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Artificial Neural Network-based Evolution Prediction Model of Propped Fracture Conductivity

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Abstract: Propped fracture conductivity (PFC) is an important parameter required for the accu-rate prediction of hydraulic fracture production performance. In this study, a new model for the prediction of PFC was proposed based on a large volume of experimental data on PFC and back propagation (BP) and artificial neural network (ANN) tools. Our results show that the relative average error between the predicted and measured PFC is 14.31%, which indicates that PFC can be predicted. Our research provides new concepts and methods for the prediction of PFC and can serve as a reference for optimizing fracturing design in unconventional reservoirs and improv-ing the efficacy of fracturing.

Keywords: Hydraulic fracturing; Propped fracture; Conductivity; Artificial neural network

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1. Introduction

"Horizontal wells + segmented multi-cluster perforation + high-volume hydraulic fracturing" are the key techniques for the commercial development of unconventional reservoirs [1,2]. Large volumes of slick water and relatively low concentrations of proppant are pumped into the formation to open natural fractures, thus creating a large complex fracture network to produce the maximum possible stimulated reservoir volume (SRV) [3]. In the stimulated fracture network, sand-filled propped fractures near the wellbore are one of the main components of hydraulic fractures, and propped fractures with high conductivity play a critical role in the successful production of unconventional oil and gas [4].

Propped fracture conductivity (PFC) is the product of the propped fracture width and proppant pack porosity, and it is a key indicator for evaluating the efficacy of fracturing [5]. Researchers can usually test fracture conductivity using laboratory experiments by simply changing some easily obtainable parameters (proppant properties, closure stress, etc.) [6–10]. These experimentally measured values of fracture conductivity can be used as estimates for the design of on-site fracture conductivity; however, conducing a large number of repetitive, non-essential conductivity tests is labor-intensive and costly. Therefore, it is important for the study of fracture conductivity and fracture design to effectively predict changes in PFC within a certain range by mathematical or statistical methods [11]. Based on a large number of laboratory experiments and theoretical analyses, a wide range of hydraulic conductivity calculation and prediction models have been derived by scholars. However, the literature has shown that many factors affect fracture conductivity, and these factors are difficult to describe with a simple equation or empirical formula. Thus, empirical models of fracture conductivity based on experimental results were poorly applied for a long time, and prediction results did not correlate with actual (field) or subsurface fracture conductivity values.

Machine learning algorithms are widely used as tools for analyzing and predicting complex parameters in practical engineering, and they have been successfully used to resolve many difficult practical problems in the fields of biology, medicine, economics, and engineering. In the petroleum field, artificial neural network (ANN) models have been used for many years for reservoir description, production prediction, history fitting, production operation optimization, and well design [12–14]. The use of machine learning to analyze nonlinear problems leads to smaller fitting errors and a larger range of applications than traditional methods, which means that machine learning can be used to predict fracture conductivity.

Therefore, an experimental database consisting of data from experiments and Chinese and international literature on PFC was established in the current study to construct a statistical model. The model developed based on this database can be used to predict the conductivity of ceramic proppant fractures with a variety of proppant properties and formation conditions. In addition, the model proposed in this paper is based on experimental conductivity data measured in different laboratories, which may reduce the errors that may occur in individual laboratory tests.

2. Analysis of Factors Influencing PFC

Studies by domestic and international scholars have shown that potentially important factors that may affect PFC include fracture closure pressure, physical proppant properties, and proppant placement concentration in the fracture, as well as factors such as reservoir rock hardness, temperature, fluid properties, fracture surface roughness, bearing time, and fracturing fluid damage.

2.1 Support Agent

It is generally believed that the proppant type, and proppant physical properties, proppant placement in the fracture, and fracture closure stress are the main factors affecting fracture conductivity. Wang et al. [15] and Zhang et al. [16] used an FCES-100 fracture conductivity evaluation system to test the long-term fracture conductivity of different combinations of proppant particle size and optimize the ratio of different particle sizes of proppant for composite fracturing. Their results show that large-sized proppants are preferable when the closure stress is low while slightly smaller-sized proppants are preferable when closure stress is high. Moreover, small proppants have a decisive influence on conductivity throughout the filled fracture under a combination of particle sizes, thereby optimizing the best proppant combination. Jin et al. [17] placed proppants of various particle size at the end, middle, and tail of the conductivity chamber as part of a combination conductivity experiment and compared fracture conductivity under various placement methods (single particle size placement, segmented placement, and mixed particle size placement). The results showed that when the closure stress was low, the combined particle size led to lower conductivity than the single particle size, while when the closure stress was high, the mixed particle size led to higher conductivity than the single particle size. Zhu et al. [18] tested various proppant types, particle sizes, and combinations of conductivity in dense sandstone reservoirs, and their experiments showed that the combination of quartz sand and different sizes of ceramic particles could maintain high fracture conductivity for a long time under high formation pressure.

