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Research Article

Prediction Model for Geologically Complicated Fault Structure Based on Artificial Neural Network and Fuzzy Logic

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The development and distribution of geologically complicated fault structure have the characteristics of uncertainty, randomness, ambiguity, and variability. Therefore, the prediction of complicated fault structures is a typical nonlinear problem. Neither fuzzy logic method nor artificial neural network alone can solve this problem well because the fuzzy method is generally not easy to realize adaptive learning function, and the neural network method is not suitable for describing sedimentary microfacies or geophysical facies. Therefore, taking the marginal subsags in the Jiyang Depression, Eastern China, as a study case, this paper uses the method of combining artificial neural network and fuzzy logic to study geologically complicated fault structure prediction model. This paper expounds on the research status and significance of geologically complicated fault structure prediction model, elaborates the development background, current status, and future challenges of artificial neural networks and fuzzy logic, introduces the method and principle of fuzzy neural network structure and fuzzy logic analysis algorithm, conducts prediction model design and implementation based on fuzzy neural network, proposes the learning algorithm of fuzzy neural network, analyzes the programming realization of fuzzy neural network, constructs complicated fault structure prediction model based on the artificial neural network and fuzzy logic, performs the fuzzy logic system selection of complicated fault structure prediction model, carries out the artificial neural network structure design of complicated fault structure prediction model, compares the prediction effects of the geologically complicated fault structure model based on artificial neural networks and fuzzy logic, and finally discusses the system design and optimization of the prediction model for geologically complicated fault structures. The study results show that the fuzzy neural network fully integrates the advantages of artificial neural network and fuzzy logic system; based on the clear physical background of fuzzy logic system, it effectively integrates powerful knowledge expression ability and fuzzy reasoning ability into the network knowledge structure of neural network, which greatly improves the prediction accuracy of geologically complicated fault structure.

1. Introduction

The development and distribution of geologically complicated fault structure have the characteristics of uncertainty, randomness, ambiguity, and variability. Therefore, the prediction of complicated fracture structure is a typical nonlinear problem. There is a highly nonlinear and complicated relationship between it and its influencing factors, which is difficult to describe with simple mechanics and mathematical models. This ambiguity and complexity can easily cause differences in understanding of the nature of complicated fault structures and bring great difficulties to engineering problems, such as oil and gas geological exploration and slope stability analysis [1].

It is difficult for traditional fault structure prediction methods to make a realistic geological evaluation of the fault structure under such fuzzy, dynamic, random, and geologically complicated conditions. Because the reasoning method of the fuzzy method is more similar to the human thinking mode, it is a powerful tool to deal with uncertainty and nonlinearity and other ill-posed problems, and it is more suitable for expressing that fuzzy and qualitative knowledge [2]. The combination of fuzzy mathematics and stochastic theory with engineering practice partially solves the ambiguity in the prediction of complicated fault structures. As a parallel computing model, artificial neural network has many advantages that traditional modeling methods do not have. It has good nonlinear mapping ability and strong adaptive learning function. Artificial neural network and fuzzy logic use grey correlation analysis method to calculate the correlation degree and correlation order of evaluation indexes, obtain the dominant index reflecting the development of fault structure, determine the weight coefficient, and constitute the weight vector on the factor set. Because fuzzy methods are generally not easy to achieve the function of adaptive learning, and neural networks are not suitable for describing sedimentary microfacies or geophysical facies [3], therefore when training a neural network, it cannot make good use of existing empirical knowledge and often can only set the initial weight to zero or a random number. In response to this problem, this paper combines artificial neural network and fuzzy logic to establish a geologically complicated fault structure prediction model. This method combines fuzzy logic and neural network, can absorb the advantages of both, and can form a model with better performance than pure fuzzy method and neural network [4].

Taking marginal subsags in the Jiyang Depression, Eastern China, as an example, this paper uses the method of combining artificial neural network and fuzzy logic to study the geologically complicated fault structure prediction model. The prediction of the complicated fault structure model is a widely used optimal model. The distribution of the membership function of the fault structure prediction model should conform to the golden ratio [5]. The accuracy of the prediction result obtained by the fuzzy system is much higher than the prediction result obtained by the traditional method. Especially when it is too complicated to analyze with traditional quantitative methods, the fuzzy system method appears very effective. Under geologically complicated conditions, the fault structure prediction model retains only one rule for repeated rules [6]. The function of the neuron class is to simulate the data structure and calculation process of a single neuron; the neuron weight class is used to save the weight of the connection between the neurons. At the same time, the neural network class also reads the connection and weight data of the network structure from external files for use when building the network. The database mainly includes the membership function of each language variable [7]. In the forward propagation process, the input information is processed layer by layer from the input layer through the hidden layer and then passed to the output layer. If the desired output cannot be obtained in the output layer, it will switch to back propagation, return the error signal along the original connection channel, and modify the weight of the neurons to minimize the error signal [8].

The detailed chapters are arranged as follows. Section 2 introduces the method and principle of fuzzy neural network structure and fuzzy logic analysis algorithm. Section 3 conducts prediction model design and implementation based on fuzzy neural network. Section 4 constructs complicated fault structure prediction model based on the artificial neural network and fuzzy logic. Section 5 compares the prediction effects of the geologically complicated fault structure model based on artificial neural networks and fuzzy logic and finally discusses the system design and optimization of the prediction model. Section 6 is conclusion.

2. Methods and Principles

2.1. Fuzzy Neural Network Structure. After inputting the learning samples, one of the main results of fuzzy neural network learning is that the geologically complicated fault structure prediction model summarizes the membership functions of each input variable from the training samples. Fuzzy networks have the ability to refine fuzzy rules and store knowledge in a distributed manner and the trained network can realize fast unmatched reasoning:

$$A_i = -a\frac{\partial b}{\partial c_i} = -a\frac{\partial b}{\partial c_i d(i)}\frac{\partial c_i d(i)}{\partial e_i}, \tag{1}$$

where A_i is the input vector of the hidden layer; a is the output vector of the hidden layer; b_i is the input vector of the output layer; c_i is the connection weight between the input layer and the intermediate layer; $d(i)$ is the threshold of each neuron in the hidden layer; and e_i is the number of sample data.

