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Application of BP Neural Network Based on Genetic Algorithm Optimization in Evaluation of Power Grid Investment Risk

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ABSTRACT The artificial intelligence calculation method can effectively solve various nonlinear mapping relationships. The strength of these nonlinear solvers is exploited for the evaluation of power grid investment risk using back propagation (BP) neural network optimized by genetic algorithm. The mathematical model of the problem is constructed by selecting the transfer function of the neural network and defining the fitness function of genetic algorithm. BP neural network has good ability of self-learning, self-adaptation and generalization, which can overcome the drawbacks of traditional evaluation methods relying on experts' experience. For the characteristics of genetic algorithm global optimization, the genetic algorithm is used to optimize the weight and threshold of BP neural network, and BP neural network is trained to obtain the optimal evaluation model. The model fully exploits the local search ability of BP neural network and the global search ability of genetic algorithm. It has obtained good evaluation accuracy for the processing of multi-dimensional influence factor problem. And the model can be adapted to different power grids by changing the training data. However, the method cannot describe the specific relationship between each impact factor and the investment risk of the grid. The case study shows that the method can accurately and effectively evaluate power grid investment risk and improve the fault tolerance of the power grid investment risk evaluation.

INDEX TERMS Power grid investment risk, risk evaluation, BP neural network, genetic algorithm.

I. INTRODUCTION

The power industry is an important part of the national economy which is indispensable in many fields and is closely related to people's life. Many countries have upgraded the power industry to the level of national strategy and regarded it as an important development target. However, at routine, there are many uncertainties and instabilities in the power grid [1], [2].

In the context of the transformation and upgrade of the electrical industry, the profit model of the power grid enterprises has changed from the traditional purchase and sale difference for electricity sales to the wheeling price for electricity sales. This change of profit model, as well as the uncertainty of transmission and distribution prices and marketization rates, will bring certain risks to power grid investment. In order to get a reasonable investment plan, it is necessary to use effective evaluation methods to screen. At this time, the power grid investment risk evaluation is particularly important.

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A. RELATED WORK

At present, there are many evaluation methods used in the world. The widely used methods of investment risk evaluation include Delphi method, principal component analysis method and fuzzy comprehensive evaluation method. In [3], [4], the regret value is used to measure the risk in the market environment. The difference of the evaluation values between the specific scheme and the optimal scheme is used as a regret value to characterize the magnitude of the loss that the scheme will might cause. In [5], considering the uncertain factors of power grid investment, a risk evaluation method of grid investment and transformation projects in a market environment is proposed. It quantifies the risk of power grid investment by calculating the expected value and variance of the project's net present value. However, this method is meaningful, only when the distribution of uncertain factors is known, and in practice, their distribution parameters may not be obtained easily. The set pair analysis theory is used to measure the investment risk of the power grid. In [6], the break-even method and sensitivity analysis method are used to analyze the risk of investment. Because they can only reflect the investment risk of the project as a whole, they cannot reflect the degree of influence of various uncertain factors, and cannot reflect the randomness of uncertain factors, so there are certain limitations. In [7], [8], the interval mathematics method is used to propose an economic evaluation method for power grid construction projects that takes into account fluctuations in electricity prices. However, this method only considers electricity prices, does not consider other risk factors such as marketization rate. It is difficult to obtain interval distribution and risk thresholds. Multi-scenario analysis is used in the literature [9], [10]. Since the multi-scenario analysis does not reflect all possible scenarios of uncertainty, it will cause deviations in the results of investment risk analysis. In [11], it used the fuzzy mathematics method. However, because the fuzzy membership function is difficult to determine. It cannot reflect the randomness of various uncertain factors. In [12], it constructs a cost-benefit net present value model of power grid investment from the perspective of cost and benefit. The set pair analysis theory is used to measure the investment risk of the power grid, and the set pair analysis coefficient of the net present value is calculated. And the correlation degree is further calculated, which is used as the evaluation indicator of the investment decision to quantify the risk of the power grid investment. In [13], various uncertain factors of distribution network operation risk are comprehensively considered. It adopts the fuzzy comprehensive evaluation theory and the analytic hierarchy process to assign weights to the risk indicators, thus constructing the distribution network operation risk evaluation model.