2.2 Test Media

The single-phase flow of oil, gas, and water is commonly used to determine fracture conductivity; however, the presence of multiple fluids (oil, gas, and water) flowing in the propped fractures of fractured shale oil and gas wells represents a non-Darcy multiphase flow, and the addition of a second or third phase will significantly reduce the original single-phase flow measurement. Milton-Taylor [19] conducted a study on the interaction of gas-water two-phase flow within a fracture, and the results showed that the difference in fracture conductivity reached 1–2 orders of magnitude in the presence of more fluid. Jiang et al. [20] conducted a laboratory-based evaluation of gas-tested short-term conductivity using the proppant conductivity test system of the American Petroleum Institute (API) and compared the results of liquid-tested conductivity. The experimental results show that the gas-tested conductivity was several times higher than the liquid value; therefore, a gas test was used instead of the traditional liquid test for gas reservoir PFC based on the real-life situation of gas reservoir fracturing. Wang et al. [21] used clean water, a 3% potassium chloride solution, and field fracturing flowback fluid to study the effect of proppant embedding on fracture conductivity. The results showed that the reduction of fracture conductivity was significantly increased after soaking in water while the change of conductivity was not significant after soaking in 3% KCl and fracturing flowback fluid.

2.3 Pressure-Bearing Time

As a rule, fractures closed for longer periods of time present greater decreases in fracture conductivity. Cobb [22] pointed out that although short-term laboratory conductivity tests may attempt to accurately simulate the actual formation conditions, they still fail to match the actual conditions. Over time, proppant binding, migration, and clogging will occur and significantly reduce fracture conductivity. Zhang et al. [23,24] conducted a week-long conductivity test on ceramic and quartz sand proppants in 2000 and 2004, respectively, and showed that conductivity decreased significantly within 24 h for both proppants. Moreover, the study obtained a long-term decreasing conductivity curve, which provided a better understanding of long-term conductivity changes in fractures. Wen et al. [25] conducted long-term fracture conductivity experiments on ceramic propped fractures in low-permeability reservoirs in the Shengli oil field in China and investigated the degree to which fracture conductivity is decreased based on closure stress, proppant embedding, and fracturing fluid concentration, and. Yang et al. [26] conducted long-term hydraulic conductivity experiments on volcanic rock samples and found that the proppant was significantly embedded in the volcanic rock samples. Compared with steel plates, the long-term conductivity of the volcanic rock samples did not fully stabilize and showed different trends after 50 h. Liu et al. [27] demonstrated the influence of time on fracture conductivity using split cores and showed that the conductivity decreased faster before 60 min but more slowly after 60 min.

2.4 Other Factors

2.4.1 Temperature

Most laboratory experiments on fracture conductivity were conducted at a room temperature of 25 °C. An increase in temperature would cause fracture conductivity to decrease. The mechanism underlying the influence of temperature on fracture conductivity is very complicated, and the associated changes are not only related to temperature but also to closure pressure and high mineralization formation water.

2.4.2 Fracturing Fluid Damage

Intrusion of fracturing fluid filtrate, incomplete gel breaking of fracturing fluid, and physicochemical changes between the proppant pack and fracture wall are the main reasons why fracture conductivity becomes impaired. Yuan et al. [28] carried out a study on damage to gas-tested conductivity caused by fracturing fluid at different intrusion stages, such as fracturing, flowback, and normal production, based on an experiment in which reservoir rocks were damaged and proppant strength was decreased by fracturing fluid remaining in the formation.

2.4. 3 Ground Stress Fluctuation

Bi et al. [29] selected three cores, namely, conglomerate, sandstone, and coal rock, together with ceramic and quartz sand proppant to study the effect of formation stress fluctuations caused by loading opening and closing of the well via cyclic stress on the conductivity of propped fractures. The experimental results showed that the formation stress fluctuations caused by the opening and closing process had a great effect on conductivity.