There are n sample sets to be trained, and each sample has m predictor eigenvalues; the physical dimensions of the m predictor eigenvalues are different, and some eigenvalues are positively correlated with the predicted object, and some are negatively correlated; for predictors with positive correlation, the relative membership degree formula is as follows:

$$B_{ij} = \frac{1}{1+\left[\left(\sum_{i=1}^{n}\sum_{j=1}^{m} a_{ij}b_{ij}c_{ij}\right)^{-1} - 1\right]^2}. \tag{2}$$

In the formula, i is the sample number; j is the input layer input; a_{ij} is the actual measured value of the predictor eigenvalue j of the training sample i; and b_{ij}, c_{ij} are the minimum and maximum eigenvalues of the prediction object, respectively.

According to the aforementioned network structure and predicted input and output variables for complicated fault structures, as well as the number of fuzzy divisions of each input component, the parameters that the grid needs to learn are mainly the functional network connection weight f and center value g and width h of the membership function of each node in feature grid. Therefore, the learning algorithm is as follows:

$$C_i = \frac{1}{f}\sum_{g=1}^{n}\sum_{h=1}^{n}\frac{a_{gh}-c_{gh}}{b_{gh}-d_{gh}}, \tag{3}$$

where C_i is the network training output variable; a_{gh} is the true value of the sample data; b_{gh} is the learning efficiency; c_{gh}

is the mean value of the membership function; and d_{gh} is the variance of the membership function.

Fuzzy neural network composes various factors that affect the evaluation of the complexity of the fault structure into a common set; for the quantitative evaluation of the fault structure, the value of the fault fractal dimension is one of the important indicators. The essence of the fuzzy artificial neural network based on the information diffusion method is to transform the contradictory samples into noncontradictory samples by spreading the information of the factors. If each factor is used as the input neuron of the network, and the deformation is used as the output of the network. The prediction model of complicated fault structure is first based on the method of fuzzy inference, and a fuzzy logic rule model is preliminarily determined according to the curve or data recorded in the experiment of the production control system [9]. According to the degree of correlation between the indicators, artificial neural network and fuzzy logic combine the indicators with the same degree of correlation into a group for clustering. The complicated fault structure prediction model substitutes the changes in the network connection weight of the trained fuzzy system into the rules. Because the output of the artificial neural network is the result of the second-level fuzzy approximation of the predictive quantity rather than a single predictive quantity, the possibility of contradictory samples is greatly reduced.

2.2. Fuzzy Logic Analysis Algorithm. In fuzzy logic analysis, the dependent variable i is a binary variable; the n independent variables that affect the value of i are $i_1, i_2, \ldots, i_n$, and the conditional probability of a complicated fault structure under the action of n independent variables is $K = k_i$; the fuzzy logic analysis model can be expressed as

$$D_i = k_0 i_0 + k_1 i_1 + k_2 i_2 + \cdots + k_n i_n = \sum_{i,j=1}^{n} \frac{k_j g_{ij}}{1 + e^{-K}}, \tag{4}$$

where D_i is regression prediction value in the ith unit; k_n is intermediate variable parameter; i_n is regression constant; k_j is regression coefficient of the jth variable; and g_{ij} is value of the jth variable in the ith unit.

In the original initialization method, the potential function is based on exponential calculations, which will affect the speed when the sample size is large. Therefore, it can be used to indicate the density of sample points in the sample space. The principle is similar to that of the potential function method, but the amount of calculation is much smaller than that of the potential function method:

$$E_i = f^{ki} - g^{ki} \frac{1}{1 + h^{ki} f^{ki} - h^{ki2}}, \tag{5}$$

where E_i is the effective radius of the field density, and its choice should be related to the distribution characteristics of the data set; f^{ki} is the denser the surrounding sample points; g^{ki} is the number of clusters in the ith unit; and h^{ki} is the function in the ith unit center.

The neural network used to implement the above fuzzy rules has three layers. The first layer is used to judge the matching between the input fuzzy variables and the rule antecedents; the second layer of neural network takes into account the rule weight and the degree of ignition of the rules; the values of these two variables are obtained in the process of neural network learning, so the activation function is

$$F_i = \begin{cases} C_i\left(f^{ki}, g^{ki}, h^{ki}\right) = -\dfrac{g^{ki} - h^{ki}}{2 f^{ki}}, \\[2ex] D_i\left(f^{ki}, g^{ki}, h^{ki}\right) = \dfrac{g^{ki} - h^{ki}}{2 f^{ki}} - \dfrac{f^{ki} - h^{ki}}{2 g^{ki}}, \\[2ex] E_i\left(f^{ki}, g^{ki}, h^{ki}\right) = -\dfrac{g^{ki} - h^{ki}}{2 f^{ki}} - \dfrac{g^{ki} - f^{ki}}{2 h^{ki}}. \end{cases} \tag{6}$$

If $F_i \geq 1$, the node is completely suppressed; if $F_i = 0$, the node is completely ignited; if $0 < F_i < 1$, the degree of ignition of the node is $D_i(f^{ki}, g^{ki}, h^{ki})$.

There are two main types of fuzzy logic methods. One is systematic clustering based on fuzzy relations, and the other is fuzzy clustering based on least squares automatic iteration. The former is easy to lose a lot of information due to the existing fuzzy operators, and the fuzzy relationship needs to be transformed from a similar relationship to an equivalent relationship, which will inevitably cause the two relationships to be far apart. The latter is based on the automatic correction method that estimates the error based on the sample and the cluster center. Fuzzy logic knowledge is easy to extract and express, and it is good at dealing with structured problems, while neural networks can learn directly from samples, which is more effective in processing unstructured information. Although some geological models of fuzzy neural networks have appeared, they are mostly limited to the fuzzy processing of the input layer data, and the integration level is low. The future development trend will be the mapping and combination of fuzzy logic to neural network structure; that is, through the replacement of fuzzy membership function and network transfer function, the connection weight of the network can be dynamically adjusted by fuzzy rules. The fuzzy neural network with this structure and performance will have greater adaptability to many uncertain problems in the prediction of geologically complicated fault structure [10].

3. Design and Implementation of Prediction Model Based on Fuzzy Neural Network

3.1. Learning Algorithm of Fuzzy Neural Network. Artificial neural network and fuzzy logic use grey correlation analysis method to calculate the correlation degree and correlation order of evaluation indexes, obtain the dominant index reflecting the development of fault structure, determine the weight coefficient, and constitute the weight vector on the factor set. Then, it uses a neural network with nonlinear characteristics and fuzzy logic operations in fuzzy inference to improve the fuzzy inference model and construct a fuzzy system. In order to make the determined membership function conform to the objective laws as much as possible, it is generally necessary to make a scatter plot of the correlation between each subsequence index and the main factor substandard so as to obtain the membership function curve between each index and the divided comment subset [11]. The fuzzy neural network combines the changes in the network connection weights of the trained fuzzy system and the changes in the membership functions of the input and output vectors into the changes in fuzzy logic rules, thereby realizing the fuzzy inference and induction from the curve or data recorded in the experiment logic control rules. If adjusting the weights from the middle layer to the output layer cannot make the error meet the requirements, the fault structure model needs to reselect the width parameter of the central function or even reselect the network structure. Figure 1 shows the design and implementation structures of prediction model based on fuzzy neural network.

