-Out Measurements for Kick Detection, Actual Response to Controlled Gas Influxes. In Proceedings of the IADC/SPE Drilling Conference, Dallas, TX, USA, 28 February–2 March 1988.
8. Schubert, J.J.; Wright, J.C. Early Kick Detection Through Liquid Level Monitoring in the Wellbore. In Proceedings of the IADC/SPE Drilling Conference, Dallas, TX, USA, 3–6 March 1998.
9. Zhu, H.-G.; Wang, S.-J.; Li, Z.-Q.; Yan, X.-L.; Song, W.-Q.; Gong, P.-B. A New Timely and High-Precision Monitoring and Metering System for Early Overflow and Leakage. *Nat. Gas Ind.* **2018**, *38*, 102–106.
10. Dale, Y.Y. Research and Design of Ground Monitoring and Diagnosis System for Early Overflow Leakage. Master' Thesis, Southwest Petroleum University, Sichuan, China, 2014.
11. Zhao, Z.; Chen, W.H.; Wu, X.M.; Chen, P.C.Y.; Liu, J. LSTM network: A deep learning approach for short-term traffic forecast. *IET Intell. Transp. Syst.* **2017**, *11*, 68–75. [CrossRef]
12. Kuremoto, T.; Kimura, S.; Kobayashi, K.; Obayashi, M. Time Series Forecasting Using a Deep Belief Network with Restricted Boltzmann Machines. *Neurocomputing* **2014**, *137*, 47–56. [CrossRef]
13. Yu, M.Y.; Shi, Y.B.; Zhao, W.J. Sensor single gas Quantitative Identification Based on BP Algorithm. *Instrum. Technol. Sens.* **2011**, *8*, 17–20. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=YBJS201108007&DbName=CJFQ2011 (accessed on 11 July 2022).
14. Han, W.-D.; Wang, C.-J. Research on Drilling Accident Prediction Based on Optimized BP Neural Network. *China Pet. Chem. Stand. Qual.* **2022**, *42*, 118–120.
15. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*; The MIT Press: Cambridge, MA, USA, 1975.
16. Yao, S.; Yanlan, Y.; Hua, Y. Verification of improved genetic algorithm in MSPSP problems. *Comput. Syst. Appl.* **2020**, *29*, 235–241.
17. Xiong, Y.; Dong, W. A Review on the Application of Genetic Algorithm in Classical Cryptanalysis. *J. Univ. Inf. Eng.* **2021**, *22*, 577–583.
18. Zheng, L.; Hao, Z. Overview of Genetic Algorithms. *Comput. Eng. Appl.* **2003**, *21*, 50–53+96. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=JSGG200321016&DbName=CJFQ2003 (accessed on 11 July 2022).
19. He, S.Z.; Yang, X.Z.; Chen, X.J. Comparison of Support Vector Machines and BP Networks for Fire Image Detection. *J. Intell. Syst.* **2011**, *6*, 339–343.