

# *Reservoir Sensitivity Forecasting Method Based on Hybrid Improved CNN and BiGRU Unit*

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**Abstract:** Reservoir sensitivity evaluation is used to evaluate the degree of damage to various operating fluids and production parameters of the reservoir in the production process of oil and gas wells. The neural network is widely used in reservoir sensitivity forecasting because of its nonlinear solid fitting and generalisation ability. Although many neural network models have been applied to reservoir sensitivity forecasting, there is still room for improvement in the accuracy of the models. Therefore, to improve the prediction accuracy of the forecasting model, this study will introduce a novel convolutional neural network model (WOA-CNN-BiGRU) integrated with a whale optimisation algorithm and bidirectional gated recurrent unit to forecast the sensitivity of low permeability reservoir. The experiment used relevant datasets to test the model strictly, and the previous BPNN, Elman, and RBF models were compared. The result shows that the percentage error of the WOA-CNN-BiGRU model was as low as 2.6%, which was lower than other forecasting models. The results show that the accuracy of the WOA-CNN-BiGRU model is not only higher than that of engineering measurement methods but also higher than that of other existing models, which has a good potential for application in the industry of reservoir sensitivity forecasting.

## 1. Introduction

Reservoir damage refers to the adverse changes in reservoir physical properties, permeability, or fluid properties caused by various factors in the oil and gas reservoir, thus affecting the production effect of oil and gas. These factors can be divided into geological, engineering, and chemical factors [1,2].

Forecasting reservoir sensitivity is very important for oil and gas exploration and development. With a deeper understanding of reservoir characteristics and properties, oil and gas companies can develop and manage resources more effectively, improve production, reduce development risk, and improve economic efficiency.

The current method of forecasting in engineering is to obtain the different sensitivity of the reservoir through many indoor core experiments. By conducting a series of experiments on cores collected from underground reservoirs, the damage degree of the reservoir was measured by

computed tomography (CT) scanning, scanning electron microscopy (SEM), and X-ray diffraction (XRD) [3-5]. Although these experiments provide valuable information in oil and gas exploration and development, collecting and obtaining representative core samples can be expensive and challenging. The experiments with indoor core require a certain amount of time and cost. It requires a lot of resources, from collecting samples to conducting a series of experiments and analyzing experimental data.

With the development of computer science, more and more techniques have been applied to evaluate reservoir sensitivity [6,7]. Nowadays, neural networks have been widely used to evaluate reservoir sensitivity. It simplifies the traditional core experiment process. Fen Chen [8] used the backpropagation (BP) neural network to predict the water sensitivity of reservoirs in the Ordos Basin and achieved good prediction results. However, the BP network is sensitive to initial weights and easily falls into local optimality. Fen Chen, Qiaozhi Wang [9,10] proposed the mathematical prediction model of the RBF neural network, which has a simple structure, strong nonlinear approximation ability, and less than 10% error between the predicted value and the actual value of the model. However, the model has poor interpretation and cannot work when the data is insufficient. Wang [11] proposed a multi-population genetic algorithm to optimize the Elman neural network model, which achieved good results in predicting the reservoir's acid, alkali, and salt sensitivity. However, due to the specific dependence of the genetic algorithm on the initial population, there is still room for improvement in the prediction accuracy. The average error of the model is around 0.025. In addition, Wang [12] established a stress sensitivity prediction model based on the XGBoost method. The correlation between the measured value and the predicted value is 0.87. The model is convenient, practical, and accurate. The above research shows that establishing a neural network model has become a meaningful way to measure the degree of reservoir damage. The current prediction model also has a lot of room for optimization.

Therefore, from the progress of artificial intelligence in the field of sensitivity prediction, most existing models are machine learning models. Compared with the current popular deep learning networks, such models' accuracy still has room for improvement. Therefore, to focus on solving the problem of dependence of initial weights existing in current neural networks and easily falling into local optimality and to improve the convergence speed and prediction accuracy of neural networks, a reservoir sensitivity forecasting model based on a convolutional neural network optimized by whale algorithm and bidirectional gated recurrent units is proposed. This study applies a deep learning network to reservoir sensitivity prediction. In addition, with the addition of an intelligent optimization algorithm and attention mechanism, the model's prediction accuracy is improved. It has a good potential for application in reservoir sensitivity prediction.

