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Intelligent Pressure Monitoring Method of BP Neural Network Optimized by Genetic Algorithm: A Case Study of X Well Area in Yinggehai Basin

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Abstract: While drilling formation pressure monitoring is an important basis for ensuring drilling safety and oil and gas discovery, the calculation of existing pressure monitoring methods is complicated and the accuracy is difficult to improve. Taking the actual well data of well area X in Yinggehai Basin as the object, correlation analysis was first carried out to select and standardize the data features, and relevant effective parameters were extracted. Two kinds of neural networks, back-propagation network BP and back-propagation network GA-BP optimized by genetic algorithm, were used to establish artificial intelligence monitoring models of formation pressure based on 10 kinds of measuring and logging data, respectively. The application effect of the model was evaluated based on the results of monitoring the pressure while drilling. The results show that the monitoring accuracy of the BP neural network model is 91.25%, and that of the GA-BP neural network model is 92.89%. The latter has a better monitoring effect on formation pore pressure. In formation pressure monitoring in areas with a high degree of well control, the introduction of artificial intelligence technology has the advantages of simplicity, speed and high precision, and can provide a reference for other areas of pressure monitoring while drilling.

Keywords: BP neural network; formation pore pressure; genetic algorithm; formation pressure monitoring; Bozhong sag

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1. Introduction

Abnormal pore pressure is a common phenomenon in petroliferous basins [1–7]. Abnormal pore pressure includes abnormal high pressure and abnormal low pressure. Hydrocarbon generation, migration, accumulation and accumulation are closely related to abnormal pressure. In some oil and gas basins in China, overpressure has been found in 29 areas, including 21 on land and 8 in the sea [8]. Accurate monitoring of pore pressure is the basis of rational casing program design, determination of drilling fluid density and adjustment of production technology; real-time monitoring of formation pressure plays a crucial role in drilling fluid density adjustment and decision-making while drilling [9–11]. Yinggehai Basin is rich in oil and gas resources, but it is faced with high-risk problems such as high temperature and high pressure, narrow drilling fluid density window, etc. At present, multiple layers and multiple pressure systems have been developed in the drilled formation, and complex downhole accidents have occurred [12–14]. At present, the commonly used pressure monitoring methods in the work area include the Eaton method, equivalent depth method, Bowers method, etc. These methods require a large number of

empirical parameters, and their evaluation accuracy is limited by the subjective experience of technical personnel; this makes it difficult to meet the needs of field operations, and the introduction of convenient and efficient new methods is urgently required [15–20].

In recent years, artificial intelligence technology has developed rapidly and set off a new wave in many fields. With the accumulation of resource data, computing power and progress of artificial intelligence technology in oil and gas exploration and development, the application of artificial intelligence in oil and gas exploration and development has gradually become a research hotspot [21–24]. Formation pressure monitoring, as a basic work in the process of oil and gas exploration, plays a crucial role in ensuring drilling safety and optimizing exploitation strategies [21–23,25–31]. Traditional formation pressure monitoring techniques, such as the rock strength method and dc index method, have some limitations and rely on complex physical models and empirical data. For example, the Eaton method needs to establish the trend line and evaluate the Eaton index, and the Bowers method needs to find the maximum velocity ground stress point, etc. [14,31–35]. Due to the formation pressure causes and formation properties, it is not only expensive, but also difficult to guarantee the real-time accuracy [36–38]. The intelligent prediction method of formation pressure using artificial intelligence can realize the effective processing of log data and seismic data, solve the problem that the traditional method cannot be used to calculate in the absence of specific formation parameters, predict the pressure of various lithologic formations without the restriction of formation lithology and effectively improve the prediction accuracy of formation pressure [9,10,39]. In the past decade or so, the data-driven exploration of intelligent pore pressure monitoring has never stopped. Wu et al. (2006) established a nonlinear relationship model between borehole seismic properties and acoustic time difference logging data of drilled sections through neural networks, and used this model to calculate formation pore pressure, which is suitable for pore pressure monitoring in exploration areas [17–20,40,41]. He et al. (2008) established a grey model group for prediction of formation pore pressure while drilling, which has been applied well in Tarim Oilfield [39]. Rashdi (2018) proposed a prediction model of pore pressure based on mechanical specific energy and drilling efficiency combined with artificial neural network [42]. Abdulmalek et al. (2018) used Fuzzy Logic technology in artificial intelligence to monitor formation pore pressure based on drilling parameters and logging data [43]. Hutomo (2019) combined Eaton's method with neural networks to predict pore pressure under complex carbonate conditions [44]. Based on petrophysical logging data, Hadi et al. (2019) established a formation pore pressure model using artificial neural networks to calculate formation pore pressure in a depleted carbonate environment [45]. Li et al. (2022) introduced a gradient lifting regression tree model (GBRT) to establish a formation pore pressure prediction model, which improved the accuracy compared with traditional formation pore pressure monitoring methods [46]. Yang (2022) combined the advantages of machine learning algorithms to propose a new hybrid decomposition integration (HP-PSO-RF-GB) formation pressure monitoring method, which solves the problem that traditional methods cannot be used to calculate in the absence of specific curves [38]. The above methods are mainly used in pre-drilling prediction, and are rarely used in the process of monitoring while drilling. Although they have achieved good application results in their respective application scenarios, reducing human error and improving prediction accuracy, these methods are only suitable for specific scenarios, and their application in the case of high temperature and high pressure, multiple layers and multiple pressure systems in the working area of Yinggehai Basin needs to be verified.

BP neural network uses the gradient descent method to converge: the stability and accuracy are greatly affected by the initial value, and may fall into the local optimal solution [27–30]. The introduction of a genetic algorithm to optimize BP neural network can effectively avoid this problem. A genetic algorithm is a global heuristic search algorithm, which can effectively find the approximate optimal solution in a large search space, thus improving the accuracy and shortening the training time. Combining the advantages of the two, the genetic algorithm is used to determine the optimal initial weight and threshold for

BP neural network, and then BP neural network is used to find the optimal solution, and finally the simulation monitoring results are obtained. In order to improve the accuracy and efficiency of formation pressure monitoring, BP neural network and GA-BP neural network were combined to establish formation pressure evaluation models based on real-time drilling and logging data sets, and formation pressure monitoring of some wells in Yinggehai Basin was applied. The results show that the introduction of artificial intelligence technology has the advantages of simplicity, speed and high precision in formation pressure monitoring in areas with a high degree of well control, and can provide reference for other areas of pressure monitoring while drilling.

2. Method Process

2.1. Method and Principle

2.1.1. BP Neural Network

BP (Back Propagation) neural network was proposed by a team of scientists led by Mccelland and Rumelhart in 1986. It is a multi-layer feedforward network that is trained by Back Propagation error algorithm and has a wide application range. BP neural networks can learn and store a large number of mapping relationships between input and output patterns without the need for a mathematical equation that reveals and describes the mapping relationships between input and output in advance of learning and storing [31,34,35]. As shown in Figure 1, the principle is to obtain an output vector by transforming an input vector through a series of hidden layers, and obtain the information of constantly adjusting the network connection weight coefficient and threshold through the reverse propagation of the output error, so as to minimize the square error of the neural network and meet the expected requirements [17].

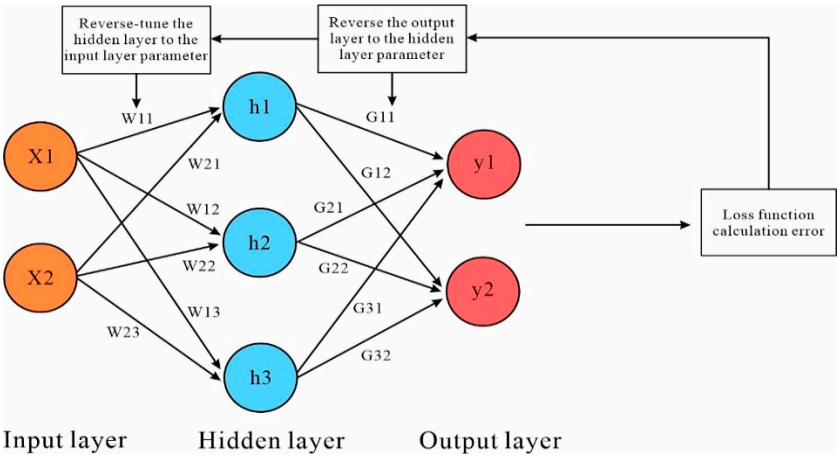

Figure 1. Classic three-layer BP neural network.