The neural network has strong self-learning ability and direct data processing ability, and the result of its learning depends entirely on the training sample. The fuzzy logic system adopts the single-value fuzzy generator type and fuzzy implication product operation, and the antifuzziness adopts the central average fuzzy eliminator type. Here, the center average blur eliminator is used to realize the antifuzziness and the formula is as follows:

$$G_i = \frac{\sum_{i=1}^{n}(l_i - p_i)}{\sum_{i=1}^{n}(o_i - q_i)}, \tag{7}$$

where G_i is the number of rules; l_i is gelatinization function; p_i is cluster center; o_i is the Euclidean distance between the ith cluster center and data points; and q_i is the output value that minimizes network output error.

The fuzzy neural network performs nonlinear curve fitting on the monitoring data to obtain the model parameters and then obtain the deformation curve. According to the fuzzy neural network combines the changes in the network connection weights of the trained fuzzy system and the changes in the membership functions of the input and output vectors into the changes in fuzzy logic rules. The correlation coefficient H_i is used to indicate the final fault structure obtained by realizing the prediction function:

$$H_i = \frac{\sum_{i=1}^{n}(r_i - s_i)(r_i - t_i)}{\sqrt{\sum_{i=1}^{n}(r_i - u_i)^2 \sum_{i=1}^{n}(r_i - v_i)^2}}. \tag{8}$$

In the formula, r_i is the iteration step length; s_i is the matrix vector; t_i is the rheological index, which reflects the speed of the accelerated deformation rate of the rock; u_i is the reference time, which can reflect the speed of the rock deformation; and v_i is the yield stress or long-term strength.

The plane closure of the geologically complicated fault structure prediction model is the most critical technical means in the spatial interpretation of seismic data. Different breakpoint closure schemes will form different structural fault systems. Therefore, the breakpoint closure must conform to the regional geological conditions. Generally speaking, the compression stress mainly forms thrust fault or reverse fault, and normal fault can also be formed; tensile stress can form normal fault or translational fault, and reverse fault is impossible. The nature and tendency of the fault must be the same and the occurrence of the fault requires high similarity. The difference between adjacent breakpoints must be as small as possible; the strata on both sides of the fault occurrence requirements are completely similar [12]. The stratigraphic requirements of faults are formed during the same period of tectonic movement; bifurcated faults need to be distinguished between main branch faults and branch faults; the closure of the faults requires the same nature. After completing the plane closure of the breakpoints according to the above principles, if the plane regularity of the fault system is poor or does not conform to the characteristics of geology, structure, and sedimentation, it is necessary to reanalyze the characteristics of each breakpoint and perform the plane closure of the breakpoint again.

3.2. Programming Realization of Fuzzy Neural Network. The key is to reflect the structural model of the geometric form of geological entities, and the other part is the attribute model that contains the internal physical parameter information of geological entities. An artificial neural network with a single hidden layer can approximate an arbitrary continuous nonlinear function. Figure 2(a) illustrates the rectangular corner-point grid meshing in programming realization of fuzzy neural network. This difference will cause the stress in the surrounding rocks on both sides of the fault to change significantly along the fault surface. If the error does not meet the requirements, the fault structure model adjusts the weights from the middle layer to the output layer and recalculates the network outputs the value until the error meets the requirements. Under the constraints of the construction model, distance-weighted spatial interpolation is used for attribute modeling. It is necessary to repeatedly correct the differences between the model structure and the interpretation plan and attribute modeling mainly uses the attribute parameters of artificial neural network and fuzzy logic. Three-dimensional fault isolation (b) in programming realization of fuzzy neural network is shown in Figure 2(b). Artificial neural networks have inherent potential fault tolerance and its execution efficiency will not be significantly reduced under certain unfavorable situations, such as neuron disconnection, interfering data, or data loss. The reliability of calculations can be verified by some experience, but it is usually uncontrolled [13].

Through fuzzy clustering analysis, divide the domain composed of units into comment subsets, each of which corresponds to a certain number of units. Suppose there are n units in subset J, and the measured values of j indicators of the ith unit are $(x_{i1}, x_{i2}, \ldots, x_{ij})$; then, the single-factor membership function is

$$J_{ij} = \frac{w_{ij} - x_{ij}}{w_{ij} - y_{ij}} - \frac{w_{ij} - y_{ij}}{w_{ij} - z_{ij}}, \tag{9}$$

where w_{ij} is the membership degree of the ith index to the j subset; x_{ij} is the actual statistical value of the ith index of the j unit; y_{ij} is the original parameter of the ith index of the ith

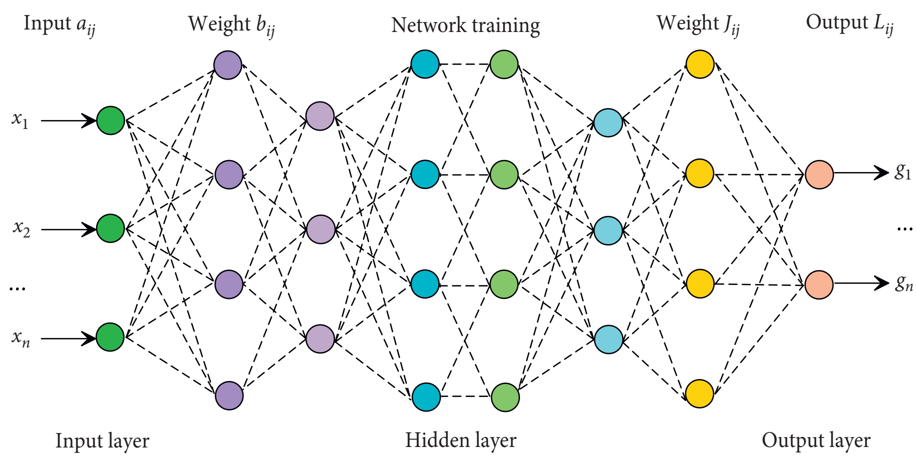

Figure 1: Design and implementation structures of prediction model based on fuzzy neural network.