## 2. Related Work

### 2.1. The Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) is proposed by Seyedali Mirjalili in 2016, was inspired by the collaborative behaviour of whales during foraging and the strategy of chasing prey [13]. The Whale Optimization Algorithm performs well in solving various optimisation problems, particularly regarding global search, lack of gradient information, and adaptability. It is widely used in optics [14], medicine [15], electrical engineering [16], and other fields. It also has a good application in the hyperparameter optimisation of neural networks [17].

The purpose of whale hunting behaviour is to catch prey, and when a whale finds the prey first, other whales will swim to the whale that found the prey. There are three main types of whales feeding behaviour:

- 1) Encircling prey: Suppose that in the D-dimensional space, the position of the current best

individual whale  $X^*$  is  $(X_1^*, X_2^*, \dots, X_d^*)$ , and the position of individual whale  $X^j$  is  $(X_1^j, X_2^j, \dots, X_d^j)$ . Then the formula for calculating the next position  $X^{j+1}$  of individual whale  $X^j$  under the influence of the best individual whale is

$$\begin{aligned} X_k^{j+1} &= X_k^* - A_1 \cdot D_k \\ D_k &= |C_1 \cdot X_k^* - X_k^j| \\ C_1 &= 2r_2 \\ A_1 &= 2a \cdot r_1 - a \end{aligned} \quad (1)$$

Where  $X_k^{j+1}$  represents the  $k$ 'th dimension of the space coordinate  $X^{j+1}$ . As the number of iterations increases,  $a$  linearly decreases by 2 to 0, and  $r_1$  and  $r_2$  are random numbers between 0 and 1.

2) Bubble net attack: Bubble net attack is a unique feeding behaviour of humpback whales. Two mathematical models are designed to simulate this behaviour.  $X^*$  represents the current position  $(X_1^*, X_2^*, \dots, X_d^*)$  of the individual whale. The individual whale's position is  $(X_1^j, X_2^j, \dots, X_d^j)$ .

Encircling prey: This predation behaviour is roughly the same as the mathematical model for encircling prey. This study just changes the range of  $A_1$  from  $[-a, a]$  to  $[-1, 1]$ .

Spiral position update: The whale individual moves in a spiral towards the best whale individual, and its position update formula is

$$\begin{aligned} X_k^{j+1} &= X_k^* + D_k \cdot e^{bl} \cdot \cos(2\pi l) \\ D_k &= |X_k^* - X_k^j| \end{aligned} \quad (2)$$

$b$  is the logarithmic spiral morphology constant and  $l$  is a random number between -1 and 1.

When whales hunt, they randomly choose between these two attack types. All of them pick one of them with a 50% chance. The mathematical model is

$$X_k^{j+1} = \begin{cases} X_k^* - A_1 \cdot D_k & p < 0.5 \\ X_k^* + D_k \cdot e^{bl} \cdot \cos(2\pi l) & p \geq 0.5 \end{cases} \quad (3)$$

3) Search for prey: In the mathematical model of encircling prey, the value range of  $A_1$  is  $[-1, 1]$ .

To improve the global search ability of the whale group, when the value range of  $A_1$  is not  $[-1, 1]$ , the individual whale may not move to the optimal individual, but to a random whale individual. Suppose that in  $d$ -dimensional space, the position of a random individual  $X^{rand}$  in the current whale population is  $(X_1^{rand}, X_2^{rand}, \dots, X_d^{rand})$ , and the position of the current whale individual  $X^j$  is  $(X_1^j, X_2^j, \dots, X_d^j)$ . Its location is

$$\begin{aligned}
X_k^{j+1} &= X_k^{rand} - A_1 \cdot D_k \\
D_k &= \left| C_1 \cdot X_k^{rand} - X_k^j \right| \\
C_1 &= 2r_2 \\
A_1 &= 2a \cdot r_1 - a
\end{aligned} \tag{4}$$

## 2.2. Convolutional Neural Networks

Convolutional neural networks are deep learning neural networks primarily used to process and analyse data with a grid structure. Their design principles have led to significant achievements in image classification, object detection, and image generation tasks. It also has a good application in analysing data sets [18-20]. Recurrent neural networks are a class of neural networks used to process sequential data. It is widely used to predict sequence data [21,22]. Unlike traditional feedforward neural networks, RNNs have a cyclic structure that allows information to be passed around the network. This structure enables RNN to consider contextual information and time dependencies when processing sequence data. This study will use those neural network structures to train the datasets.