BP neural network is a three-layer network, which consists of input layer, hidden layer and output layer. The hidden layer can contain multiple layers and can have multiple nodes. The number of nodes in the input layer and output layer is determined by the problem to be solved. Each layer is composed of many parallel operation neurons, which are similar to those in the biological system, but the structure of the neural network is simple, and the function is far less abundant than that of the neurons in the biological system [1–7,34,35,40,42,47]. All the neurons between two adjacent layers are connected to each other, and the connection weight coefficient between layers acts as a bridge and transmits features. But the neurons in the same layer are not connected to each other.

BP network model includes input model, output model, action function model, error calculation model and self-learning model. The node output model includes the hidden node output model and the output node output model.

Hidden node output model:

$$O_j = f\left(\sum W_{ij} \times X_i - q_j\right) \tag{1}$$

Output node output model:

$$Y_k = f\left(\sum T_{jk} \times O_j - q_k\right) \tag{2}$$

where, X_i is the input value of the input layer, O_j and Y_k are the hidden layer output and output layer output results, respectively. W_{ij} and T_{jk} are the weight from input layer to hidden layer, and the weight from hidden layer to output layer, respectively; q is the neural unit threshold; f represents the nonlinear action function, which reflects the stimulus intensity of the lower input to the upper node, also known as the excitation function, and generally takes continuous values within 0–1, generally using Sigmoid function, Relu function and Tanh function. The Sigmoid function model is:

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

The error calculation model is a function reflecting the error size between the expected output and the calculated output of the neural network. The model is as follows:

$$E_p = \frac{1}{2}\sum (R_k - Y_k)^2 \tag{4}$$

Here R_k is the expected output value of the node, Y_k is the calculated output value of the node, E_p is the total error.

BP neural network is a supervised learning process; it is actually an error correction process for the weight W_{ij} between the lower node and the upper node. The self-learning model is:

$$\Delta W_{ij}(n+1) = h \times \varnothing_i \times O_j + \alpha \times \Delta W_{ij}(n) \tag{5}$$

Here, h is the learning factor, $\varnothing_i$ is the calculation error of output node I, O_j is the calculated output of the output node j, α is the momentum factor.

As a common feedforward neural network, BP neural network has attracted wide attention for its superiority in pattern learning and approximation function. It can not only deal with nonlinear relations, but also realize the approximation of complex models by constantly adjusting parameters through training, and has strong adaptive and generalization ability.

2.1.2. Genetic Algorithm

Genetic algorithm is a heuristic search algorithm inspired by the theory of natural evolution that optimizes and learns problems to provide high-quality solutions by mimicking the processes of natural selection and reproduction. John H. Holland proposed in the 1970s that the problem to be solved mimicked the process of biological evolution the survival of the fittest. Through operations such as selection, crossover and variation among populations, individuals with low fitness function are gradually eliminated, individuals with high fitness are increased and individuals with the optimal solution of the problem are selected through multiple iterations [29]. This method is a global search algorithm, and it is easy to get the global optimal solution. Genetic algorithms usually follow the following steps:

(1) Code. Use the prescribed method to encode text, numbers and other information, or convert the parameters in the problem into genes of the chromosome. Generally choose binary coding, easy to follow the operation (crossover and mutation);

(2) Initialization. The initial population is generated randomly, in which there are good and bad individuals, and the individual randomness is increased.

(3) Individual fitness assessment. The size of fitness represents the pros and cons of individual genes and reflects the results of parameter calculation. According to the fitness, the probability of retaining each individual is determined, so as to screen out excellent individuals and increase the number of their individuals. The greater the fitness, the smaller the probability of being selected; otherwise, the negative value of MSE is taken as fitness.

$$fitness = -\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n} \quad (6)$$

Here, fitness is the fitness value; $\hat{y}_i$ is the calculated value; y_i is the actual value of the data; n is the total number of individuals.

(4) Select operation: After calculating the fitness of individuals, individuals with higher values are more likely to be selected and pass on their genes to the next generation; individuals with lower fitness are also likely to be selected, but the probability is lower, and their genes will not be completely discarded.

(5) Cross-operation: To create the next generation of individuals, parts of each parent's chromosomes are swapped to create two new chromosomes, a new generation (Figure 2);

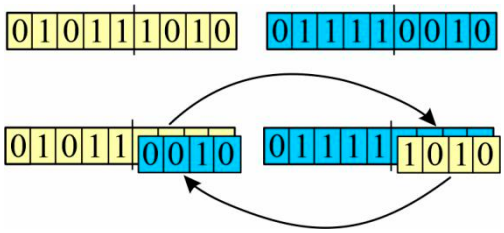

Figure 2. Cross-operation of genetic algorithm.

(6) Mutation operation: By randomly changing one or more chromosomes, manifested as random changes in genes, to renew the population, to explore unknown regions of the solution space (Figure 3);

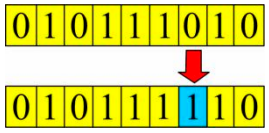

Figure 3. Genetic algorithm variation operation.

(7) Population assessment: After the next generation of the population, the individual fitness is recalculated. If the individual fitness meets the termination condition, the update is terminated; otherwise, the iteration continues until the target optimal solution is found.

The most important difference between genetic algorithm and traditional search optimization algorithm (such as gradient-based algorithm) is that genetic algorithm is carried out for multiple candidate schemes, while the traditional algorithm is carried out in an iterative scheme. Genetic algorithm uses the randomness of its next generation points to lead the search direction to the unknown region, so as to have more opportunities to improve the results. Thus, there is a greater probability of obtaining the global optimal solution, while the traditional algorithm may fall into the local optimal solution, resulting in poor application of the model. As a powerful optimization tool, genetic algorithm has been widely studied and applied in academia and industry. With the improvement of computing power and the proposal of new algorithms, the efficiency and application range of genetic algorithm will be further expanded.

2.2. Data Processing

The Yinggehai Basin is a Cenozoic transformational extension basin developed in the passive continental margin of the northern South China Sea. The Miocene Meishan

Formation and Sanya Formation shallow-sea mudstones are considered to be the main hydrocarbon source rocks in the basin [48]. At present, more than 60 wells have been drilled in the field of high temperature and high pressure: the temperature range is 150~249 °C, the pressure gradient is 1.90~2.30 g/cm^3 and the maximum mud gravity is 2.38 g/cm^3. Drilling risks are high and costs are high, and pressure monitoring is one of the key factors to ensure safe drilling, as shown in Figure 4.