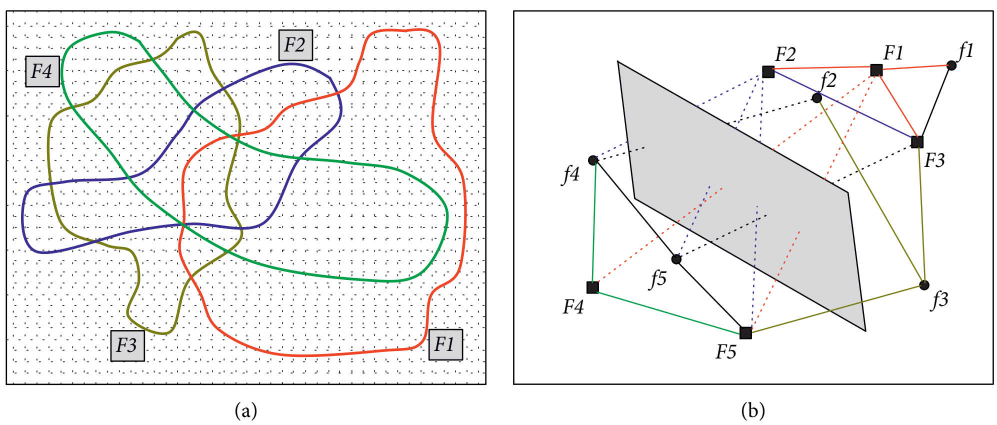

Figure 2: Rectangular corner-point grid meshing (a) and three-dimensional fault isolation (b) in programming realization of fuzzy neural network.

subregion; and z_{ij} is the average value of the ith subregion of the jth index of the district.

In the quantitative evaluation of the development degree of different fault structures, different classification results may be obtained based on different factor indicators, but the effects of these factors in the quantitative evaluation are not the same. In order to comprehensively consider various factors and obtain a comprehensive and objective evaluation result, the fuzzy comprehensive evaluation obtains the fuzzy comprehensive evaluation vector L_{ij} by multiplying the single-factor evaluation set and the weight set:

$$L_{ij} = B_{ij}G_{ij} = (b_1, b_2, \cdots b_n)\begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1m} \\ g_{21} & g_{22} & \cdots & g_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nm} \end{bmatrix}, \quad (10)$$

where $0 \leq g_{nm} \leq 1$ $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ is measured by the jth factor, and the degree of membership of the judging object to L_{ij} in the comment set.

Fuzzy neural network composes various factors that affect the evaluation of the complexity of the fault structure into a common set; for the quantitative evaluation of the fault structure, the value of the fault fractal dimension is one of the important indicators. Therefore, some scholars apply neural network to complicated faults to construct predictions. However, neither fuzzy methods nor neural networks can well solve the problem of fault structure prediction under geologically complicated conditions. The determination of the fault structure prediction model is mainly based on the statistical results of each area and clustering according to four categories: simple, simple, complicated, and complicated. Weight refers to the degree of importance or contribution of a certain evaluation factor in determining the complexity of a certain fault structure [14]. According to the degree of correlation between the indicators, artificial neural network and fuzzy logic combine the indicators with the same degree of correlation into a group for clustering. In order to make the determined membership function conform to the objective laws as much as possible, it is generally necessary to make a scatter plot of the correlation between each subsequence index and the main factor substandard so as to obtain the membership function curve between each index and the divided comment subset.

4. Complicated Fault Structure Prediction Model Based on Artificial Neural Network and Fuzzy Logic

4.1. System Selection of Fuzzy Logic for Complicated Fault Structure Prediction Model. Due to the limitations of geological conditions, current data, research methods, and other issues, it is difficult to deal with the reliability of the location of the breakpoint and the reliability of the layered data for the complicated fault areas where the sedimentation becomes faster. Based on artificial neural network and fuzzy logic, it is a good solution to introduce three-dimensional visualization technology into stratigraphic comparison work. Artificial neural network and fuzzy logic use the combination of human-computer interactive editing and stratigraphic recomparison to correct each other, taking into account the inheritance of regional structural changes [15]. The system selection results of fuzzy logic for complicated fault structure prediction model show that in the Jiyang Depression, the Wuli Fault and Chengnan Fault are both reverse faults, which go through the Donging, Shahejia, and Kongdian Formation, respectively (Figure 3). Fuzzy neural network adjusts or changes the location of breakpoints and corresponding horizon data in the study area and manually edits the calculation results of the layer model according to the drilling layer data and corrects the structural surface layer by layer to make it consistent with the drilling layer data. For areas that are not controlled by hierarchical data, the overall structural trend is used to implement the three-dimensional structural form, which is the accuracy of the structural research work that cannot be achieved by the previous two-dimensional structural research.

The fuzzy neural network combines the changes in the network connection weights of the trained fuzzy system and the changes in the membership functions of the input and output vectors into the changes in fuzzy logic rules, thereby realizing the fuzzy inference and induction from the curve or data recorded in the experiment logic control rules. The prediction model of complicated fault structure is first based on the method of fuzzy inference, and a fuzzy logic rule model is preliminarily determined according to the curve or data recorded in the experiment of the production control system. Then, it uses a neural network with nonlinear characteristics and fuzzy logic operations in fuzzy inference to improve the fuzzy inference model and construct a fuzzy system. Through error reverse transmission learning, its connection weight corresponds to the parameters of fuzzy inference. The relationships between fuzzy regression variables and different numbers of training samples are shown in Figure 4. This difference will cause the stress in the surrounding rocks on both sides of the fault to change significantly along the fault surface. The complicated fault structure prediction model substitutes the changes in the network connection weight of the trained fuzzy system into the rules and can obtain fuzzy logic control rules that are inferred and summarized from the experimentally recorded curves or data. The complicated fault structure prediction model substitutes the finally obtained changes in the network connection weight into the fuzzy system network, which can realize fuzzy logic control with parallel information processing.