Analyses of the factors that influence PFC demonstrated that relevant factors are complex and establishing a mathematical model to calculate and predict conductivity is difficult.

3. Back Propagation (BP) Neural Network-based Conductivity Prediction Model Construction

3.1 Basic Principles of ANNs

ANNs are a class of statistical learning models inspired by central neural networks (in the brain), and they obtain the closest possible result to the desired output value given the input value [30,31]. In general, the architecture of ANNs is composed of an input layer, an output layer, and, most importantly, a hidden layer. A typical ANN structure and its computation process are shown in Figure 1.

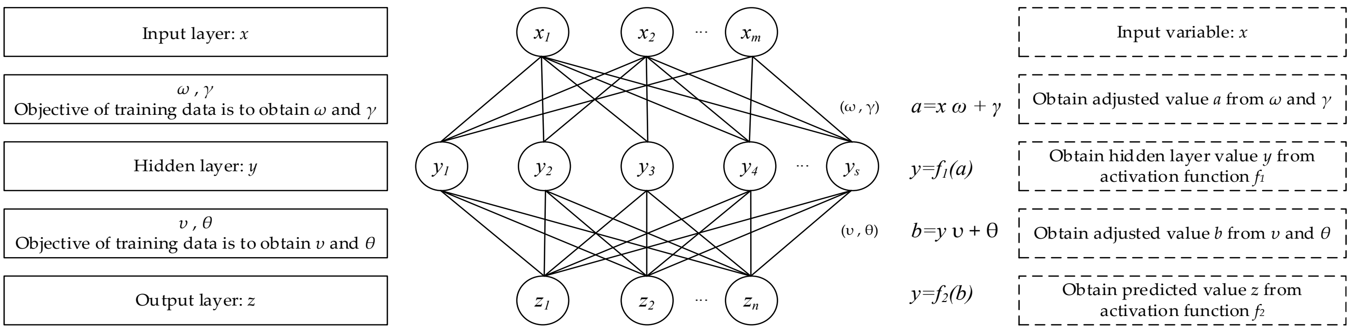

Figure1. Artificial neural network structure.

The characteristics of ANNs are as follows.

1. Structured: ANNs are structured models consisting of several interconnected neurons. The outputs of neurons are connected to the inputs of other neurons according to certain weights by adjusting the interconnections between a large number of internal nodes.

2. Self-adaptation and self-learning capability: ANNs can find the intrinsic connection between input and output values by training

sample data, and this process does not depend on the empirical rules of the problem and has good adaptability.

3. Generalization capability: ANNs can process untrained data and obtain potential association rules for these data. In addition, they can provide accurate predictions in the presence of uncertain data and measurement errors.

4. Nonlinearity: ANNs enable nonlinear mapping between multiple variables and provide an effective tool for dealing with these problems.

The use of ANNs to analyze nonlinear problems leads to smaller fitting errors and a larger range of applicability. These characteristics determine the applicability and superiority of neural networks in the prediction of fracture conductivity. A BP ANN is actually a multilayer feedforward ANN with reverse error propagation. This method was first proposed by Rumelhart and McClelland in 1986, and due to its simple principles, the model is now used in a wide range of applications and fields. The standard BP network is a data-driven nonlinear mapping model that includes two processes: forward propagation and error BP [32]. Forward propagation is a kind of propagation that initially transmits information from the first layer (input layer) to the hidden layer and then to the next layer (output layer). The input value is transmitted from the input layer to the output layer via the hidden layer. If the output does not meet the desired value, then the error is calculated and the input error is back-propagated. The BP of error feeds the error in the output layer by layer to the correction weights and error thresholds of the neurons at each level, thereby obtaining error information and using this information as the basis for the correction weights and error thresholds [33]. The essence of the BP network is an unconstrained optimization forward network based on gradient descent, which uses the gradient search technique to find the minimum value of the error between the actual output value and the desired output value [34].

The basic steps for using a neural network to predict fracture conductivity are to select the input parameters that affect fracture conductivity as well as the experimental parameters and then adjust the weights and biases of the network to minimize the objective function of fracture conductivity. The training process is performed by BP and completed when the closest expected output is obtained. Finally, the untrained data are processed by a trainer generated during the training process to obtain the predicted values of PFC.