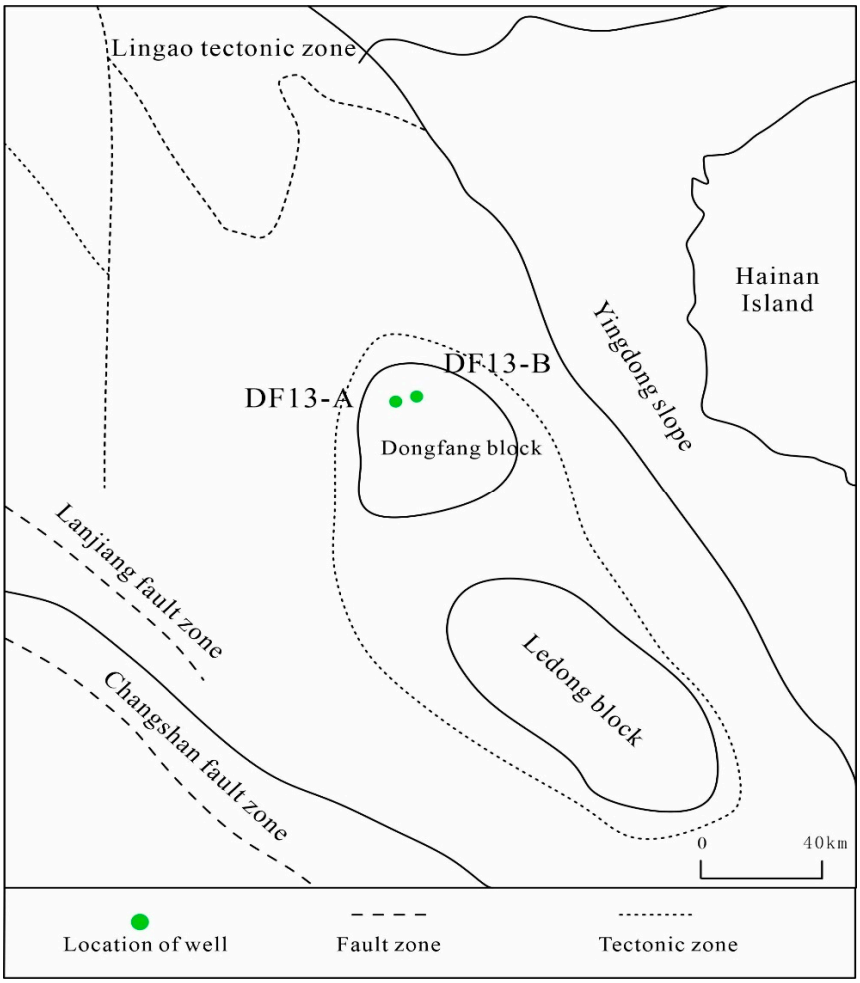

Figure 4. Well location map.

Taking 11 Yinggehai Basin wells in DF13 structure as the research object, a total of 32 items of drilling and logging data such as weight on bit, drilling rate and sonic time difference were collected and collated. Three wells were monitored for pressure while drilling. The Prevue data were used as the label and the other drilling and logging parameters were used as the characteristics to establish the model. In view of the missing and abnormal data of some wells, a borehole pressure data set containing 14 kinds of data characteristics is established by deleting the abnormal values and automatic interpolation. Well DF13-A is located in the local concave uplift between the southwest sub-depression of Yinggehai Basin and the low convex and gentle slope zone of Chengbei. According to the completed evaluation results of well DF13-A, it is a complex oil–gas accumulation area with abundant oil and gas resources and good accumulation conditions. As can be seen from the evaluation results of formation pore pressure in this well (Figure 5), the middle and upper strata are all normal pressure. After reaching 3312 m, the formation pressure gradually increases, and the formation pressure reaches its highest, 1.50 g/cm^{3,} when the well depth reaches 3564 m. The well section of 3564.00–4044.00 m is a large set of sandstone formations, and the thickness of sandstone in the logging lithology section is up to 480 m.

After drilling to the well depth of 3660 m, the drilling rate is significantly slower than that of the formation, with lowest rate of 1–2 m/h. According to the curve of weight on bit, rate of penetration and time of drilling, the formation pressure gradient is in the middle and bottom of this set of sandstones, and the formation pore pressure gradient gradually decreases from 1.52 g/cm^3 to 1.37 g/cm^3 at the middle completion depth of 4044 m. From 4044 m to 4180 m, the formation pressure returned to normal.

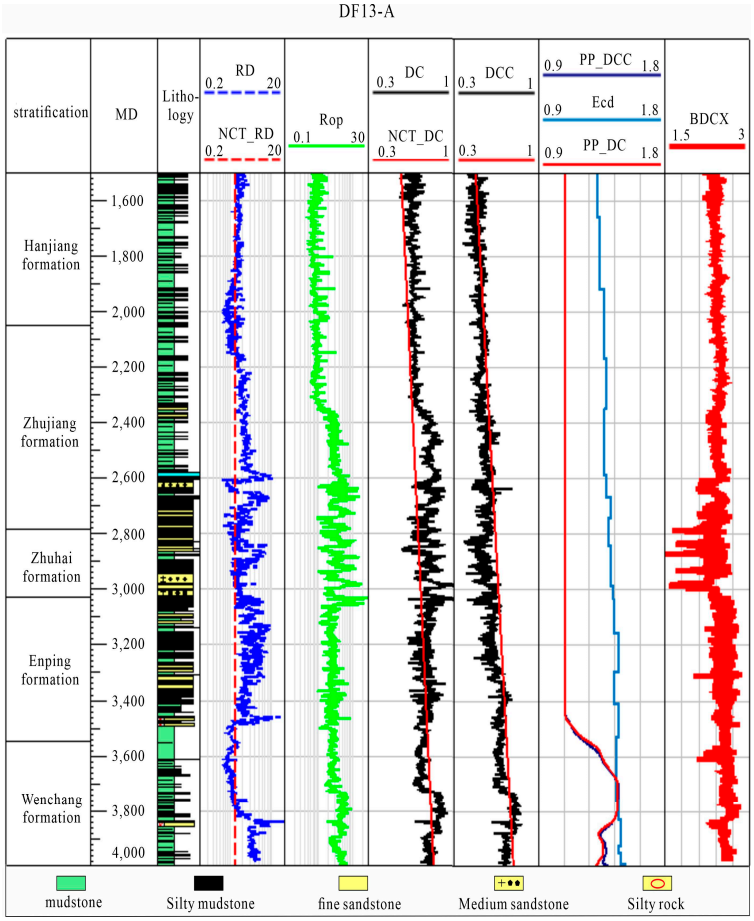

Figure 5. Formation pore pressure analysis diagram of well DF13-A.

2.2.1. Correlation Analysis

Feature selection plays an extremely important role in the process of machine learning and is an important link in the process of data preprocessing. Under the condition of limited samples, it is inappropriate to design classifiers with a large number of features from both the cost and the performance of the classifier. Feature selection can not only remove redundant and useless features, greatly reduce the dimension of input features, avoid dimension disasters and accelerate the training speed of the model, but also effectively reduce overfitting, improve the generalization ability of the model and make the model more explanatory [8,49–52]. The selection methods mainly include filtering method, wrapping method and embedding method. Based on time and economic cost, Pearson coefficient in filtering method is used to select features.

Pearson correlation coefficient method is a commonly used feature analysis method. The principle of this method is to calculate the covariance between two variables by dividing their standard deviation product, obtaining a value ranging from −1 to 1 calculating the correlation coefficient between each feature and the output value, reflecting the degree of linear correlation between two variables. A value of −1 means a perfect negative correlation, +1 means a perfect positive correlation and 0 means no linear correlation. Pearson correlation coefficient is expressed as

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{7}$$

where $\rho_{X,Y}$ is the Pearson correlation coefficient of X and Y; $cov(X,Y)$ is the covariance of X and Y; $\sigma_X \sigma_Y$ is the standard deviation of X and Y.

As shown in Figure 6, a total of 14 input parameters were selected by calculating the Pearson correlation coefficient between drilling and logging parameters and formation pore pressure, and considering the relationship between formation pore pressure parameters calculated by traditional geology. Combined with p-value significance verification, the characteristic p-value less than 0.05 indicates a significant correlation. Combined with Pearson coefficient correlation analysis and p-value verification, parameters such as torque, resistivity, pump pressure and temperature are divided into weakly correlated parameters, and the remaining 10 parameters are relatively strongly correlated parameters. In order to analyze the influence of weakly correlated parameters on the model monitoring results, a neural network model was established for non-weakly correlated parameters and all parameters, respectively.

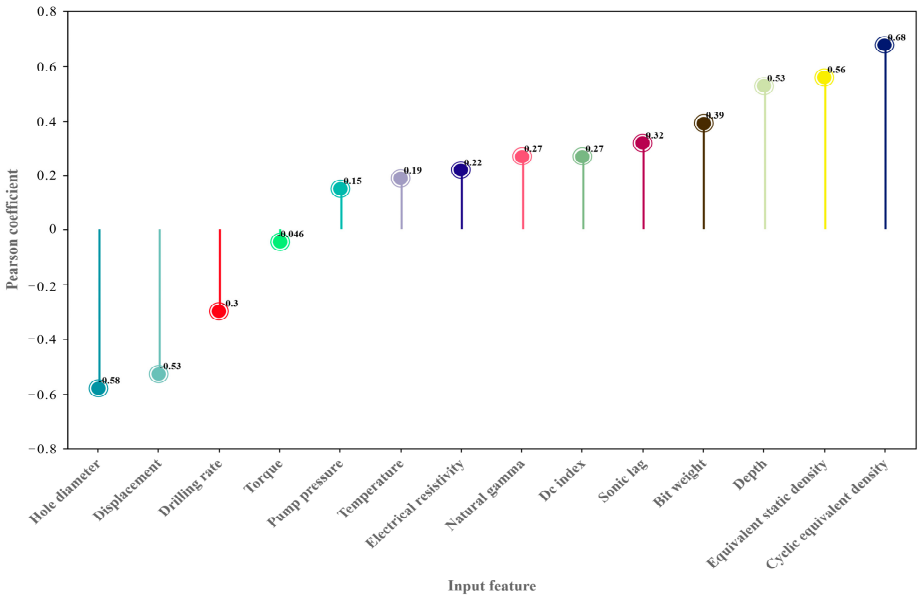

Figure 6. Pearson correlation coefficient.