Fuzzy logic system is composed of four parts: fuzzy generator, knowledge base, fuzzy inference engine, and defuzziness. The fuzzy generator blurs the input precise quantity and expresses it with the corresponding fuzzy set. The combination of neural network learning algorithm and fuzzy logic theory can use normalized fuzzy neural network to realize fuzzy logic system [16]. It uses fuzzy rules to represent the neural network, initializes it in the form of fuzzy rules with preexpert knowledge, uses the neural network learning algorithm to train the fuzzy system, and then combines the characteristics of neural computing to realize the inference process. When the program is running, the neural network class instance is firstly generated by the application program, and then the layer class instance is established for this network class instance, and then the layer class instance is established for each layer of neuron instance. Fuzzy systems generally consist of fuzziness, knowledge base, fuzzy reasoning, and defuzziness. The fuzziness is mainly through the creation of fuzzy sets, which converts the precise input quantity into the fuzzy output quantity. This model can be used to obtain better results when the membership degree is unknown. The function of the neuron layer class is to generate the neurons of each layer and perform the calculation of each layer. It accepts the call of the neuron network class and calls the function of the neuron class to realize the calculation of each layer.

4.2. Structure Design of Artificial Neural Network for Complicated Fault Structure Prediction Model. The geomechanical environment of the fault is also changing with time. It is these differences that make the fault show different motion characteristics under a specific geomechanical environment and show different friction characteristics at different locations of the fault. There are many methods for determining weights, among which has the advantages of simple calculation method and reliable calculation result. The fuzzy neural network first selects the structural area loss coefficient that indirectly reflects the complexity of the fault structure as the parent factor and takes the geological indicators that reflect or affect the complexity of the fault structure from all sides as the subfactors. As shown in Figure 5, the Shichun Fault and Qingcheng Fault control the deepest deposition point of Jiyang Depression. The Gudao Fault and Zhanhua Fault control another subdeep disposition point. The structural deformation under geologically complicated conditions is strong, and the coarsening of the grid in conventional numerical simulations will inevitably cause the loss of reserves in the numerical simulation prediction model of the complicated reverse fault block fault

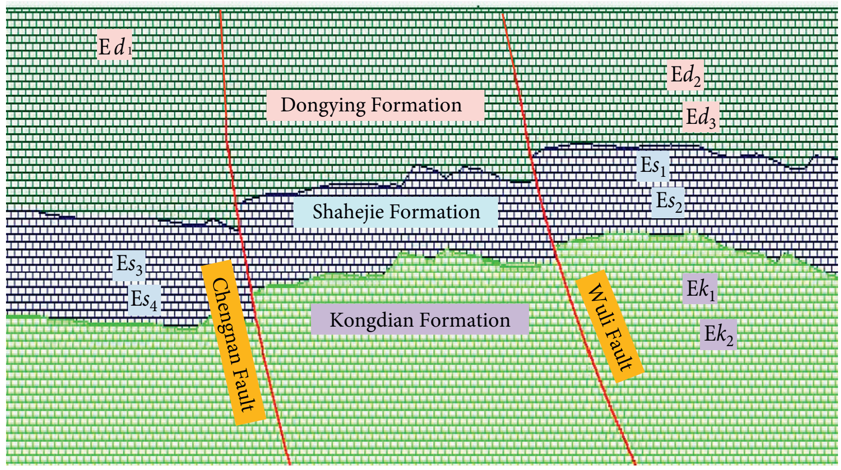

FIGURE 3: System selection results of fuzzy logic for complicated fault structure prediction model in the Jiyang Depression, Eastern China.

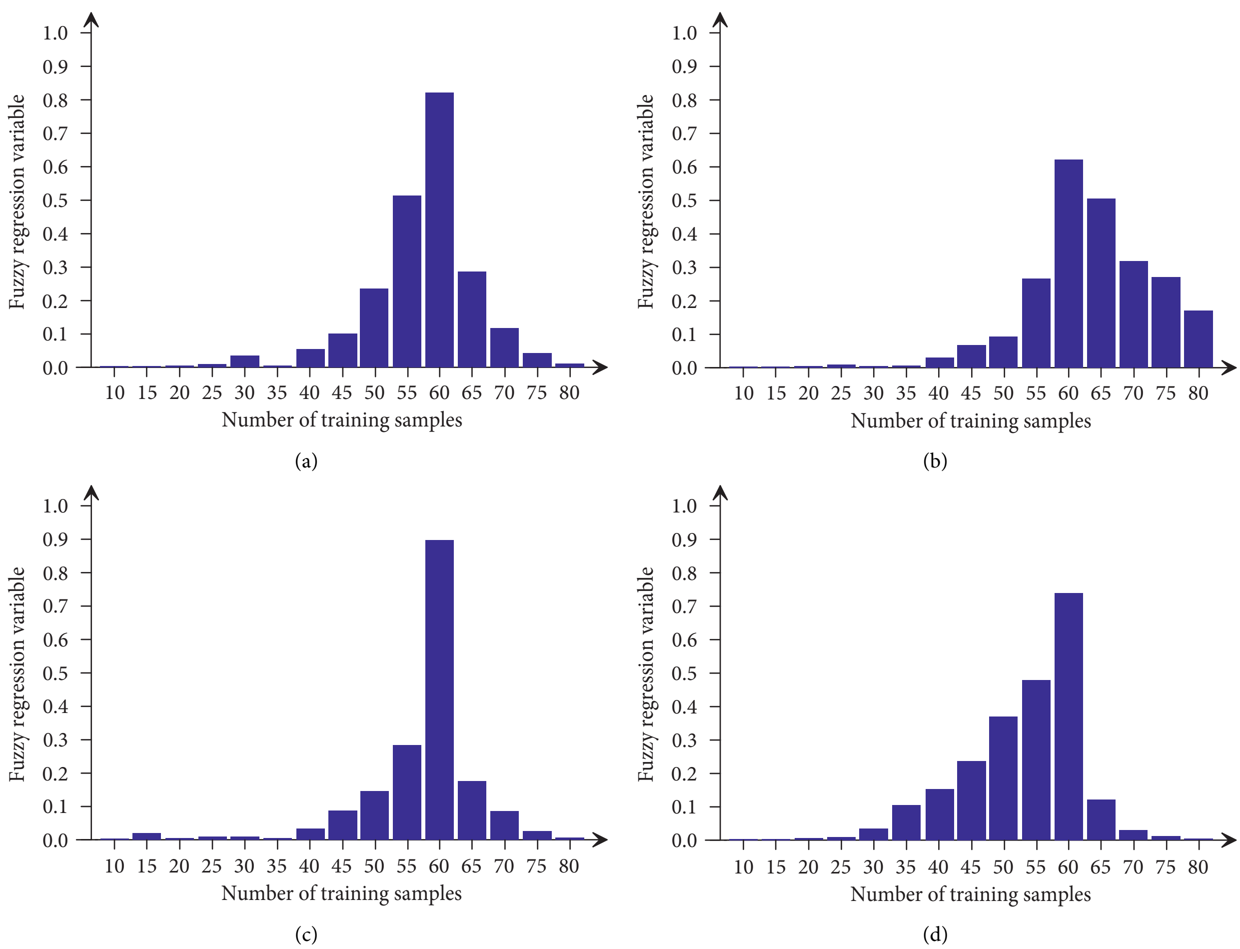

FIGURE 4: Fuzzy regression variables with different numbers of training samples in learning algorithm of fuzzy neural network (a), programming realization of fuzzy neural network (b), system selection of fuzzy logic (c), and structure design of artificial neural network (d).