## 3. The Proposed Model

This section of this study will cover the entire model-building process. It includes the construction of a convolutional neural network and the optimisation of the whale algorithm.

### 3.1. The CNN-BiGRU Model

#### 3.1.1. Bidirectional Gated Recurrent Unit

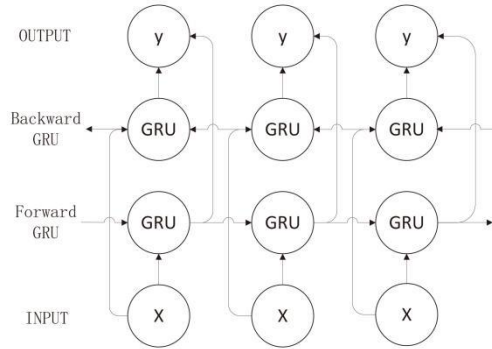


Figure 1: The bidirectional gated recurrent network.

BiGRU is a variant of recurrent neural networks that combines a bidirectional processing approach with a gated recurrent unit structure. As shown in Fig.1, a bidirectional GRU introduces two independent sequences of hidden states, one from front to back and the other from back to front. This allows the network to capture both past and future information simultaneously, which is very helpful for understanding context. BiGRU is widely used to predict sequence data [23,24]. Log data is a time series collected by logging instruments along the depth of the reservoir. Therefore, the information of a certain depth can be obtained from the log characterisation of the current depth and the log characterisation of the adjacent depth at that location. Aiming at the sequence characteristics of logging characterisation, this study will combine the BiGRU unit with the model to extract the sequence characteristics of logging data.

### 3.1.2. Squeeze-and-Excitation Attention

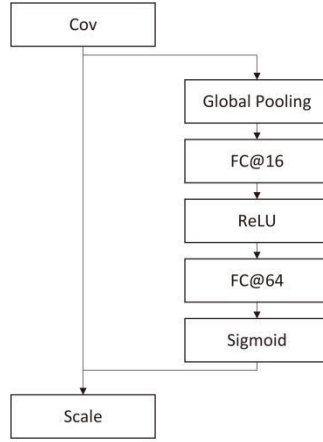


Figure 2: The Squeeze-and-Excitation attention.

Jie Hu originally proposed SE mechanism [25] aimed to improve convolutional neural networks' representational power. By learning to adjust the weight of each feature graph, the network pays more attention to the important features. This mechanism is widely used in neural networks [26,27]. As shown in Fig.2, this study will use this attention mechanism before the input of the BiGRU unit to improve the network's attention to important features and the efficiency of the model's information extraction. The feature map of the Conv layer is used as the network input. The second step is Squeeze. The feature map is globally average pooled to obtain a value within the channel's global receptive field. The third step of excitation is to learn the weight coefficient of each channel through the full connection layer so that the model can better distinguish the characteristics of each channel. In the fourth step, the Scale will generate the weight vector in the third step and assign the weight to the feature map to get the desired feature map.

### 3.1.3. The CNN-BiGRU model

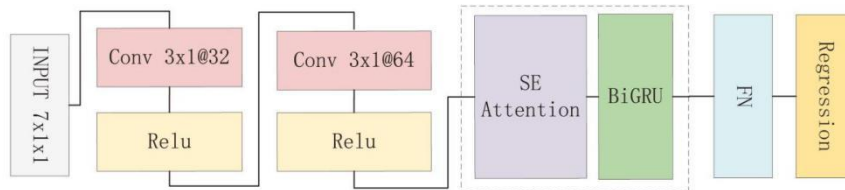


Figure 3: The CNN-BiGRU model.

Combining the BiGRU unit and the attention mechanism, this study will build the CNN-BiGRU model. As shown in Fig.3, the input layer of the model in the experiment is a  $7 \times 1 \times 1$  data, which contains seven input features. The data is then fed into two convolutional layers to extract local features of the data, allowing the network to learn a more abstract and high-level representation. The first convolution layer uses 32 convolution kernels of  $3 \times 1$  and uses the same padding strategy with stride size 1. Therefore, this layer will output 32  $7 \times 1$  feature maps. The data then enters the activation layer using the Relu function. The second convolution layer uses 64 convolution kernels of size  $3 \times 1$ . After two convolutions, the neural network generates 64  $3 \times 1$  feature maps. Then, the

data passes through the layer of attention mechanism and BiGRU. Finally, the data will pass through all the connection and regression layers and output the final result.