All these deterministic methodologies are effective with their own advantages and limitations in terms of solution quality, convergence rate, and applicability domain. However, there are mostly qualitative analysis of risks, lacking quantitative analysis. The influence of random factors can't be neglected, and the results are easily affected by the subjective consciousness of the reviewers. Besides the evaluation will be limited by the sample, which is less versatile for power grids with different time and space.

B. INNOVATION CONTRIBUTION

The number of illustrative applications of these solvers based on back propagation (BP) neural networks and genetic algorithms is seen in the literature, such as nonlinear optics problems [14], nonlinear nanofluidic systems of Jeffery-Hamel flow [15], the dynamics of nonlinear singular heat conduction model of the human head [16], nonlinear Painlev'e II systems in applications of random matrix theory [17], hermal analysis of porous fin model [18], Nonlinear Singular Thomas-Fermi Systems [19], credit evaluation for listed companies [20], vibration dynamics of rotating electrical machines [21], environmental quality assessment [22], grid fault diagnosis [23], wind speed soft sensor [24], prediction of postgraduate entrance examination [25], fault section locating in distribution net-work with DG [26], crude oil production prediction [27], prediction of junction temperature for high power LED [28].

BP neural network can achieve a mapping function from input to output, which makes it particularly suitable for solving complex mapping problems with internal mechanisms. The genetic algorithm is very suitable for solving optimization problems [25]. Therefore, based on the characteristics of multi-dimensional, nonlinear and strong correlation of power grid investment risk, this paper proposes a power grid investment risk evaluation model based on GA-BP neural network. The model uses only evaluation functions instead of gradients and other ancillary information. The optimization process starts from the set of spatial points of the solution until the global optimum. After the successful training, the network no longer relies too much on the impact of the new input samples, which reduces the possibility of training failure, and the output accuracy and convergence speed are improved. Moreover, as long as the training data has changed, a power grid investment risk evaluation model, which is suitable for each power grid investment risk, can be obtained.

C. ORGANIZATION

The organization of the paper is as follows: In Sect. 2, the risk factors which affect the power grid investment are screened and a power grid investment risk evaluation indicator system is established. In Sect. 3, the modeling process and algorithm steps of the power grid investment risk evaluation model based on GA-BP neural network are described. In Sect. 4, the parameters of the model are set and the inputs and outputs of the neural network are explained. The necessary neural network architecture is also given in this section. An example analysis of the model and comparative analyses of the proposed algorithms are listed in Sect. 5. Concluding inferences along with future research perspectives are provided in Sect. 6.

II. POWER GRID INVESTMENT RISK INDICATORS

In the process of power grid investment risk evaluation, it is very crucial to establish an evaluation indicator system, which will directly affect the scientific and rationality of power grid investment risk evaluation.

In order to ensure the accuracy of the power grid investment risk evaluation, we select indicators through the following procedures. First of all, with reference to the risk

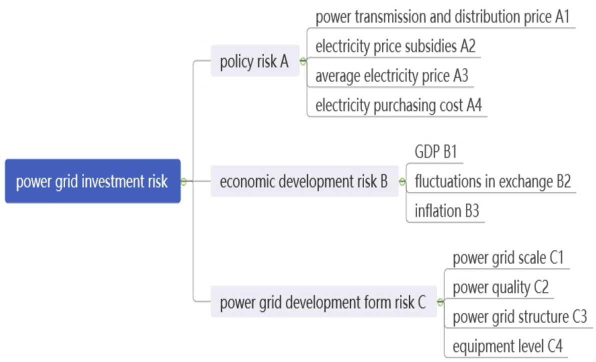

FIGURE 1. Power grid investment risk evaluation indicators.

evaluation criteria and the actual situation of the industry risk evaluation, we reviewed a number of related papers and selected 30 indicators [29], [30]. Then, through the discussion of the expert meeting and the analysis of the past data, 11 indicators were finally extracted as the main research object of the power grid investment risk evaluation. Therefore, this paper only considers three main risk aspects of power grid investment risk: policy risk A, economic development risk B, and power grid development form risk C. Risk factors refer to factors that can cause or increase the probability of a risk event or the extent of the loss. On this basis, the three main risks are divided into 11 secondary indicators: risk factors. The policy risk is divided into power transmission and distribution price A1, electricity price subsidies A2, average electricity price A3 and electricity purchasing cost A4; economic development risk is divided into GDP B1, fluctuations in exchange B2 and inflation B3; power grid development form risk is divided into power grid scale C1, power quality C2, power grid structure C3 and equipment level C4. Its main hierarchy is shown in Figure 1.