structure. The knowledge base provides the fuzziness interface with the membership function form of the fuzzy quantity so that the fuzziness interface can convert it into the corresponding fuzzy quantity and membership degree after receiving the external precise quantity input. The knowledge base also provides the membership function form of the fuzzy quantity to the antifuzziness interface, and the antifuzziness interface converts the output fuzzy quantity and the degree of membership into the corresponding accurate quantity.

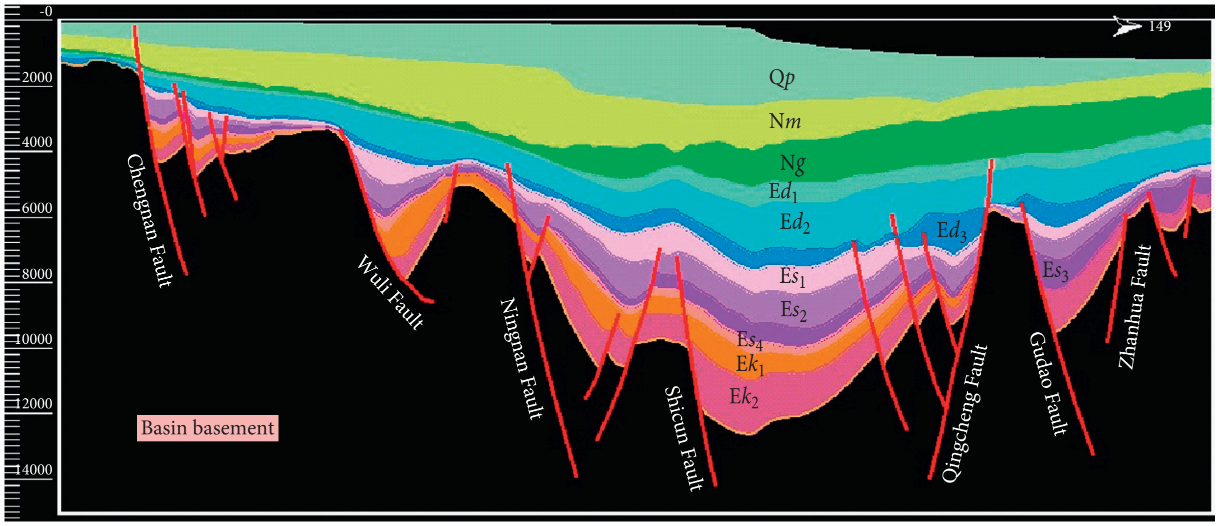

Figure 5: Structure design results for complicated fault structure prediction model in the Jiyang Depression, Eastern China.

Since the same coordinate system is used when modeling, each fault block has its own accurate spatial location. It manages the detailed fault structure prediction model data body of each block according to the block number, the sublayer number and its spatial coordinates, which completes the fine modeling of the fault structure under geologically complicated conditions. The best way to check whether a fault structure prediction model is reliable is to compare its built model with the actual geological conditions in geologically complicated conditions. The closer the fitting index, the more correct the prediction model and the higher the accuracy, which also means that the more reliable the geological modeling and numerical simulation grid coarsening technology. Based on the seismically interpreted marker layer structure and fault data of the block, combined with the development of fine stratigraphic correlation data, it can determine the location of the fault line that passes through each small layer or even a small sand body between the two marker layers. Artificial neural network and fuzzy logic are used to determine the grid size of the numerical simulation model, and then the small layers of each fault block are numbered uniformly, and the shallowest layer is selected as the top layer of the entire fault structure, and the deepest layer is used as the bottom layer of the entire fault structure. Finally, the fuzzy neural network will input the fine data volume into the numerical simulation data volume generation system to obtain a static model that maintains the complicated geometry of the original inverse fault block and meets the accuracy requirements of the numerical simulation [17].

The structural modeling is mainly based on the layers and faults explained in the work area. Based on the clear physical background of fuzzy logic system, its powerful knowledge expression ability and fuzzy reasoning ability are effectively integrated into the network knowledge structure of neural network. The geologically complicated fault structure prediction model uses the excellent self-learning ability of the neural network and other intelligent characteristics to perfect the knowledge structure of the fuzzy neural network to meet its adaptive requirements for handling complicated objects or complicated environments. The structural deformation under geologically complicated conditions is strong, and the coarsening of the grid in conventional numerical simulations will inevitably cause the loss of reserves in the numerical simulation prediction model of the complicated reverse fault block fault structure [18]. The determination of the fault structure prediction model is mainly based on the statistical results of each area. Due to the complexity of the structure, it is difficult to model the fault structure prediction model, and the model is difficult to build successfully at one time. Through error reverse transmission learning, its connection weight corresponds to the parameters of fuzzy inference. Weight refers to the degree of importance or contribution of a certain evaluation factor in determining the complexity of a certain fault structure.