### 3.2. The WOA-CNN-BiGRU Model

First, the number of hidden layer nodes, initial learning rate, and regularisation parameters significantly impact model training results when setting hyperparameters for the CNN-BiGRU model. However, it is impossible to know under what value the model has the best training effect. Therefore, the whale optimisation algorithm will be used here to find the optimal number of hidden layer nodes, initial learning rate, and regularisation parameters. Then, the model starts training to get the final training effect.

However, when solving complex optimisation problems, the whale optimisation algorithm is sensitive to the initial value, making it challenging to jump out of the local optimal value. It has a slow convergence speed, which limits the algorithm's optimisation performance. Therefore, many researchers optimised the whale optimisation algorithm and achieved a good application in the industry. Therefore, in this experiment, based on the original whale optimisation algorithm, various strategies will be used to optimise the whale optimisation algorithm.

When the whale population is initialised, the position of the individual whales is entirely random. This may result in uneven distribution of the population in the solution space. As a result, the algorithm converges slowly and even falls into local optimal solutions. Therefore, a chaotic mapping method is used to initialise the whale population. The role of chaotic mapping in population initialisation is mainly to help the population explore more widely in the search space by introducing randomness and nonlinearity. It increases the diversity of the algorithm and the global search capability. The randomness generated by chaotic mapping can help the population avoid falling into the local optimal solution while maintaining a certain continuity, which is conducive to effective iterative optimisation in the search process. Chaotic maps are often introduced in computer engineering to generate random numbers and are used to replace the pseudo-random numbers distributed in Gaussian distributions [28-30]. The Circle chaotic mapping formula is

$$X_{i+1} = \text{mod} \left( X_i + 0.2 - \left( \frac{0.5}{2\pi} \right) \sin(2\pi X_i), 1 \right) \quad (5)$$

According to Eq. (1),  $a$  is a weight factor that balances global and local search ability. In the original paper,  $a$  decreases linearly from 2 to 1 with the number of iterations. This monotone-decreasing method will have a robust global search ability at the beginning and a robust local search ability at the end. This can cause the final fitness to fall into a local optimal value. So, let's change the value of  $a$ .

$$a = a_{\min} + (a_{\max} - a_{\min}) \cdot \sin\left(\frac{t \cdot \pi}{t_{\max}}\right) \quad (6)$$

$a_{\min}$  and  $a_{\max}$  are the minimum and maximum values of weights. Respectively, the value is 0 and 2.  $t_{\max}$  represents the maximum number of iterations, and  $t$  is the current number.

This study introduces the sine factors in the updated method of  $a$ . At the beginning of the algorithm, the value of  $a$  is low, and it pays more attention to local search. In continuous iteration, the value of  $a$  gradually increases, and the local search turns into a global search. Finally,  $a$  gradually decreases, and the optimal solution is found in the local region.

According to Eq. (3), whales will choose the encircling prey or spiral swimming with the

probability of  $p = 50\%$ . The two methods tend to be local search and global search, respectively. Therefore, to balance global and local search capabilities,  $P$  is optimised.

$$P = \begin{cases} 0.6 & t < 0.5 * t_{\max} \\ 0.4 & t \geq 0.5 * t_{\max} \end{cases} \quad (7)$$

After modifying  $p$ , the algorithm pays more attention to global search in the early stage and local search in the later stage.

The detailed steps of the WOA-CNN-BiGRU model are as follows (see Fig.4):

Build the CNN-BiGRU model (Fig.3) and initialize the network weights and hyperparameters.

1) Input the training datasets processed into the whale optimization algorithm to calculate the fitness later.

2) The parameters to be optimized (initial learning rate, number of hidden layer nodes, regularization parameters) are taken as inputs to the whale optimization algorithm. The dimension of the search space is 3. Then, the population initialization is carried out, and in the initialization process, the circle chaotic map (Eq. (5)) is used to optimize the population distribution.

3) The whale optimization algorithm starts to iterate. Each whale's fitness is calculated through the neural network's training, and the fitness is sorted to obtain the best and worst individuals in the current iteration population.