3.2 BP Neural Network-based Conductivity Prediction Model Construction

In this paper, an experimental database was established based on PFC experimental data and PFC data reported in Chinese and international literature to construct a statistical PFC model. The model developed based on this database can be used to predict the conductivity of ceramic propped fractures based on the proppant properties and formation conditions. In addition, the model proposed in this paper is based on experimental test data from different laboratories, which may reduce the possible bias in individual laboratory tests. The specific conductivity prediction model building process and test results are described in detail in the next section.

3.1.1 Conductivity Data Collection and Collation

Due to the complexity of potentially important factors affecting PFC, this study focused on developing an empirical model that considers easily accessible experimental parameters, such as proppant size, concentration, closure stress, and roughness. The data were obtained from experimental data of ceramic PFC and collected from literature. A total of 1230 data points were obtained, and 1220 sets of conductivity data were obtained after excluding abnormal data. A database of ceramic PFC was established accordingly. Table 1 shows some of the experimental data. Finally, 1200 sets of data were randomly selected as training data, and the remaining 20 sets of data were used as test data.

Table 1. Experimental data sources from fracture conductivity literature.

Serial number	Author	Title
1	Van (1975) [8]	Criteria For Proppant Placement and Fracture Conductivity
2	McDaniel (1986) [35]	Conductivity Testing of Proppants at High Temperature and Stress
3	Fredd (2000) [36]	Experimental Study of Hydraulic Fracture Conductivity Demonstrates the Benefits of Using Proppants
4	Zhang (2000) [23]	Experimental Study on Short-term Conductivity of Ceramic Proppant for Fracturing
5	Lu and Guo (2008) [7]	Experiments on Proppant Embedding and Damage to Fracture Conductivity
6	Rivers and Hill (2012) [37]	Proppant Fracture Conductivity with High Proppant Loading and High Closure Stress

Serial number	Author	Title
7	Zou (2012) [9]	Evaluation of the Effectiveness of Propped Fractures in Shale Gas Reservoirs
8	Awoleke (2012) [38]	Experimental Investigation of Propped Fracture Conductivity in Tight Gas Reservoirs Using Factorial Design
9	Zhang and Hill (2014) [39]	Laboratory Measurement of Hydraulic-Fracture Conductivities in the Barnett Shale
10	Qu (2014) [40]	Experimental Study on the Factors Influencing the Fracture Conductivity of Fractured Gas Reservoirs
11	Briggs and Hill (2014) [41]	The Relationship Between Rock Properties and Fracture Conductivity in the Fayetteville Shale
12	Li (2015) [42]	New Mathematical Models for Calculating Proppant Embedment and Fracture Conductivity
13	McGinley and Zhu (2015) [43]	The Effects of Fracture Orientation and Elastic Property Anisotropy on Hydraulic Fracture Conductivity in the Marcellus Shale
14	Bi (2016) [44]	Experimental Study on the Influence Capacity of Propped Fractures in Shale Reservoirs
15	Perez and Zhu (2016) [45]	The Effect of Rock Properties on Fracture Conductivity in the Marcellus Shale
16	Chen and Lu (2016) [46]	Experimental Study on the Effectiveness of Using 3D Scanning and 3D Engraving Technology to Accurately Assess Shale Fracture Conductivity

Table2. Selected experiments and collected conductivity data.

No.	Roughness (τ)	Proppant particle size (mm)	Proppant concentration (kg/m^2)	Closed stress (MPa)	Fracture conductivity (μm^2 -cm)
1	1.141	0.329	0.1	34.50	4.50
2	1.143	0.748	0.7	27.60	158.70
3	1.084	0.309	0.3	62.10	2.20
4	1.062	0.236	5.0	55.20	14.28
5	1.021	0.194	2.0	48.30	6.68
6	1.020	0.315	2.0	41.40	103.17
7	1.011	0.358	2.0	13.96	187.00
8	1.027	0.315	2.0	69.00	92.77
9	1.000	0.445	4.0	55.06	106.00
10	1.096	0.299	0.5	34.50	36.83
11	1.061	0.317	5.0	6.90	80.89
12	1.029	0.322	1.0	82.80	5.95
13	1.040	0.126	3.0	27.60	14.58
14	1.024	0.222	0.3	13.80	4.74
15	1.025	0.445	6.0	20.73	256.06
16	1.010	0.315	0.1	49.03	3.60
17	1.018	0.222	0.5	13.80	114.51
18	1.028	0.315	1.0	55.20	8.53
...	...	...	...	...	...
1217	1.028	0.222	0.4	13.80	10.39
1218	1.042	0.315	0.2	48.30	8.85
1219	1.041	0.315	0.5	20.70	22.26
1220	1.018	0.445	8.0	69.00	84.83

3.1.2 BP Neural Network Model Construction

The design framework of the BP neural network prediction model is shown in Figure2.