2.2.2. Data Standardization Processing

Data standardization is one of the important steps of data preprocessing. The data generated in the real environment are incomplete and have different dirty data, which cannot be directly used for modeling or data analysis. In order to improve the quality of the data, it is necessary to standardize the data. Due to the large difference in the value interval of each feature, if the original index value is directly used for analysis, the role of the index with higher value in comprehensive analysis will be highlighted, and the role of the index with lower value level will be weakened. In order to remove the unit limitation of data, they are converted into dimensionless pure values, so that data of different magnitude, different units or different ranges can be converted into unified standard values for comparative analysis and weighting, which can greatly improve the accuracy of the classifier and the robustness of the model [31]. Commonly used data standardizations are Min-Max standardization, Z-Score standardization, decimal scaling standardization, mean normalization method, vector normalization and exponential conversion. When sorting the data, outliers have been removed; there is no extreme maximum and minimum value, and the data are relatively stable. Min-Max standardization is a linear change in the original data, which can better represent the characteristics of the original data, so Min-Max standardization is adopted. The original data are linearly

transformed by Min-Max normalization, and the values are mapped between [0, 1], and the data distribution remains unchanged.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{8}$$

where, x' represents the result after the standardization of variable Min-Max; x is the original data value; $\min(x)$ is the minimum value in the original data; $\max(x)$ is the maximum value in the original data.

2.3. Establishment and Optimization of the Model

2.3.1. Model Correlation Parameter

The main optimization parameters of BP neural network include the number of neural network layers, learning rate, number of neurons, activation function, number of training iterations and batch size. BP neural networks usually include one input layer, one or more hidden layers and one output layer. The number of hidden layers can affect the complexity and learning ability of the network. Generally speaking, increasing the number of hidden layers can make the network more complex and improve its ability to fit nonlinear functions. The learning rate is used to adjust the updating amplitude of the network weight. If the learning rate is too high, the network may not converge; if the learning rate is too low, more training times are needed to achieve the ideal accuracy. The number of neurons in the hidden layer is also an important parameter in the BP neural network: too many neurons will make the network easy to overfit, and too few neurons may lead to an unsatisfactory learning effect of the network and fail to reach the expected goal. The activation function is used to convert the input of the neuron into the output, and the choice of different activation functions also affects the learning ability of the BP neural network. The number of iterations refers to the number of updates of network weights in the training process. Increasing the number of iterations can improve the accuracy of the network, but too many iterations will increase the training time and cause waste of resources. Batch size is a balance parameter between computing efficiency and memory capacity. In random gradient descent, the number of gradients is used; that is, batches of data samples are used each time to train and update weight parameters. If the batch size is too small, it will cause underfitting. When the batch is too large, the processing speed is accelerated, but the demand for computer hardware equipment is also increased [19,20,41,49].

The main parameters optimized by genetic algorithm are population size, mutation probability, crossover probability and evolutionary algebra. The population size is the number of individuals (random solutions) at the beginning of the algorithm. If the population size is too small, it may cause inbreeding and produce inferior genes. Even if the mutation operator with greater probability is adopted, the possibility of generating competitive higher-order patterns is still small, and it will prevent the correct propagation of effective patterns in small populations. The population evolution cannot produce the expected number according to the model theorem; too large population size leads to difficult convergence of results, waste of resources and decline in robustness. The mutation probability can increase the diversity of the population and prevent the algorithm from falling into the local optimal solution. If the mutation probability is too small, the diversity of the population is too small, which easily leads to the rapid loss of effective genes and is not easy to repair. The probability of variation is too large, and although the genetic diversity is increased, the probability of higher-order patterns being destroyed is also greater. The crossover probability determines the generation mode of new individuals. If the crossover probability is too large, the existing favorable model will be destroyed and the randomness will increase. If the crossover probability is too small, the population cannot be effectively renewed. The number of evolutionary rounds affects the search depth and the quality of the algorithm. If the number of evolutionary rounds is too small, the population is immature, which leads to poor convergence effect of the algorithm. If the number of evolutionary

rounds is too large, the algorithm may have already reached the ideal effect, and continuing to evolve will only increase the time cost and waste resources.

2.3.2. GA-BP Network Implementation Process

The pore pressure monitoring model was established using the data of single well DF13-A, and the migration ability of adjacent well DF13-B was tested. In order to compare the results before and after genetic algorithm optimization, BP neural network and GA-BP neural network models are used to establish formation pore pressure monitoring models, respectively. The flow chart of optimizing BP neural network by genetic algorithm is shown in Figure 7. The main steps are as follows:

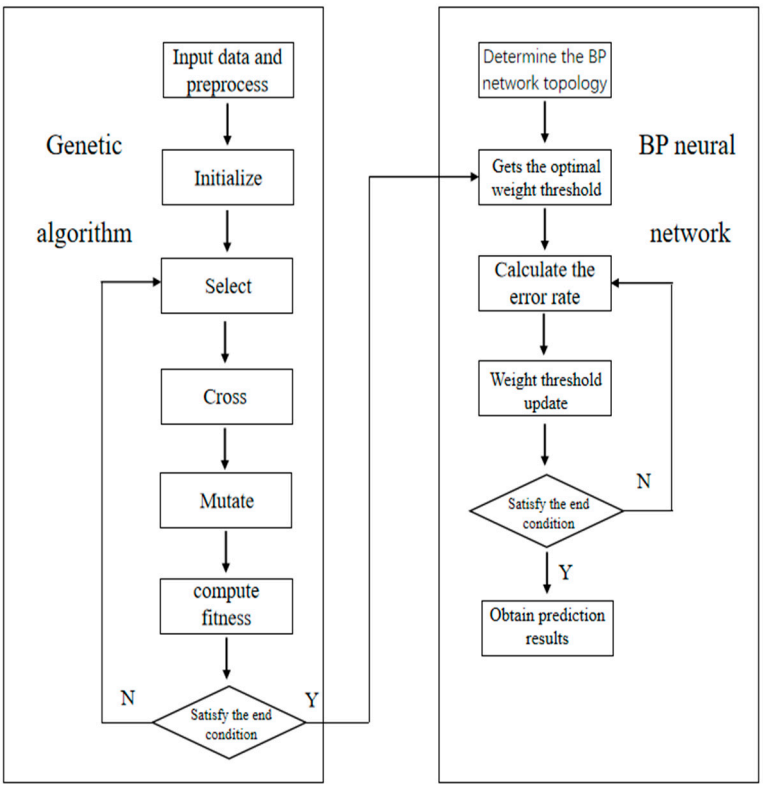

Figure 7. GA-BP neural network flow chart.

Import the sorted training set and test set, and conduct data preprocessing on them, including outlier processing and Min-Max data standardization processing. Min-Max standardization formulas are as follows, so that the data can meet the training requirements;

Randomly generate a set of populations with m individuals, each of which contains connection weights and biases;

Set the parameters of genetic algorithm, including population size, crossover rate, mutation rate and evolutionary algebra, to initialize the population and carry out selection, crossover and mutation operations;

The fitness of each individual is evaluated according to the fitness function value, and the output Error value of the neural network is calculated. The fitness function is the reciprocal of MSE (Mean Squared Error), as shown in the formula: the higher the fitness, the individual is better and the probability of selection is greater; otherwise, the probability of selection is smaller;

$$f = \frac{1}{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{9}$$

where Y_i represents the true value, $\hat{Y}_i$ represents the simulation value calculated using the genetic algorithm.