4) Then the position of the whale is updated, and the position of each whale is updated using the algorithm with the position update formula having the adaptive weight (Eq. (6)) and the adaptive  $P$  probability formula (Eq. (7)) to obtain the population distribution of the next iteration. If the maximum number of iterations is not reached, continue to start from (4); otherwise, enter (6).

5) The parameters corresponding to the optimal whale individual of the last iteration population are the optimal initial hyperparameters of the neural network.

6) The optimal hyperparameters are used in the neural network for training. We use the mean squared error as an objective function. When the requirements of the train are met, the training of the neural network will be stopped.

7) Use the test datasets to evaluate the current neural network and get the prediction.

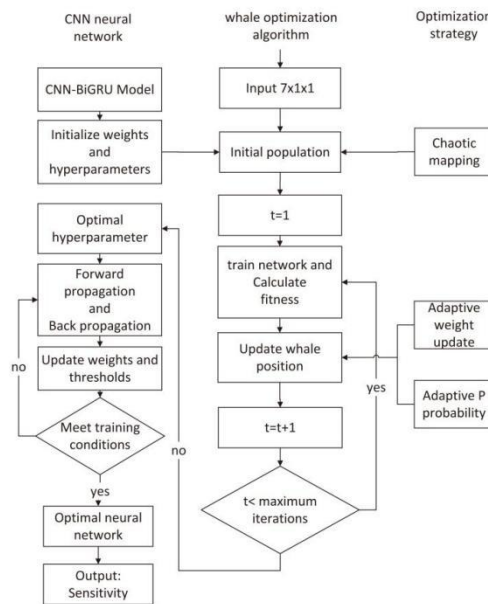


Figure 4: The flow chart of WOA-CNN-BiGRU.

## 4. Experiments and Discussions

### 4.1. Construction of Datasets

In this study, the well logging characteristics of wells in a western oilfield in China were selected as the experimental data set, and the well depths were 1820.5 m~1903.1 m. The sampling interval is 0.1 m.

The original dataset contained 826 pieces of data. Nine input characteristics are permeability, porosity, loss rate, illite-montmorillonite mixed layer, chlorite, illite, clay, carbonate, and iron. The target feature is acid sensitivity.

#### 4.1.1. Preprocessing of DataSets

The original dataset contains nine input features and one output feature. This study will use the Spearman correlation coefficient to calculate the correlation of each input feature with the target feature. The result show that the correlation coefficients between permeability, chlorite, and acid sensitivity are very low. These two parameters are, therefore, removed from the dataset.

To eliminate the influence of possible outliers on the model's training, the box diagram is used to find the outliers of the dataset. Some data exceeds the upper limit ( $Q3+1.5\times IQR$ ). Therefore, this part of the abnormal data is deleted.

This study will adopt the maximum-minimum normalisation to eliminate the scale difference between different features, accelerate the convergence process of the algorithm, and improve the training efficiency.

After data preprocessing, the final dataset input to the model contains seven input features and one output feature. The dataset contains 817 data, of which 681 are used as training sets, and 136 are used as test sets. Table 1 shows some of the data in the dataset.

Table 1: The partial final data set.

depths(m)	poro(%)	lose (%)	ill-mon(%)	illite(%)	clay (%)	carbo (%)	iron (%)	acid
1820.5	0.343	0.093	0.699	0.539	0.456	0.336	0.566	0.590
1823.8	0.671	0.552	0.188	0.161	0.305	0.719	0.719	0.293
1832.9	0.106	0.483	0.985	0.277	0.735	0.531	0.786	0.609
1851.2	0.526	0.397	0.919	0.408	0.622	0.898	0.011	0.384
1855.3	0.430	0.687	0.278	0.292	0.832	0.584	0.487	0.572
1877.5	0.022	0.765	0.418	0.071	0.797	0.377	0.799	0.821
1890.9	0.110	0.534	0.367	0.036	0.129	0.943	0.794	0.232

poro means porosity, lose means loss rate, ill-mon means illite-montmorillonite mixed layer, carbo means carbonate, acid means acid sensitivity

### 4.2. Model Initialization

Six models are established in the whole reservoir sensitivity prediction experiment. The BP model, the Elmann model, the RBF model, the XGBoost model, and the original CNN model were also constructed for comparison and verification to compare the prediction effect of the WOA-CNN-BiGRU model.