Where, A1 (power transmission and distribution price) refers to the general price of the service provided by the power grid management enterprise for access systems, networking, power transmission and sales; A2 (electricity price subsidies) means the subsidy which is announced by the government and generally depends on the cost and installation cost of such an energy generation facility; A3 (average electricity price) equals to total electricity sales divided by total electricity output; A4 (electricity purchasing cost) means the unit price of electricity purchased by power companies from power plants; B1 (GDP) refers to the final result of production activities of all resident units of a country at a market price for a certain period of time; B2 (fluctuations in exchange) refers to fluctuations in the external value of money, including currency depreciation and currency appreciation; B3 (inflation) refers to the situation where the money supply is greater than the actual demand of the currency under the condition of currency circulation; C1 (power grid scale) means the overall size of the substation and transmission and distribution lines of various voltages in the power system; C2 (power quality) refers to the quality of electrical energy in the power system; C3 (power grid structure) refers to the layout of power plants, substations and switchyards within the power grid, and the connection of their various voltage and power lines; C4 (equipment level) refers to the level of power generation equipment and power supply equipment.

III. ESTABLISHMENT OF POWER GRID INVESTMENT RISK EVALUATION MODEL

The power grid investment is a comprehensive, professional and technical activity, and it is also a high-input and high-risk investment process. Therefore, it is essential to find a scientific and accurate method to evaluate the risk of power grid investment. The power grid investment risk evaluation model based on GA-BP neural network proposed in this paper is aimed at the characteristics of multi-dimensional, nonlinear and strong correlation of power grid investment risk, which solves the problem that the existing model is not accurate and practical.

The basic idea is: Take the expert rating of 11 secondary indicators as the input of GA-BP neural network, and the evaluation value of power grid investment risk as the output. By training GA-BP neural network, the nonlinear mapping between the factors and the evaluation of power grid investment is realized.

The working mechanism of the model is: Use the global search ability of genetic algorithm to determine the optimal range of BP neural network weights and threshold, and then use the BP neural network to search the local optimal solution. When the BP neural network training has a slow convergence or even no convergence, the threshold and weight of each hidden layer node and output layer node of the BP neural network are used as the input information of the genetic algorithm. The optimal solution of BP neural network is obtained by using the selection operator, crossover operator and mutation operator of genetic algorithm. Continue to train the neural network and repeat this step until the required error accuracy is achieved [31], [32].

The process of the power grid investment risk model mainly includes four parts: the determination of BP neural network connection structure, the optimization of BP neural network weight and threshold by genetic algorithm, the training of BP neural network, and the risk evaluation of power grid investment, as shown in Figure 2.

The power grid investment risk model process based on GA-BP neural network is as follows:

(1) The weights and thresholds of the BP neural network are cascaded in order. That is: the weight between the input layer and the hidden layer, the weight between the hidden layer and the output layer, and the threshold of the hidden layer and the output layer. Randomly generating 50 chromosomes with a coding length of 196 ($11*12 + 12*4 + 12 + 4 = 196$);

(2) According to the characteristics of the power grid investment risk evaluation model, the parameters of genetic algorithm process and BP neural network training process are set, including population size, selection operator,