The optimal weight and bias obtained by genetic algorithm are used to initialize the BP neural network model to avoid falling into the local optimal solution;

Input the training sample, calculate the output value through the network, reverse propagation of the output error, constantly adjust the network connection weight coefficient and threshold and finally make the square error of the neural network minimum meet the expected requirements;

Output simulation monitoring results.

2.3.3. Optimization of Model

Two monitoring models were established with 14 types of full parameters as input features, and the optimal parameters of the two network models were obtained through experiments, as shown in Table 1. The optimal parameter combination of the BP neural network model is as follows: the number of neural network layers is 3, the learning rate is 0.01, the number of neurons is 8, the activation function is Relu function, the number of iterations is 500 and the batch size is 256. The optimal parameter combination of GA-BP neural network model is 3 layers and the learning rate is 0.01. The number of neurons is 10, the activation function is Sigmoid function, the number of iterations is 300, the batch size is 256, the population size is 100, the mutation probability is 0.01, the crossover probability is 0.5 and the evolutionary algebra is 100 generations. The formation pore pressure monitoring model is established with full parameters, and the optimal parameters of the two models are selected through experiments. Well DF13-A is used as the training set, and well DF13-B is used as the test set to verify the monitoring model. The comparison of formation pore pressure results is shown in Figure 8.

Table 1. Parameter optimization results of 14 features input.

Model	Parameter	Value	Optimal Result
BP neural network	Number of floors	3, 4, 5	4
	Learning rate	0.01, 0.1	0.01
	Number of neurons	5, 8, 10, 12	8
	Activation function	Relu, Sigmoid, Tanh	Relu
	Number of iterations	300, 500	300
	Lot size	64, 128, 256	256
GA-BP neural network	Number of floors	3, 4, 5	3
	Learning rate	0.01, 0.1	0.01
	Number of neurons	5, 8, 10, 12	10
	Activation function	Relu, Sigmoid, Tanh	Sigmoid
	Number of iterations	200, 300	200
	Lot size	64, 128, 256	256
	Population size	20–100	100
	Variation probability	0.001, 0.01, 0.1	0.01
	Crossover probability	0.4, 0.5, 0.6	0.5
	Evolutionary algebra	100–500	100

After eliminating four drilling and logging parameters, including torque, resistivity, pump pressure and temperature, two neural network models are established based on 10 non-weakly correlated drilling and logging parameter characteristics of well DF13-A. The optimal selection results of each parameter in the model are shown in Table 2. The optimal parameter combination of the BP neural network model is as follows: the number of neural network layers is 3, the learning rate is 0.01, the number of neurons is 9, the activation function is Relu function, the number of iterations is 150 and the batch size is 256. The optimal parameter combination of GA-BP neural network model is 3 layers and the learning rate is 0.01. The number of neurons was 8, the activation function was Sigmoid function, the number of iterations was 300, the batch size was 256, the population size was 100, the mutation probability was 0.01, the crossover probability was 0.7 and the evolutionary algebra was 150 generations. Non-weakly correlated drilling and logging

parameters were used to establish formation pore pressure monitoring models, and the optimal parameters of the two models were selected through experiments. Well DF13-A was used as the training set and well DF13-B was used as the test set to verify the monitoring model. The comparison of formation pore pressure results is shown in Figure 9.

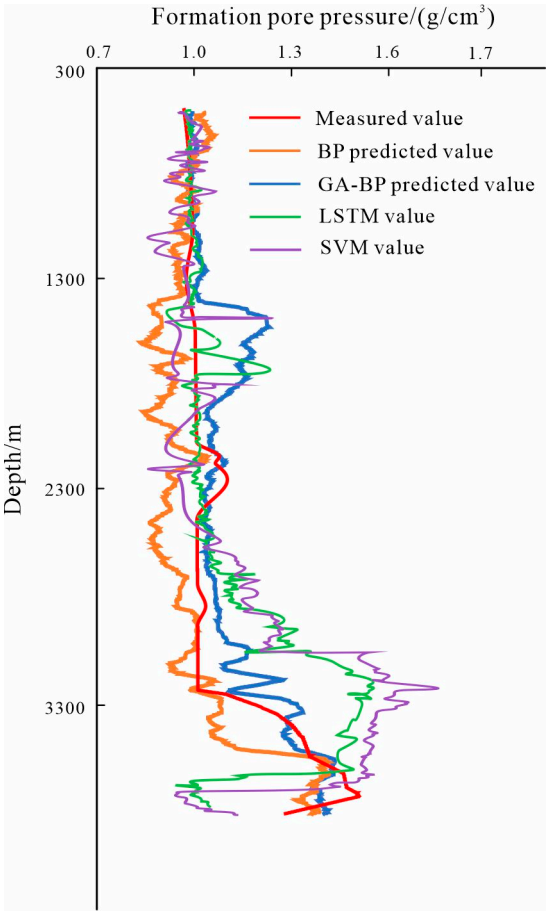

Figure 8. Comparison of formation pore pressure results in well DF13-B with input of 14 features.

Table 2. Parameter optimization results of 10 features input.

Model	Parameter	Value	Optimal Result
BP neural network	Number of floors	2, 3, 4	3
	Learning rate	0.01, 0.1	0.01
	Number of neurons	5, 8, 9, 10	9
	Activation function	Relu, Sigmoid, Tanh	Relu
	Number of iterations	300, 500	500
	Lot size	64, 128, 256	256
GA-BP neural network	Number of floors	2, 3, 4	3
	Learning rate	0.01, 0.1	0.01
	Number of neurons	5, 8, 10, 12	8
	Activation function	Relu, Sigmoid, Tanh	Sigmoid
	Number of iterations	200, 300	200
	Lot size	64, 128, 256	256
	Population size	20–150	100
	Variation probability	0.001, 0.01, 0.1	0.01
	Crossover probability	0.4, 0.5, 0.6	0.7
	Evolutionary algebra	100–500	150

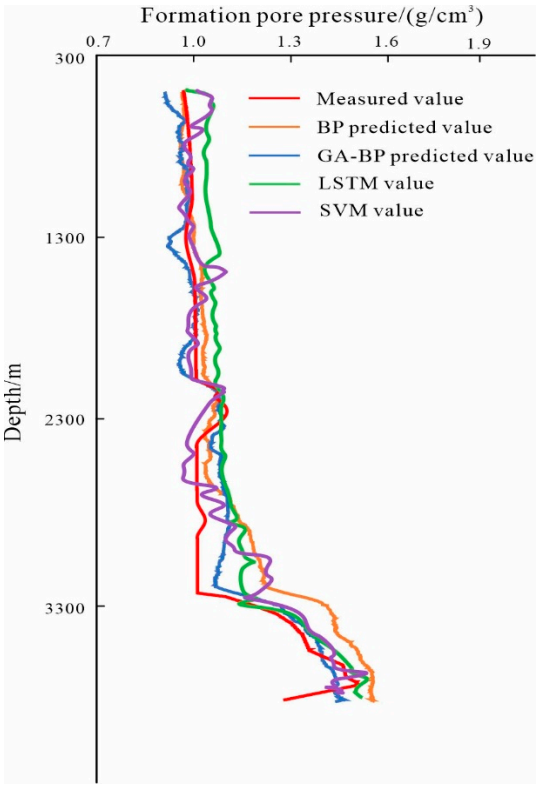

Figure 9. Comparison of formation pore pressure results in well DF13-B with input of 10 features.

3. Results: The Phenomenon Is Analyzed and Discussed

According to the monitoring results of an adjacent well model, under the conditions of input of 14 kinds of drilling and logging parameters, the test set evaluation results are as shown in Tables 3 and 4. The accuracy of the BP neural network DF13-B well monitoring model is 86.42%, the average absolute percentage error is 13.58%, the mean square error is 0.02 g/cm^3 and the average absolute error is 0.14 g/cm^3. The accuracy of the GA-BP neural network DF13-B well monitoring model is 90.68%, the average absolute percentage error is 9.32%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.09 g/cm^3. The accuracy of the LSTM monitoring model is 87.25%, the average absolute percentage error is 12.75%, the mean square error is 0.02 g/cm^3 and the average absolute error is 0.11 g/cm^3. The accuracy of the SVM monitoring model is 88.36%, the average absolute percentage error is 11.64%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.12 g/cm^3. The monitoring accuracy of the two models is above 85%; both can be used to guide in-situ formation pore pressure monitoring. The monitoring accuracy of the GA-BP neural network model is significantly higher than other models, and the monitoring accuracy reaches 90.68%. After removing the weak correlation parameters and inputting only 10 drilling and logging parameters, the evaluation results of the test set are shown in Tables 5 and 6.