5. Discussions

5.1. Comparison of Model Prediction Effects between Based on Artificial Neural Network and Based on Fuzzy Logic. The geologically complicated fault structure prediction model first selects the minimum membership degree of each condition in the reasoning premise; then it synthesizes the conclusions of each rule and selects the part with the largest degree of adaptation. This is a common reasoning method, and the reasoning result is not enough smooth, so the small operation is changed to product, and the large operation is changed to consider all possible results and perform a weighted average. The fuzzy neural network structure and algorithm obtained according to fuzzy logic inference are mainly due to the difference in the expression of rules and the inference of neural networks in the flexibility of process simulation (Figure 6(a)). The prediction of the complicated fault structure model is a widely used optimal segmentation model. This model can be used to obtain better results when the membership degree is unknown. The distribution of the membership function of the fault structure prediction model

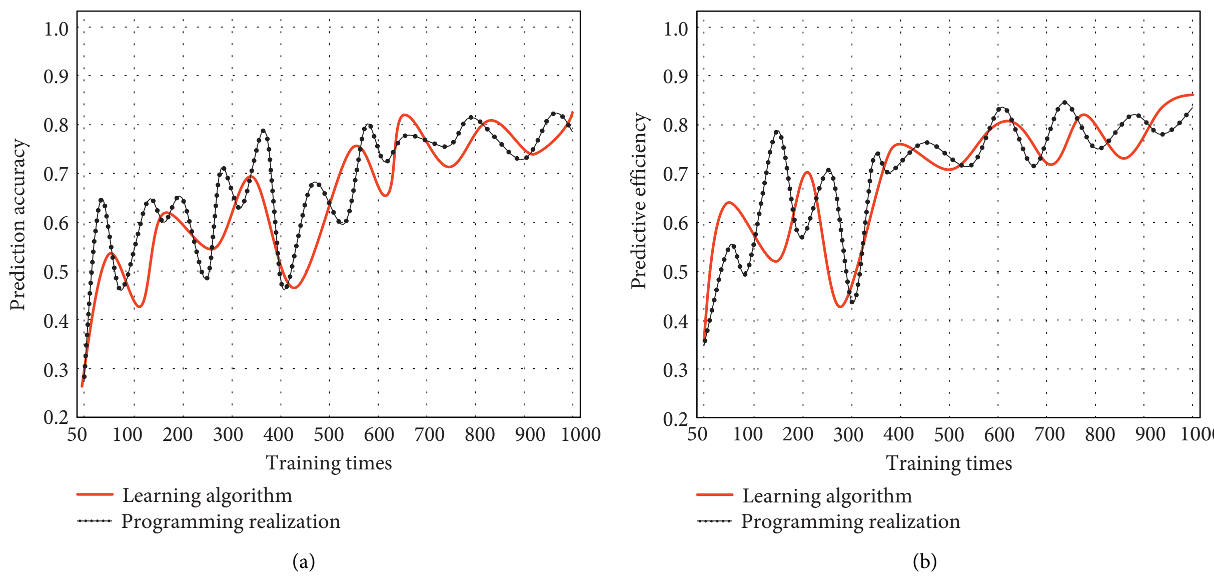

Figure 6: Relationships between geologically complicated fault structure prediction accuracies and training times of fuzzy neural network.

should conform to the golden ratio. If a bell-shaped membership function is used, the closer to the center of the universe of discourse, the smaller the coverage. Every time a sample is input, the rule can be obtained (Figure 6(b)). Under geologically complicated conditions, the fault structure prediction model retains only one rule for repeated rules, while for contradictory rules. Each neuron in the rule layer represents a rule, according to the rule set, can determine the connection between the rule layer and the fuzziness layer [19].

Under geologically complicated conditions, the free surface of the overlying strata of the faulted structure is getting larger and larger, and the surrounding rock is constantly moving and deforming towards the faulted structure. When the rock mass overlying the fault structure reaches its ultimate strength and plastic failure produces cracks, after the cracks expand and penetrate, they collapse under the action of their own weight and accumulate in the fault structure to form a caving zone. This phenomenon is more pronounced in rock masses with weak structures such as joints and fissures; when the rock masses in the caving zone are gradually filled with fault structures, the rock mass in the overlying fault zone will no longer fall, which is mainly due to the development of cracks and separation. The upper part of the fault zone is under the weight of its own gravity and the pressure of the overlying strata, and the entire fault zone bends downward along with the rock formation in the fault zone, but neither breaks nor falls off, so it is called the bending zone. This deformation and failure feature has been transmitted upwards from the roof. Due to the swelling of the rock, when the scope of the falling body expands to a certain extent, the fault structure is filled with broken rock mass. The distance that the rock mass in the caving zone collapses from bottom to top is getting smaller and smaller, and the amount of deformation during the collapse stage is getting smaller and smaller. Since the collapse stage is an instantaneous deformation process, the speed reaches the maximum; it is at the inflection point in the deformation curve, and from the bottom of the caving zone upwards, the tangent slope at the inflection point gradually decreases.

The establishment of structural hierarchy shows that the dominant complicated fault structure deformation mechanism and complicated fault structure combination characteristics of the rock mass in different complicated fault structure levels are different, and the corresponding rock mass structure types and geomechanical properties of the rock masses are also different. Therefore, geological construction activities will not only involve the real complicated fault structure on the surface of the rock mass, but may also involve the false complicated fault structure on the surface, which is actually the rock mass of the middle and deep complicated fault structure. The content of the rock mass should be studied accordingly and the method is also different. For the surface and shallow complicated fault structural layer rock mass, the typical brittle fault complicated fault structure deformation research method should be used to study the fault complicated fault structure and its combined characteristics [20]. But for the deep complicated fault structure layer, ductile and rheological deformation methods are dominant, and obvious brittle faults are rarely developed. Complex fault structures are replaced by ductile shear zones, flakes, cleavage, and other complicated fault structures. These discontinuous complicated fault structures are more developed. Although the scale is small, it has the characteristics of human nature. Although this type of rock mass does not have large-scale fault zones, the risk of deformation of ductile fault rock masses often exceeds that of brittle fault rock masses.

5.2. System Design and Optimization of Geologically Complicated Fault Structure Prediction Model. The rule applicability network structure is a four-layer artificial neural network, which is responsible for calculating the