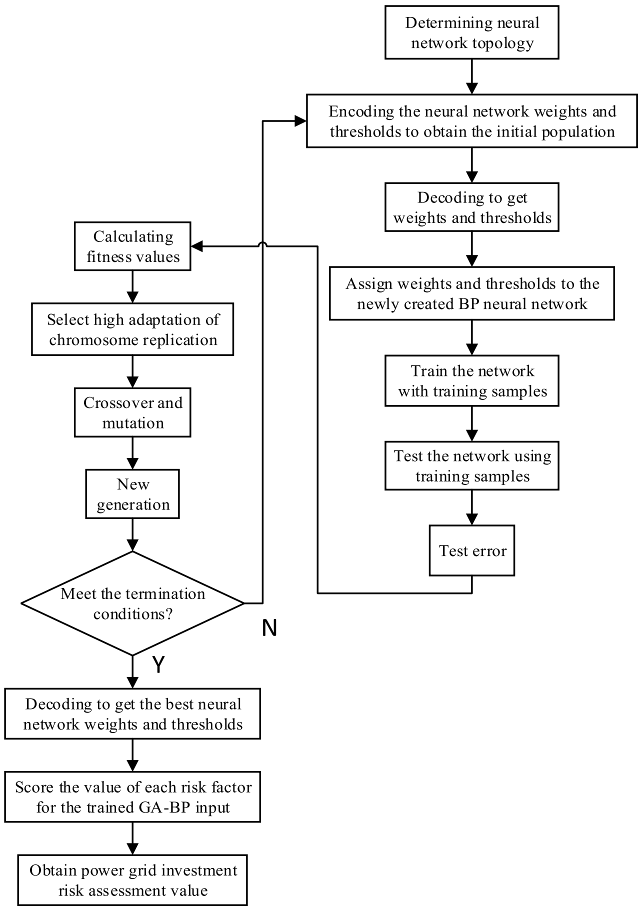

FIGURE 2. Flow chart of power grid investment risk evaluation model based on GA-BP neural network.

crossover operator, mutation operator, network layer number, training accuracy, etc.;

(3) The reciprocal of the neural network error function is chosen as the fitness function of the genetic algorithm. If the error is larger, the fitness value will be smaller and the adaptability will be lower correspondingly. And determine whether the result meets the optimization criteria or not. If yes, skip to the step 6);

(4) Selection. The populations are ranked according to fitness values from large to small, and individuals with greater adaptability are selected to ensure that the original good properties are maintained in the genetic process;

(5) Crossover and mutation. Select crossover and mutation operators as needed to cross and mutate contemporary individuals and form new populations;

(6) Check whether the new generated individuals meet the criteria of the optimal individual or not. If they meet, continue the next step, if they do not, return to step 3);

(7) The optimal individuals are sequentially split into the weights and thresholds of the BP neural network;

(8) The BP neural network performs forward propagation, calculates global errors, and adjusts network parameters (weights and thresholds). Repeat the learning training until the required accuracy or the upper limit of learning;

(9) Input the risk factor score into the network to get the risk evaluation value of power grid investments.

IV. DETERMINATION OF THE POWER GRID INVESTMENT RISK MODEL BASED ON GA-BP NEURAL NETWORK

The evaluation model of power grid investment risk can be seen as the non-linear mapping from input: expert scoring value of each risk factor of power grid investment to output: power grid investment risk evaluation value.

A. THE DETAILED DESIGN OF BP NEURAL NETWORK

1) DETERMINATION OF INPUT NODE

We selected the 11 most important factors which affect the results of the power grid investment risk evaluation as the input of the GA-BP neural network. The 11 indicators were scored by considering the risk weights, probability of occurrence, magnitude of impact, and degree of association with risk. The scores are divided into five levels: very low (0.1), lower (0.3), average (0.5), higher (0.7), very high (1.0). The larger the value, the greater the impact of this factor on the power grid investment risk. When scoring, the experts fully review and analyze the investment plan, and give the scores of each risk indicator to measure the performance of the evaluated project on the indicator and the related risks that may arise as a result [33].

$$X_i = \{X_{i1}, X_{i2}, \ldots, X_{i11}\} \tag{1}$$

where X_i is the input vector of the i-th sample; X_{i1}, X_{i2}, …, X_{i11} correspond to power transmission and distribution price A1, electricity price subsidies A2, average electricity price A3, electricity purchasing cost A4, GDP B1, exchange rate changes B2, inflation B3, power grid scale C1, power quality C2, power grid structure C3 and equipment level C4 respectively.

2) DETERMINATION OF OUTPUT NODE

Because the output of the GA-BP neural network corresponds to the risk evaluation value of policy risk A, economic development risk B, power grid development form risk C and the power grid investment risk, then the number of output nodes is 4.

$$O_i = [O_{i1}, O_{i2}, O_{i3}, O_{i4}] \tag{2}$$

where, O_i is the output vector of the i-th sample; O_{i1} is the policy risk evaluation value; O_{i2} is the economic development risk evaluation value; O_{i3} is the power grid development form risk evaluation value; and O_{i4} is the total risk evaluation value of the power grid investment.

For a more intuitive and unified response to power grid investment risks, the output value of the GA-BP neural network is limited to any value between [0, 1]. Among them, 0 is no impact, 1 is serious impact, and the larger the value,

TABLE 1. Power grid investment risk evaluation indicators.