Table 3. Simulation results of two models with 14 features input (partial depth).

Depth (m)	Pore Pressure Equivalent Density/(g/cm^3)	BP Neural Network Monitoring Value/(g/cm^3)	Accuracy/%	GA-BP Neural Network Monitoring Value/(g/cm^3)	Accuracy
625	0.98	0.90	91.84	0.95	96.94
1574	1.01	0.87	86.14	1.18	83.17
2873	1.02	0.88	86.27	1.06	96.08
3710	1.47	1.36	92.52	1.35	91.84

Table 4. Comparison of model evaluation indexes when 14 features were input.

Evaluation Index	BP Neural Network	GA-BP Neural Network	LSTM	SVM
Accuracy (%)	86.42	90.68	87.25	88.36
Mean absolute percentage error (%)	13.58	9.32	12.75	11.64
Mean square error	0.02	0.01	0.02	0.01
Mean absolute error	0.14	0.09	0.11	0.12

Table 5. Simulation results of two models with 10 features input (partial depth).

Depth (m)	Pore Pressure Equivalent Density/(g/cm^3)	BP Neural Network Monitoring Value/(g/cm^3)	Accuracy	GA-BP Neural Network Monitoring Value/(g/cm^3)	Accuracy
625	0.98	0.97	98.98	0.97	98.98
1574	1.01	1.04	97.03	1.02	99.01
2873	1.02	1.14	88.24	1.11	91.18
3710	1.47	1.55	94.56	1.44	97.96

Table 6. Comparison of model evaluation indexes when 10 features were input.

Evaluation Index	BP Neural Network	GA-BP Neural Network	LSTM	SVM
Accuracy (%)	91.25	92.89	89.75	91.48
Mean absolute percentage error (%)	8.75	5.69	10.25	8.52
Mean square error	0.01	0.01	0.01	0.01
Mean absolute error	0.09	0.08	0.09	0.09

The accuracy of the BP neural network DF13-B well monitoring model is 91.25%, the average absolute percentage error is 8.75%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.09 g/cm^3. The accuracy of the GA-BP neural network DF13-B well monitoring model is 92.89%, the average absolute percentage error is 5.69%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.08 g/cm^3. The accuracy of the LSTM monitoring model is 89.75%, the average absolute percentage error is 10.25%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.09 g/cm^3. The accuracy of the SVM monitoring model is 91.48%, the average absolute percentage error is 8.52%, the mean square error is 0.01 g/cm^3 and the average absolute error is 0.09 g/cm^3. For GA-BP compared with BP neural network, the accuracy of the neural network is increased by 1.06 percentage points. As can be seen from Figure 10, the GA-BP neural network model is also superior to the BP neural network model in other evaluation indicators.

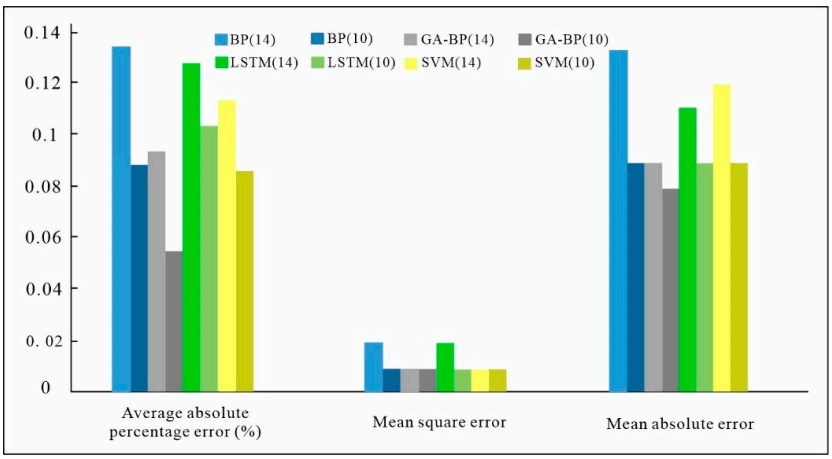

Figure 10. Comparison of input evaluation indexes with different features of the four models.

Whether the input is 10 parameters or 14 features, the monitoring effect of the GA-BP neural network model is better than that of the BP neural network model, indicating that the performance of BP neural network depends largely on the initial weight setting. The genetic algorithm provides a better starting point for BP neural network by optimizing the initial weight, thus improving the learning efficiency and the final monitoring accuracy. The genetic algorithm and BP neural network are based on the research results in biology, in line with the survival of the fittest law of nature. BP neural network uses the gradient descent method to converge: the stability and accuracy are greatly affected by the initial value, and may fall into the local optimal solution. The genetic algorithm is a global heuristic search algorithm, and the introduction of a genetic algorithm to optimize BP neural network can effectively avoid this problem. Combining the advantages of the two, the genetic algorithm is used to determine the optimal initial weight and threshold for BP neural network, and then BP neural network is used to find the optimal solution, and finally the simulation monitoring results are obtained. This method significantly reduces the production cost, improves the monitoring accuracy and efficiency and provides a strong technical support for the dynamic management of oil and gas reservoirs.

After the weak correlation parameters were removed and 10 medium and strong correlation parameters were input, it was found that the average absolute percentage error, mean square error and average absolute error of the four models decreased (Tables 4 and 6), and the monitoring accuracy of BP neural network increased from 86.42% to 91.25%—an increase of 4.83 percentage points. GA-BP neural network monitoring accuracy increased from 90.68 to 92.89%—an increase of 2.21 percentage points. When the input parameters reduce the weakly correlated parameters, the simulation monitoring effect of both models is improved, and the monitoring accuracy of BP neural network is improved greatly, while the accuracy of GA-BP is improved slightly. The author believes that the monitoring accuracy of GA-BP neural network is originally high under the condition of 14 parameters input, but the scope of improvement is limited, resulting in a non-obvious accuracy improvement. However, under the input conditions of 14 parameters, the monitoring accuracy of BP neural network is significantly lower than that of the optimized BP neural network. When the weak correlation parameters are reduced, the accuracy is improved significantly. The reduction in input features leads to the improvement of accuracy, which is also in line with the law of natural operation. When some organs of an organism are not suitable for the environment, the role of these organs will gradually weaken or even disappear with evolution. Feature selection for the model is just like organs corresponding to biological individuals; not all features are helpful for monitoring tasks. Removing some irrelevant or redundant features can reduce the complexity of the model, reduce the risk of overfitting and improve the accuracy and generalization ability of the model.

The shallow pressure of well DF13-B is relatively normal, and it enters the formation of the overpressure section after 3300 m, with the highest formation pressure coefficient of 1.5. In the actual drilling process, it is found that the causes of overpressure are complicated. In the process of 3400–3600 m depth, traditional methods such as the Eaton method are used to calculate the acoustic velocity data, with serious distortion and the result deviation is large. However, the artificial intelligence calculation method is not affected by the causes of overpressure and the properties of strata, and the results are better. The current formation pressure monitoring technology generally adopts the empirical method and the classical formula method, which are mainly based on the sedimentary theory of geology and rock mechanics and other disciplines. In some mature exploration blocks, the formation pressure indicator parameters such as resistivity, sonic time difference and seismic zone velocity are given higher computational weight and importance, and the results can better reflect the actual formation pressure. But this is all based on a lot of drilling data and experience. However, for some new exploration areas or non-sedimentary rock strata, due to the influence of many parameters, the traditional calculation methods may face the selection error of "human subjectivity" [23,26–28]. In this case, a biological genetic algorithm and BP neural network can quickly select the middle weight parameters from

many relevant parameters, eliminating the interference and influence of non-relevant or weakly relevant parameters. At the same time, avoiding the trouble of selecting multiple calculation methods, the results can often achieve better results through multiple artificial intelligence method iterations, which is of great significance for petroleum exploration and development [5].