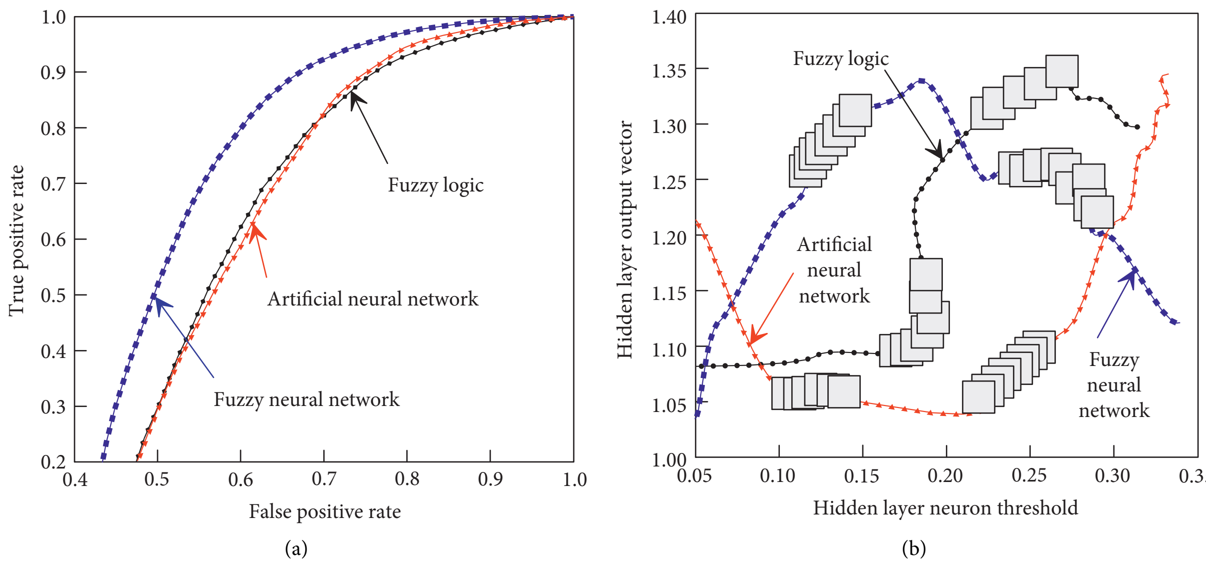

Figure 7: Receiver operating characteristic curve (a) and hidden layer optimization results (b) of prediction model for geologically complicated fault structure based on artificial neural network, fuzzy logic, and fuzzy neural network.

applicability of each rule to the input sample, that is to say, calculating the degree of membership of the input sample to the rule input space. The geologically complicated fault structure prediction model divides the sample input space into multiple categories according to the division of training samples, and each category is a fuzzy rule used to describe a sedimentary microfacies or geophysical facies. The membership of each sample corresponding to the fuzzy rule set is used as the supervision information to train the network to obtain the comprehensive membership degree [21]. The fault structure prediction model trains the membership network through the above algorithm to determine the center vector corresponding to each cluster center (Figure 7(a)). The process of making a balanced profile based on artificial neural network and fuzzy logic is to restore the deformed complicated fault structure form on the geological profile to the original complicated fault structure form through geometric principles. In order to accurately reflect the characteristics of the complicated fault structure on the geological section, the direction of the balanced section should be consistent with the direction of the regional complicated fault structure movement. After the balanced profile is selected reasonably, certain basic principles must be met during the production process, namely, the principle of constant volume, constant area, constant length, and the principle of consistent length of each layer (Figure 7(b)).

As a framework model, the structural geological model is the basis for the calculation of complicated structural fault structures and calculations of pore pressure bodies and in-situ stress bodies. Part of the task of artificial neural network and fuzzy logic is to reflect the structural model of the geometric form of geological entities, and the other part is the attribute model that contains the internal physical parameter information of geological entities. The structural modeling is mainly based on the layers and faults explained in the work area. The structural deformation under geologically complicated conditions is strong, and the coarsening of the grid in conventional numerical simulations will inevitably cause the loss of reserves in the numerical simulation prediction model of the complicated reverse fault block fault structure. Therefore, the vertical contact relationship between the layers must be fully considered, the contact relationship between the sections and the relationship between the plane and the section, so as to ensure that the model is consistent with the actual geological understanding. Due to the complexity of the structure, it is difficult to model the fault structure prediction model, and the model is difficult to build successfully at one time. It is necessary to repeatedly correct the differences between the model structure and the interpretation plan and attribute modeling mainly uses the attribute parameters of artificial neural network and fuzzy logic. Under the constraints of the construction model, distance-weighted spatial interpolation is used for attribute modeling.

One of the main results of fuzzy neural network learning is that the geologically complicated fault structure prediction model summarizes the membership functions of each input variable from the training samples. For the fuzzy neural network of the above example, the membership functions of the four input variables before and after the learning process all input variables need to be normalized in advance. Another result of the fault structure prediction model is to determine the connection weights between the third and fourth layers of neurons and the threshold of conclusion neurons [22]. There are no fillings in some places in the fault, but there are a lot of fillings in some places; the properties of the fillings are also quite different. Through different learning rules and algorithms, artificial neural networks can meet the needs of different network models. Fuzzy rules are a commonly used method to express uncertain knowledge. If the knowledge obtained from domain experts is expressed in the form of fuzzy rules, these fuzzy rules can be converted into corresponding fuzzy neural networks by the method described above. Fuzzy neural networks have the ability to refine fuzzy rules and store knowledge in a distributed manner and the trained network can realize fast unmatched reasoning. Therefore, the organic combination of neural network and fuzzy logic has many advantages.

6. Conclusion

This paper conducts prediction model design and implementation based on fuzzy neural network, proposes the learning algorithm of fuzzy neural network, analyzes the programming realization of fuzzy neural network, constructs complicated fault structure prediction model based on the artificial neural network and fuzzy logic, performs the fuzzy logic system selection of complicated fault structure prediction model, carries out the artificial neural network structure design of complicated fault structure prediction model, compares the prediction effects of the geologically complicated fault structure model based on artificial neural networks and fuzzy logic, and finally discusses the system design and optimization of the prediction model for geologically complicated fault structures. The fuzzy neural network combines the changes in the network connection weights of the trained fuzzy system and the changes in the membership functions of the input and output vectors into the changes in fuzzy logic rules, thereby realizing the fuzzy inference and induction from the curve or data recorded in the experiment logic control rules. Complex fault structures are replaced by ductile shear zones, flakes, cleavage, and other complicated fault structures. These discontinuous complicated fault structures are more developed. Although the scale is small, it has the characteristics of human nature. Although this type of rock mass does not have large-scale fault zones, the risk of deformation of ductile fault rock masses often exceeds that of brittle fault rock masses. The fuzzy neural network uses the unified modeling technology of faults and strata; that is, according to the fault data, each stratigraphic level in the study area is simulated as a whole. It combines the three-dimensional visualization function of the modeling software with basic geological research and corrects the problems in stratigraphic correlation with the fitting of faults and layers. The study results show that the fuzzy neural network fully integrates the advantages of fuzzy logic system and artificial neural network; based on the clear physical background of fuzzy logic system, it effectively integrates powerful knowledge expression ability and fuzzy reasoning ability into the network knowledge structure of neural network, which greatly improves the prediction accuracy of geologically complicated fault structure. The study results of this paper provide a reference for further researches on geologically complicated fault structure prediction model based on artificial neural networks and fuzzy logic.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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