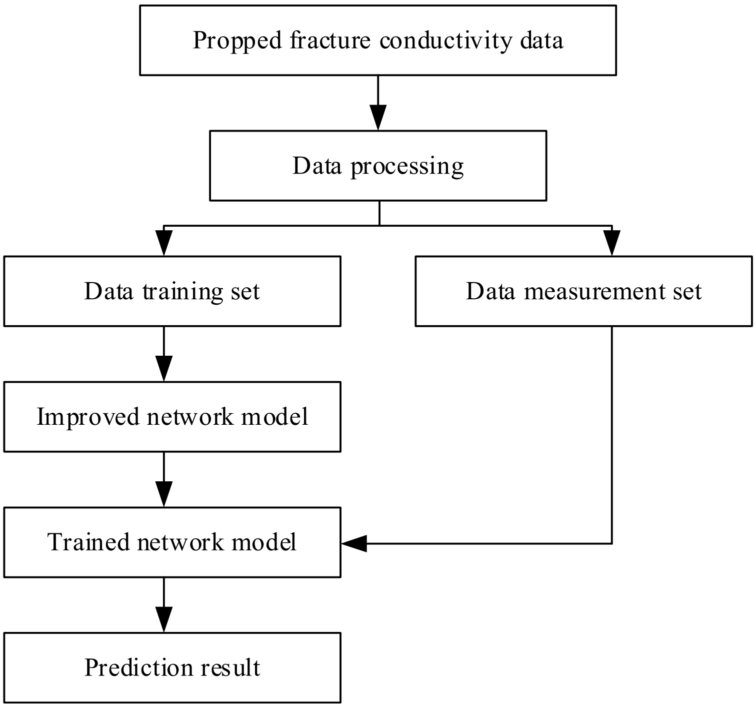

Figure3. BP neural network framework diagram.

The specific process of the model includes the following aspects:

1. Data pre-processing: Due to the considerable number of databases and data sets from the test results of various laboratories, the collected data inevitably contains some erroneous, missing, and abnormal data. Therefore, the collected data needed to undergo cleaning, integration, normalization, transformation, and other operations to obtain accurate fracture conductivity data.

2. Data normalization: Normalization of data is the process of scaling or transforming data features to the same order of magnitude range. This ensures that each data feature fed into the classifier has the same magnitude. The raw conductivity data were normalized to linear variation by min-max normalization, i.e., discrete normalization, with the data transformed to a range of [0,1] using the following transformation function:

$$\bar{x} = \frac{x - min}{max - min} \tag{1}$$

3. Input parameter and output parameter selection: In the output layer, ceramic PFC was used as the target value parameter, and in the input layer, the parameters were the main factors that controlled conductivity, such as proppant particle size, concentration, closure stress, and roughness. In total, 70% of the data were used to develop the model and 30% were used to validate the model.

4. Number of selected hidden layer neurons: The number of neurons in the input layer and the number of neurons in the output layer of the BP ANN that needs to be constructed has been determined, and the remaining, and most important, problem is to determine the number of neurons in the hidden layer. Although increasing the number of hidden layers in the ANN can reduce errors, having more hidden layers not only increases the training time but can also cause model overfitting. For a general BP ANN model, the number of hidden layer neurons is determined by a continuous trial-and-error optimization process, which usually uses a combination of empirical methods and experimental validation. The empirical formulas for determining the number of neurons in the hidden layer are as follows:

$$s = \sqrt{m+n} + a \tag{2}$$

$$s = (2m+1) \pm 3 \tag{3}$$

Where s is the number of neurons in the hidden layer; m is the number of neurons in the input layer; n is the number of neurons in the output layer; and a is the adjustment coefficient with values in a range of [1,10].

In this study, 5 neurons were included in the input layer and 1 neuron was included in the output layer; therefore, the number of hidden neurons ranged from 6 to 12. Table3 shows the root mean square error (RMSE) corresponding to different numbers of hidden neurons, which were input one by one to ensure the training accuracy and lack of overfitting. The results showed that when the number of hidden neurons is 10, the RMSE is the smallest. Therefore, 10 hidden neurons were used for training.

$$RMSE = \sqrt{\sum_{i=1}^{N} \left(y_i - m_i\right)^2} \qquad (4)$$

Table3. Root mean square error calculation results for different numbers of hidden neurons.