4. Conclusions and Suggestion

(1) In summary, the GA-BP neural network model has the best performance compared with other machine learning models in formation pressure monitoring. Aiming at the advantages and disadvantages of the traditional BP model in the monitoring model, the genetic algorithm is used to optimize the BP neural network to seek the global optimal solution. The results show that the initial weight value has a great impact on the model performance, and the genetic algorithm can provide high-quality initial weight setting for the BP neural network and effectively improve the model monitoring accuracy.

(2) Comparing the calculation results of 10 input parameters and 14 input parameters, it is found that feature engineering is very important for model performance. Too many noise features will increase the complexity of the model, and removing irrelevant or redundant features will help capture the general law of the data and improve the generalization ability of the model.

(3) Compared with traditional formation pressure monitoring methods, the use of artificial intelligence technology reduces the complex calculation of relevant parameters, does not require empirical parameters and is not affected by the causes of overpressure and formation properties. The application of BP neural network and GA-BP neural network in Yinggehai Basin shows that the formation pressure monitoring accuracy is above 85%, the GA-BP neural network model is better than other monitoring models and the monitoring accuracy is 92.89%, which can effectively guide the drilling operation in this area.

(4) Experiments show that the GA-BP neural network formation pressure monitoring model has a high accuracy, which is helpful to reduce the workload of staff and economic expenses, and can effectively guide the drilling operation in this work area, and provide theoretical basis for actual formation pressure monitoring. The disadvantage is that the amount of data is not enough, but when there is a rich amount of data, it can be applied to other blocks for verification.

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References

1. Ren, Z.; Cui, J.; Qi, K.; Yang, G.; Chen, Z.; Yang, P.; Wang, K. Control effects of temperature and thermal evolution history of deep and ultra-deep layers on hydrocarbon phase state and hydrocarbon generation history. *Nat. Gas Ind.* **2020**, *40*, 22–30. (In Chinese) [CrossRef]

2. Sheng, Y.N.; Li, W.; Guan, Z.C.; Jiang, J.; Lan, K.; Kong, H. Pore pressure prediction in front of drill bit based on grey prediction theory. *Pet. Explor. Prod. Technol.* **2020**, *10*, 2439–2446. [CrossRef]
3. Shi, S.; Liu, J.; Hu, H.; Zhou, H. A research on a GA-BP neural network based model for predicting patterns of oil-water two-phase flow in horizontal wells. *Geoenergy Sci. Eng.* **2023**, *230*, 212151. [CrossRef]
4. Sun, H.; Xia, C.; Li, Y.; Yu, Y.; Yang, Z.; Xu, L. Formation pressure prediction in carbonate reservoirs based on machine learning. *China Offshore Oil Gas* **2024**, *36*, 129–140. (In Chinese)
5. Wan, C.; Xie, R. Genetic Algorithm Optimized BP Neural Network for High-Speed Signal State Judgment. *J. North Univ. China (Nat. Sci. Ed.)* **2024**, *45*, 695–705. (In Chinese)
6. Wang, F. Application of formation pressure monitoring technology while drilling in drilling engineering. *Pet. Chem. Equip.* **2022**, *25*, 122–124.
7. Liu, Y.; Peng, Z.; Liu, Z.H.; Wu, L.; Wu, Y.; Guo, J. Formation Pressure Prediction in Oil Wells Based on CNN-BiGRU-MLP Fusion Network. *Drill. Prod. Technol.* **2023**, *46*, 21–28. (In Chinese)
8. Zhang, Q.; Dong, W. Overpressure system in petroliferous basins in China. *Acta Pet. Sin.* **2000**, *2000*, 1–11+127.
9. Hosseini, E.; Gholami, R.; Hajivand, F. Geostatistical modeling and spatial distribution analysis of porosity and permeability in the Shurijeh-B reservoir of Khangiran gas field in Iran. *Pet. Explor. Prod. Technol.* **2019**, *9*, 1051–1073. [CrossRef]
10. Hu, L.; Deng, J.; Zhu, H.; Lin, H.; Chen, Z.; Deng, F.; Yan, C. A new pore pressure prediction method-back propagation artificial neural network. *Electron. J. Geotech. Eng.* **2013**, *18*, 4093–4107.
11. Huang, H.; Li, J.; Zhang, G.; Yang, H.; Gao, R.; Wentuo, L.I.; Zhang, W. Method for predicting pore pressure of whole well interval in slope zone in Yinggehai Basin. *Oil Drill. Prod. Technol.* **2022**, *44*, 401–407. (In Chinese) [CrossRef]
12. Zhong, L.; Zhenxiang, Z.; Jin, Y.; Yi, H.; Yanjun, L.; Wentuo, L.; Jiang, W. Research and Application of Formation Pressure Monitoring While Drilling in Deepwater with High Temperature and High Pressure. *Earth Sci.* **2019**, *44*, 2597–2602. (In Chinese) [CrossRef]
13. Liu, Y.; Deng, J.; Cui, G.; He, P.; Yu, Z. Precise detection technology of formation pressure while drilling in BZ19-6 structure of Bozhong sag. *Oil Drill. Prod. Technol.* **2018**, *40*, 125–128. (In Chinese) [CrossRef]
14. Liu, J.; He, X.; Huang, H.; Yang, J.; Dai, J.; Shi, X.; Xue, F.; Rabczuk, T. Predicting gas flow rate in fractured shale reservoirs using discrete fracture model and GA-BP neural network method. *Eng. Anal. Bound. Elem.* **2024**, *159*, 315–330. [CrossRef]
15. Zhang, J.; Yin, S. Real-time pore pressure detection: Indicators and improved methods. *Geofluids* **2017**, *2017*, 3179617. [CrossRef]
16. Zhang, J.; Hou, X.; Liu, S.; Chen, L.; Wang, Y. New data-driven method for in situ coalbed methane content evolution: A BP neural network prediction model optimized by grey relation theory and particle swarm. *Energy Fuels* **2023**, *37*, 10344–10354. [CrossRef]
17. Zhang, T.; Shuai, J.; Shuai, Y.; Hua, L.; Xu, K.; Xie, D.; Mei, Y. Efficient prediction method of triple failure pressure for corroded pipelines under complex loads based on a backpropagation neural network. *Reliab. Eng. Syst. Saf.* **2023**, *231*, 108990. [CrossRef]
18. Zhao, X.; Chen, X.; Lan, Z.; Wang, X.; Yao, G. Pore pressure prediction assisted by machine learning models combined with interpretations: A case study of an HTHP gas field, Yinggehai Basin. *Geoenergy Sci. Eng.* **2023**, *229*, 212114. [CrossRef]
19. Zhou, D.; Li, C.; Du, J.; Wang, X.; Zhu, Y.; Chang, X.; Li, J. Research on Formation Pressure Monitoring and Prediction technology while drilling. *Drill. Prod. Technol.* **2011**, *34*. 27–28+40+6–7 (In Chinese)
20. Zhu, Z.; Liu, Z.; Song, X.; Zhu, S.; Zhou, M.; Li, G.; Duan, S.; Ma, B.; Ye, S.; Zhang, R. A physics-constrained data-driven workflow for predicting bottom hole pressure using a hybrid model of artificial neural network and particle swarm optimization. *Geoenergy Sci. Eng.* **2023**, *224*, 211625. [CrossRef]
21. Bahmaei, Z.; Hosseini, E. Pore pressure prediction using seismic velocity modeling: Case study, Sefid-Zakhor gas field in Southern Iran. *Pet. Explor. Prod. Technol.* **2020**, *10*, 1051–1062. [CrossRef]
22. Baouche, R.; Sen, S.; Sadaoui, M.; Boutaleb, K.; Ganguli, S.S. Characterization of pore pressure, fracture pressure, shear failure and its implications for drilling, wellbore stability and completion design–a case study from the Takouazet field, Illizi Basin, Algeria. *Mar. Pet. Geol.* **2020**, *120*, 104510. [CrossRef]
23. Chen, W.; Li, Y.; Liu, Z.; Zhang, C.; Zhao, Y.; Yan, X. Prediction model for bearing surface friction coefficient in bolted joints based on GA-BP neural network and experimental data. *Tribol. Int.* **2024**, *201*, 110217. [CrossRef]
24. Li, P.; Yu, C.; Wang, J.; Yang, H.; Jia, P.; Li, D.; Feng, Y. Intelligent Prediction of Pore Pressure Using Real-time Drilling Parameters. *China Pet. Mach.* **2019**, *52*, 1–8. (In Chinese)
25. Ahmed, S.A.; Mahmoud, A.A.; Elkatatny, S.; Mahmoud, M.; Abdulraheem, A. Prediction of pore and fracture pressures using support vector machine. In Proceedings of the International Petroleum Technology Conference, IPTC, Beijing, China, 26–28 March 2019; p. D021S018R002. [CrossRef]
26. Chen, R.; Song, J.; Xu, M.; Wang, X.; Yin, Z.; Liu, T.; Luo, N. Prediction of the corrosion depth of oil well cement corroded by carbon dioxide using GA-BP neural network. *Constr. Build. Mater.* **2023**, *394*, 132127. [CrossRef]
27. Delavar, M.R.; Ramezanzadeh, A. Pore pressure prediction by empirical and machine learning methods using conventional and drilling logs in carbonate rocks. *Rock Mech. Rock Eng.* **2023**, *56*, 535–564. [CrossRef]
28. Shaoqun, D.O.; Lianbo, Z.E.; Xiangyi, D.U.; Mingyang, B.A.; Wenya, L.Y.; Chunqiu, J.I.; Jingru, H.A. An intelligent prediction method of fractures in tight carbonate reservoirs. *Pet. Explor. Dev.* **2022**, *49*, 1179–1189. (In Chinese)
29. Gao, Y.; Zhang, R. Analysis of House Price Prediction Based on Genetic Algorithm and BP Neural Network. *Comput. Eng.* **2014**, *40*, 187–191. (In Chinese)