#### 4.2.1. The Contrast Model

A three-layer BP neural network with seven input layer nodes, 15 hidden layer nodes and one



output layer node is established through the neural network toolbox. The training times are set to 1000, the learning rate is set to 0.01, the target minimum error is set to 0.0001, and the momentum factor is set to 0.01. The Elman neural network contains seven hidden layers, and the maximum number of iterations of training is 1000. The RBF neural network's radial basis function expansion rate is 35, and the number of hidden layer neurons is 25.

In this experiment, the XGBoost model will be used as the comparison model, in which the initial parameter learning rate is set to 0.1, the maximum depth of the tree is set to 3, the subsample proportion is set to 0.8, and the feature proportion is set to 0.8.

#### 4.2.2. The WOA-CNN-BiGRU Model

As shown above, the experiment will build a CNN-BiGRU model optimised by the whale optimisation algorithm. In the initial parameters of the whale optimisation algorithm, the maximum iteration is set to 8, and the population number is set to 10. The search range for the learning rate is [0.001,0.01], the number of hidden layer nodes is [5,30], and the regularisation coefficient is [0.0001,0.1].

The maximum training time for the initial training parameters of the WOA-CNN-BiGRU model is 600. The whale optimisation algorithm gives the batch size, initial learning rate, and regularisation parameters.

#### 4.3. Performance Comparison

To quantify the accuracy of various models for reservoir sensitivity forecasting, root-mean-square error, mean absolute error and mean absolute percentage error are selected as evaluation indexes.

The BP, Elman, RBF, XGBoost, original CNN, and WOA-CNN-BiGRU models were trained based on the same data set. Through the prediction of the same test set, the evaluation indicators of each model are obtained, as shown in Table 2.

Table 2: Evaluation index of each model

Model	RMSE	MAE	MAP
BP	0.038	0.024	7.140
Elman	0.035	0.024	0.024
RBF	0.025	0.017	5.180
XGBoost	0.028	0.020	5.328
CNN	0.022	0.013	3.881
WOA-CNN-BiGRU	0.018	0.009	2.642

As shown in Table 2, the error of the traditional BP neural network model is relatively large due to its sensitivity to initial weights, with RMSE, MAE, and MAP reaching 0.038, 0.024, and 7.14%. During this experiment, the Elman and RBF models were trained in reservoir sensitivity forecasting. This model has some improvement in prediction accuracy, but the improvement is limited. This study also used the popular XGBoost model in the experiment. XGBoost's performance and flexibility make it one of the most efficient tools for many data scientists and machine learning practitioners. The prediction effect of this model is relatively good, with RMSE, MAE, and MAP reaching 0.028, 0.020, and 5.32%. Moreover, this study also used the original convolutional neural network model to compare the optimised convolutional neural network model. Finally, the research results have demonstrated the superiority of the WOA-CNN-BiGRU model in reservoir sensitivity forecasting. The accuracy of the WOA-CNN-BiGRU model is better than the BP, Elman, RBF, and XGBoost models proposed before. By optimising the WOA and BiGRU unit, the model has higher accuracy than the original convolutional neural network. The RMSE, MAE, and MAP of the WOA-CNN-

BiGRU model are 0.019, 0.012, and 3.590%. Similarly, when analysing the error of the models, as shown in Fig.5, the error of the WOA-CNN-BiGRU model is the smallest, and its error curve is kept near the 0-horizontal line, which is better than the other five models. The results show that our model obtains more competitive results than the other five models.