Risk Evaluation Value	Risk Degree	Risk Dade
[0,0.2)	Very small	1
[0.2,0.4)	Small	2
[0.4,0.6)	General	3
[0.6,0.8)	Large	4
[0.8,1]	Very large	5

the more serious the impact of the risk. At the same time, the grade of risk and the degree of risk are divided into five grades according to the output value interval: grade 1, grade 2, grade 3, grade 4, and grade 5 (the degree of risk is strengthened in turn). The correspondence between the output and the risk grade and the degree of risk is established, as shown in Table 1.

3) DETERMINATION OF NETWORK STRUCTURE

The model uses a typical three layer BP neural network. The determination of the number of hidden layer nodes in a neural network is a complex problem. It affects the results of risk evaluation. If the number of nodes is too small, the effective diagnostic information obtained during the diagnosis process is relatively less, and it is difficult to achieve accurate diagnosis. If the number of nodes is too large, not only will the network learning and training time be too long, but also the fault tolerance will be poor, and the generalization ability will be reduced.

$$N = \sqrt{L+M} + a \tag{3}$$

$$N = bL \tag{4}$$

where, L is the number of the input layer; M is the number of the hidden layer; N is the number of the output layer; a is an integer in the interval [1, 10]; b is a value within [0, 1].

Therefore, this paper limits the range of hidden layer nodes in the power grid investment risk model according to empirical formula (3) (4), and then uses the training error and the training speed to select the optimal number of nodes in the hidden layer [34]. Finally, the number of hidden layers is determined to be 12.

4) DETERMINATION OF NETWORK TRANSFER FUNCTION

When choosing a transfer function, two main aspects are considered: 1) non-linear; 2) guaranteed output in the range [0,1]. Only changing the transfer function and other parameters are fixed, it is found that the hidden layer transfer function uses the tansig function with less error than the sigmoid function when the GA-BP neural network is trained with the samples in Table 3.

Therefore, the nonlinear function tansig is selected as the transfer function in the hidden layer.

$$f(x) = \frac{1-e^x}{1+e^x} \tag{5}$$

TABLE 2. Genetic algorithm parameter settings.

Parameter	pop	gen	Pc	Pm	q
Value	50	1000	0.3	0.001	0.01

TABLE 3. Power grid investment risk evaluation risk data.

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4
1	0.3	0.1	0.1	0.3	0.3	0.5	0.3	0.5	0.3	0.1	0.3
2	0.3	0.1	0.1	0.3	0.3	0.5	0.1	1.0	0.3	0.7	0.3
3	0.1	0.1	0.1	0.3	0.3	0.1	0.1	1.0	0.5	0.5	0.7
4	0.3	0.1	0.1	0.3	0.3	0.1	0.3	0.5	0.3	0.1	0.5
5	0.3	0.7	0.7	0.5	0.3	0.7	0.3	0.5	0.3	1.0	0.3
6	0.3	0.7	0.7	0.3	0.3	0.5	0.7	0.5	0.3	0.1	0.3
7	0.5	0.3	0.3	0.3	0.3	0.1	0.3	0.5	0.1	0.5	0.3
8	0.3	0.7	0.3	0.5	0.7	1.0	0.3	0.3	0.3	0.1	0.3
9	0.3	0.3	0.3	0.3	0.5	0.1	0.3	1.0	0.1	0.3	0.3
10	0.3	0.3	0.3	0.3	0.3	0.5	0.3	0.5	0.5	0.1	0.3
11	0.5	0.3	0.3	0.3	0.3	0.1	0.3	1.0	0.1	0.1	0.3
12	0.3	0.7	0.3	0.3	0.7	0.5	0.3	0.5	0.5	0.5	0.3
13	0.7	0.3	0.3	0.5	0.5	0.1	0.7	0.5	0.3	0.1	0.3
14	0.3	0.3	0.7	0.5	1	0.5	0.3	0.5	0.3	0.7	0.7
15	0.3	0.3	0.3	0.1	0.3	0.5	0.3	0.3	0.7	0.7	0.3
16	0.7	0.1	0.1	0.5	0.1	0.7	0.5	0.7	0.5	0.3	0.5
17	0.5	0.3	0.1	0.3	0.5	0.1	0.5	0.5	0.3	0.3	0.7
18	0.3	0.3	0.5	0.1	0.5	0.5	0.3	0.5	0.3	0.1	0.5
19	0.5	0.3	0.3	0.1	0.5	0.5	0.5	0.7	0.3	0.1	0.5
20	0.3	0.5	0.1	0.3	0.7	0.3	0.5	0.7	0.7	0.3	0.1