Number of hidden layers	6	7	8	9	10	11	12
Root mean square error	45.1054	32.0589	25.2194	18.5823	11.4053	13.7456	21.1819

5. Other model parameters: The initial weights and thresholds of the BP ANN designed in this paper were obtained randomly by the random function to initialize the BP neural network and obtain the initial weights and thresholds. The number of nodes in the input layer, hidden layer, and output layer of the conductivity prediction model was set to 4, 10, and 1, respectively, and the Sigmoid function was used as the BP neural network activation function. The network model was trained according to the Levenberg-Marquardt BP algorithm, and the maximum number of iterations of the prediction model was 1000. The minimum training rate was 1/10, and the error performance target was 1/1000.

6. Model validation: Finally, the BP neural network model of fracture conductivity was created using the newff function, and the neural network model was trained using the train function. The neural network model was simulated and tested by the sim function, and the data from the fracture conductivity test set were imported into the trained prediction model for prediction.

3.3 BP Neural Network Training and Testing

3.3.1 BP Neural Network Model Training Results

During the training process of the neural network model, the prediction results were continuously approximated to the true values by finding the parameters of the model so that the predicted output fit the training results. The training results of the fracture conductivity model are shown in Figure4. As the number of model iterations (epochs) increased, the RMSE of the training curve (Train) and the test curve (Test) decreased. When the number of training epochs was 325, the RMSE of the training set was 11.4053, which was the lowest RMSE, and the neural network prediction model of fracture conductivity had the best fit.

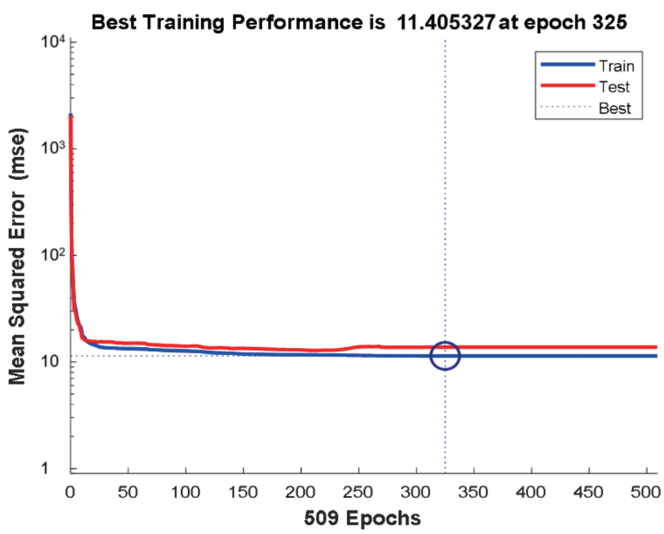

Figure4. Training results of the BP neural network model for fracture conductivity.

By linearly fitting the model-predicted conductivity values to their true values and testing the training results, the fracture conductivity training set regression curve was obtained Figure5). The regression (R) value was used to measure the correlation between the input and target values. When the R value is close to 1, it indicates that the correlation between the input and target values is strong and the prediction accuracy of the model is high. The R value of the fit coefficient obtained by fitting the predicted values of conductivity of the training set to the true values was 0.88156, and its relative error coefficient was 0.11844.

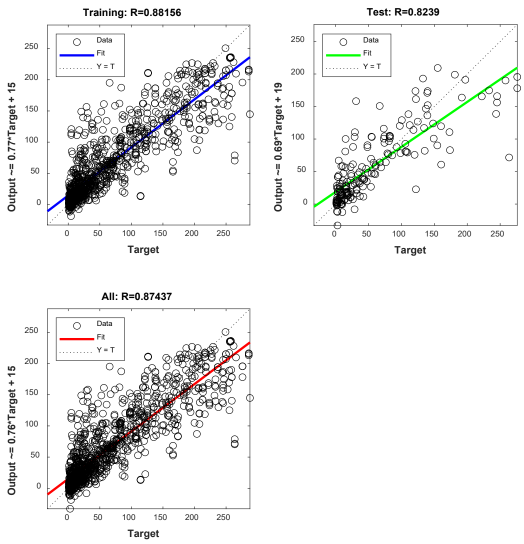

Figure5. Regression parameters of the fracture conductivity training set.