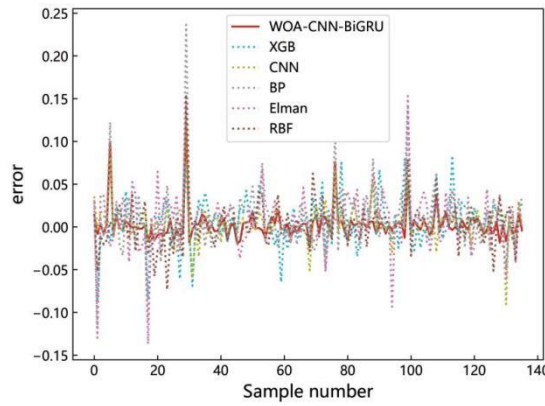


Figure 5: Error of 6 models

The predicted value and actual value of the BP model, Elman model, RBF model, CNN model, XGB model, and WOA-CNN-BiGRU model for acid sensitivity of the reservoir were made into an intersection diagram, as shown in Fig.6. The figure shows that the errors of the BP model are relatively large due to the dependence on initial weights and the problem of local optimality. There are a lot of points that deviate from the  $y=x$  line. The predicted value of the CNN model is in good agreement with the actual value. However, with the WOA and BiGRU units, the predicted value of the WOA-CNN-BiGRU model for acid sensitivity best agrees with the actual value. The model makes finding the global optimal solution easier and reduces the situation of falling into the local optimal. Most points in Fig.6(f) are concentrated on  $y=x$ . As shown in Fig.6, The prediction error of the model is negligible for most data. The prediction error of some data is large for all models. We can see that almost all models have a large error near the point of 0.3. Examining these data individually, they may have abnormal values or noise due to measurement errors.

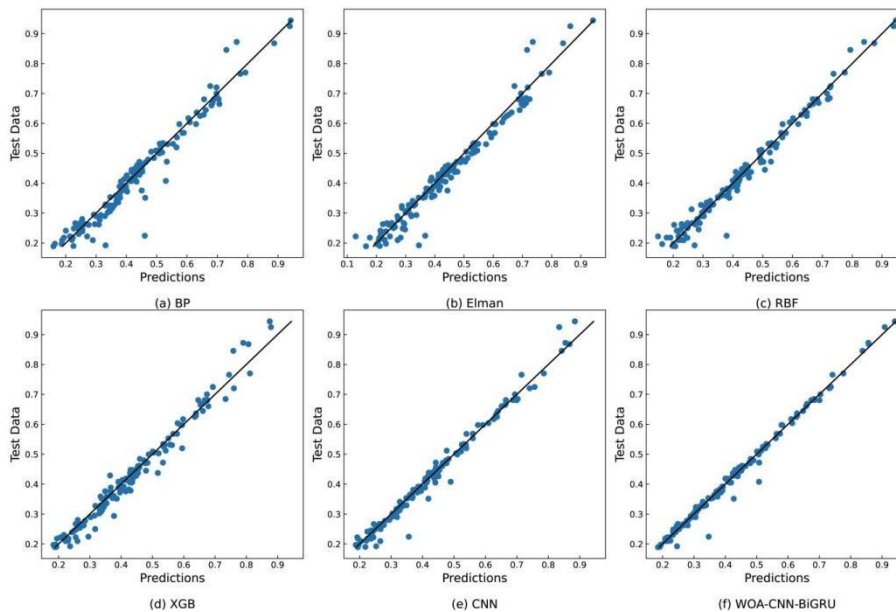


Figure 6: Intersection diagram of the predicted and true values of 6 models

Based on the above analysis of experimental results, the WOA-CNN-BiGRU reservoir sensitivity model proposed in this paper has a specific improvement in accuracy and strong competitiveness compared with the traditional BP neural network model, Elman neural network model, RBF neural network model and machine learning method (XGBoost). The accuracy of the CNN model under optimisation of WOA and BiGRU has been further improved. This model has a specific reference value in reservoir sensitivity forecasting engineering practice.

## 5. Conclusions

Currently, most models used in reservoir sensitivity prediction are machine learning models and some simple neural network models. Some of the existing models depend on the initial weight value, which is easy to fall into the local optimisation problem. Their models' prediction accuracy has room for improvement. To solve these problems and improve the convergence speed and prediction accuracy, we propose a novel deep-learning model based on the hybrid optimisation of CNN and BiGRU units. We integrate the whale optimisation algorithm and BiGRU unit into the convolutional neural network, which improves the prediction accuracy of the neural network model and reduces the risk of falling into the local optimal. Compared with the BP model, the RBF model, and the Elman model used by predecessors, the accuracy of the WOA-CNN-BiGRU model to forecast reservoir sensitivity has been improved to a certain extent.

The WOA-CNN-BiGRU model proposed in this paper can effectively alleviate the problems of time-consuming and high costs in laboratory experiments. This model maintains high accuracy, has strong universality, and can be quickly applied to other reservoirs. The proposed model has specific significance for building other forecasting models in reservoir sensitivity.

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