30. Jianchun, G.U.; Wenxi, R.E.; Fanhui, Z.E.; Yang, L.U.; Yulin, L.I.; Xiaoyang, D.U. Unconventional Oil and Gas Well Fracturing Parameter Intelligent Optimization: Research Progress and Future Development Prospects. *Pet. Drill. Tech.* **2023**, *51*, 1–7+179. (In Chinese)
31. Faqiang, L.U.O.; Jingtao, L.I.U.; Xiuping, C.H.E.N.; Shaoan, L.I.; Xuezhe, Y.A.O.; Dong, C.H.E.N. Intelligent method for predicting formation pore pressure in No. 5 fault zone in Shunbei oilfield based on BP and LSTM neural network. *Oil Drill. Prod. Technol.* **2022**, *44*, 506–514. (In Chinese) [CrossRef]
32. Liu, L.; Shen, G.; Wang, Z.; Yang, H.; Han, H.; Cheng, Y. Abnormal formation velocities and applications to pore pressure prediction. *J. Appl. Geophys.* **2018**, *153*, 1–6. [CrossRef]
33. Liu, Y.; He, Z.; He, S.; Zhang, D.; Li, T.; Wang, X. A new quantitative model and application for overpressure prediction in carbonate formation. *Pet. Sci. Eng.* **2021**, *198*, 108145. [CrossRef]
34. Ma, X.; Liu, M.; Hou, Z.; Guo, M.; Yu, Z.; Tong, X.; Liu, H.; Guo, F. Optimization of process parameters for *Trifolium pratense* L. seed granulation coating using GA-BP neural network. *Heliyon* **2024**, *10*, e38003. [CrossRef]
35. Nwonodi, R.I.; Dosunmu, A. Analysis of a porosity-based pore pressure model derived from the effective vertical stress. *Pet. Sci. Eng.* **2021**, *204*, 108727. [CrossRef]
36. Liang, X.U.; Shaohua, G.U.; Jiabao, W.A.; Yuetian, L.I.; Bin, T.U. Production dynamic prediction of gas well based on particle swarm optimization and long short-term memory. *Oil Drill. Prod. Technol.* **2021**, *43*, 525–531. (In Chinese) [CrossRef]
37. Yang, J.; Gao, D. Technologies for inspecting and predicting formation pressure while drilling. *J. Univ. Pet. (Nat. Sci. Ed.)* **1999**, *1999*, 48–50+7. (In Chinese)
38. Yang, Q.; Huang, H.; Luo, M.; Wu, Y.; Li, W.; Xiao, P. Monitoring Method for Formation Pore Pressure While Drilling Based on Rate of Penetration. *Oil Drill. Prod. Technol.* **2023**, *45*, 548–554. (In Chinese) [CrossRef]
39. He, S.; An, W.; Wang, S.; Luo, F.; Zuo, X.; Chen, M.; Zhou, Z. Pore pressure prediction while drilling based on grey theory. *Drill. Prod. Technol.* **2008**, *31*, 18–19+150. (In Chinese)
40. Wu, C.; Chen, M.; Jin, Y. Model Used f or Pre-drilling Prediction of Formation Pore Pressure Based on Seismic Attribute. *J. Oil Gas Technol. (J. Jianghan Pet. Inst.)* **2006**, *28*, 66–69+165. (In Chinese)
41. Ziegler, F.E.; Jones, J.F. Predrill pore-pressure prediction and pore pressure and fluid loss monitoring during drilling: A case study for a deepwater subsalt Gulf of Mexico well and discussion on fracture gradient, fluid losses, and wellbore breathing. *Interpretation* **2014**, *2*, SB45–SB55. [CrossRef]
42. Rashidi, M.; Asadi, A. An artificial intelligence approach in estimation of formation pore pressure by critical drilling data. In Proceedings of the ARMA US Rock Mechanics/Geomechanics Symposium, ARMA-2018-1098, Seattle, WA, USA, 17–20 June 2018.
43. Abdulmalek, A.S.; Elkatatny, S.; Abdulraheem, A.; Mahmoud, M.; Abdulwahab, Z.A.; Mohamed, I.M. Pore Pressure Prediction While Drilling Using Fuzzy Logic. SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition. *Soc. Pet. Eng.* **2018**, SPE-194851-MS. [CrossRef]
44. Hutomo, P.S.; Rosid, M.S.; Haidar, M.W. Pore pressure prediction using eaton and neural network method in carbonate field "X" based on seismic data. IOP conference series: Materials science and engineering. *IOP Publ.* **2019**, *546*, 032017. [CrossRef]
45. Hadi, F.; Eckert, A.; Almahdawi, F. Real-time pore pressure prediction in depleted reservoirs using regression analysis and artificial neural networks. In Proceedings of the SPE Middle East Oil and Gas Show and Conference, Manama, Brahrain, 18–21 March 2019; p. SPE-194851-MS. [CrossRef]
46. Li, C.; Xu, Y.; Liu, H.; Liu, H.; Gai, S. Research on Formation pore pressure Prediction based on Grey Theory. *China Pet. Chem. Stand. Qual.* **2022**, *42*, 119–120. (In Chinese)
47. Xia, G.; Liu, X.; He, Y.; Zhong, J.; Jin, Z.; Zhu, F.; Zhang, Z.; Liu, W. GA-BP Neural Networks for Optimal Design of Multistage Depressed Collector for 340-GHz Traveling Wave Tubes. *IEEE Trans. Electron Devices* **2024**, *71*, 1–8. [CrossRef]
48. Hao, F.; Zou, H.; Huang, B. Natural gas generation model and reservoir forming fluid response in Yinggehai Basin. *Sci. China (Ser. D Earth Sci.)* **2002**, *32*, 889–895. (In Chinese)
49. Yang, T.; Guo, Y. Application of Time Series Prediction based on the Genetic Algoriths and BP Neural Network. *Comput. Knowl. Technol.* **2015**, *11*, 160–162. (In Chinese) [CrossRef]
50. Zhi, Y.; Honghai, F.A.; Jun, C. Investigation and application of a discrimination method for abnormal high formation pressure forming mechanism. *J. China Univ. Pet. (Nat. Sci. Ed.)* **2012**, *36*, 102–107. (In Chinese)
51. Ye, Z.; Fan, H.; Ji, R.; Li, C.; Cai, J. Investigation and Application of Pore Pressure Monitoring Method Based on LWD Data. *Pet. Drill. Technol.* **2014**, *42*, 41–45. (In Chinese)
52. Zhang, Z.; Yang, J.; Sun, T.; Yan, L.; Zhang, Y.; Ou, Q.; Li, W. A method for predicting the pressure of unloading-type abnormal pressure formation. *Oil Drill. Prod. Technol.* **2020**, *42*, 553–557. (In Chinese) [CrossRef]

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