3.3.2 BP Neural Network Model Validation

The established fracture conductivity neural network model is considered reasonable when the model maintains a high accuracy on both the training and test sets.Figure6 shows the results of the model validated on the test set with a fit coefficient R value of 0.8239, which is slightly lower than the fit coefficient on the training set, and an error coefficient of 0.1761 on the test set.

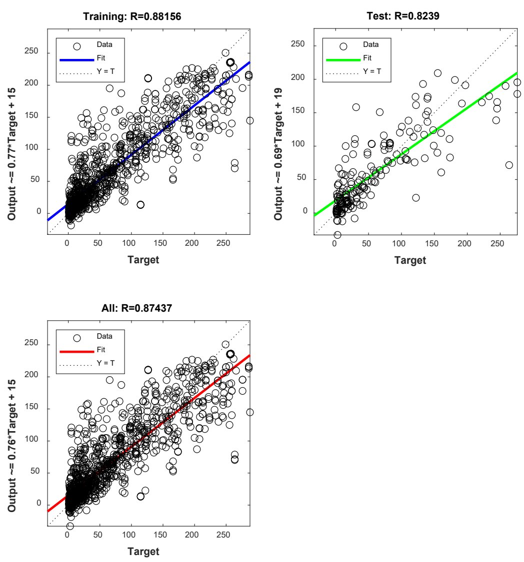

Figure6. Regression parameters of the fracture conductivity test set.

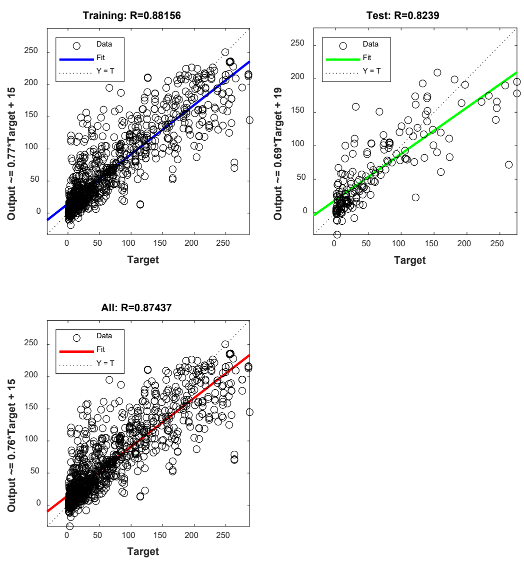

Figure7. Comprehensive validation regression parameters of fracture conductivity.

Figure7 shows that the results of the combined validation regression parameters of this prediction model on both the training and test sets had a linear fit coefficient R value of 0.87437 and an error coefficient of 0.12563 for the combined set. These findings confirm that the model has a good prediction effect on both the training and test sets and verify the rationality and feasibility of using this prediction model.

3.3.3 Analysis of the Training Results of Predicted and Measured Values

The model was trained using the processed training data, and predictions were carried out with the test set data. Twenty sets of sample data of fracture conductivity from the test set were input into the model to verify the prediction accuracy. The prediction results and relative errors of PFC are shown in Table 4.

Table4. Prediction results and relative errors of proppant fracture conductivity.

Prediction sample	Roughness	Proppant particle size (mm)	Proppant concentration (kg/m)^2	Closure pressure (MPa)	Conductivity measured value (μm^2 -cm)	Conductivity predicted value (μm^2 -cm)	Conductivity error (μm^2 -cm)	Relative error
1	1.145	0.265	0.3	13.80	216.32	279.00	-62.67	28.97%
2	1.024	0.315	0.5	27.69	49.87	51.67	-1.79	3.60%
3	1.007	0.315	2.0	6.75	227.29	199.46	27.84	12.25%
4	1.010	0.445	8.0	68.85	13.08	15.55	-2.47	18.89%
5	1.099	0.284	0.7	62.10	3.53	4.57	-1.04	29.53%
6	1.141	0.283	5.0	13.80	58.09	64.18	-6.09	10.48%
7	1.002	0.358	2.0	30.33	186.22	177.10	9.12	4.90%
8	1.143	0.339	1.0	82.80	3.33	3.29	0.04	1.31%
9	1.082	0.289	0.5	13.80	135.40	128.01	7.39	5.46%
10	1.082	0.289	0.5	13.80	135.40	166.05	-30.65	22.64%
11	1.030	0.445	6.0	68.93	85.97	108.96	-22.99	26.74%
12	1.140	0.613	0.3	27.60	65.88	83.07	-17.18	26.08%
13	1.142	0.301	3.0	48.30	14.23	15.65	-1.42	10.01%
14	1.005	0.358	2.0	89.83	64.28	74.83	-10.55	16.42%
15	1.014	0.315	2.0	69.00	92.77	77.86	14.91	16.07%
16	1.027	0.358	2.0	41.40	114.76	135.48	-20.72	18.06%
17	1.084	0.227	5.0	27.60	40.31	34.77	5.54	13.75%
18	1.146	0.267	5.0	20.70	43.52	40.07	3.45	7.93%
19	1.043	0.315	2.0	6.31	254.95	286.57	-31.62	12.40%
20	1.049	0.157	0.1	3.43	12.12	12.22	-0.10	0.78%

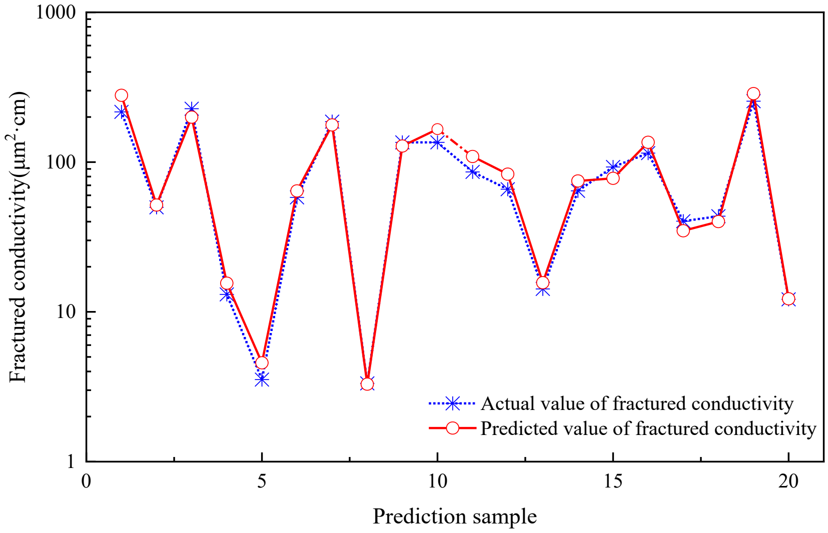

Figure8. Comparison of the predicted and measured results of fracture conductivity predicted by the model.

Table4 and Figure8 show that the predicted values of fracture conductivity obtained from most of the predictions were relatively close to the actual measured data, with a maximum relative error of 29.53%, minimum relative error of 0.78%, and average relative error of 14.31%. This may be due to the large volume of data, randomness, and interference from human factors, which can lead to bias during data sampling. However, in general, the error is acceptable compared with the empirical formula; thus, the conductivity prediction model of this neural network can be considered to have good predictive ability.

4. Discussion

In this paper, research and analyses of the influencing factors of the conductivity of propped fractures were performed to conduct BP neural network modeling and analysis based on experimental conductivity data and data collected from the research literature. Multiple parameters were selected as the input layer, and 1200 sets of measured data were used as the output layer for training and prediction of PFC. The following conclusions were drawn based on the experimental results.

1. The factors affecting fracture conductivity are complex. The type of proppant and its physical properties and placement as well as closure stress are the main factors affecting fracture conductivity. Certain semi-empirical and empirical formulas of fracture permeability and conductivity established based on laboratory experimental results are not applicable.

2. The correlation coefficient between the predicted and measured values of fracture conductivity obtained by constructing a model with the BP neural network was greater than 0.88, and the relative average error of the test set was 14.31%; thus, the proposed model can predict the conductivity of proppant packs.

3. The model still has many shortcomings, such as the high number of parameters selected as factors that influence conductivity in the model; the low accuracy of model predictions; and errors produced by predictions of conductivity of actual strata. Therefore, in the future, it is necessary to overcome the “data silo,” expand the conductivity database, increase the volume of parameter data of different factors influencing conductivity, and consider how to better adapt the model to field PFC predictions. Such changes will promote the accurate prediction of conductivity of different lithologies in different areas.

Author Contributions:

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