Select the sigmoid function as the transfer function in the output layer.

$$g(x) = \frac{1}{1+e^x} \tag{6}$$

5) FORMULAS BETWEEN INPUT AND OUTPUT

Supposing there are 11 inputs and 4 outputs in the network, and 12 neurons in the hidden layer, the threshold value of the hidden layer is

$$\{\theta_{h1}, \theta_{h2}, \ldots, \theta_{h12}\} \tag{7}$$

The threshold value of the output layer is

$$\{\theta_{o1}, \theta_{o2}, \theta_{o3}, \theta_{o4}\} \tag{8}$$

The weight from input layer to hidden layer is

$$\omega_{IH} = \{\omega_{p,k}\} = \begin{Bmatrix} \omega_{1,1}, \omega_{1,2}, \ldots, \omega_{1,12} \\ \ldots \quad \ldots \quad \ldots \quad \ldots \\ \omega_{11,1}, \omega_{11,2}, \ldots, \omega_{11,12} \end{Bmatrix} \tag{9}$$

The weight from hidden layer to output layer is

$$\omega_{HO} = \{\omega_{q,j}\} = \begin{Bmatrix} \omega_{1,1}, \omega_{1,2}, \omega_{1,3}, \omega_{1,4} \\ \ldots \quad \ldots \quad \ldots \quad \ldots \\ \omega_{12,1}, \omega_{12,2}, \omega_{12,3}, \omega_{12,4} \end{Bmatrix} \tag{10}$$

The output is calculated as following

$$O_j = f(\sum_{q=1}^{12}(g(\sum_{p=1}^{11}\omega_{p,k}x_p - \theta_k)\omega_{q,j} - \theta_j)) \quad (k = 1, 2, \ldots, 12;\ j = 1, 2, 3, 4) \tag{11}$$

where, O_j is the actual j-th output of GA-BP neural network.

B. THE DETAILED DESIGN OF GENETIC ALGORITHM

1) CODING

In order to improve the precision and expand the search space, we choose the real number coding. Because the structure of BP neural network is 11-12-4, according to the formula [35], the number of weights to be optimized is 11*12+12*4 = 180, the number of threshold to be optimized is 12+4 = 16. So the encoding length is 180 + 16 = 196.

2) FITNESS FUNCTION

The error function of the power grid investment risk model is

$$E = \sum_{i=1}^{15}\sum_{j=1}^{4}(y_{ij} - O_{ij})^2 \tag{12}$$

where, O_{ij} is the actual j-th output of the i-th sample of GA-BP neural network; y_{ij} is the expected j-th output of the i-th sample of GA-BP neural network.

The role of the genetic algorithm is to find the best weights and thresholds, and to minimize the value of the BP neural network's error function. Therefore, the reciprocal of the error function of BP neural network is chosen as the fitness function of the genetic algorithm [36].

$$fit = \frac{1}{E} = \frac{1}{\sum_{i=1}^{15}\sum_{j=1}^{4}(y_{ij} - O_{ij})^2} \tag{13}$$

3) GENETIC OPERATORS

In the process of using genetic algorithms to optimize weight values, the most common genetic operators are used, namely operator selection, crossover operator and mutation operator.

Using the control variable method, multiple training and testing to obtain the parameters of the genetic algorithm. The genetic algorithm selects the roulette selection as the selection operator. The population size, crossover probability, mutation probability and evaluation parameters involved in genetic process are defined as: population size is pop = 50, genetic algebra gen = 1000, crossover probability Pc = 0.3, mutation probability Pm = 0.001, evaluation parameter q = 0.01.

V. CASE STUDY

The data of power grid investment evaluation that have been verified in four typical cities and towns in a province were taken as examples to analyze. As shown in Table 3.

We take a "10-fold cross-validation method" for these 20 sets of data. The simulation experiments of the power grid investment risk evaluation model based on BP Neural Network and the power grid investment risk evaluation model based on GA-BP neural network are realized by Matlab 2016a.

Compare the results of the two sets of experiments with the real results. The results are shown in Table 4.

TABLE 4. Comparison of BP neural network and GA-BP neural network.

	Actual Value	BP Neural Network		GA-BP Neural Network	
		Predictive Value	Relative Error	Predictive Value	Relative Error
1	0.313	0.321	2.24%	0.305	-2.56%
2	0.291	0.297	2.06%	0.296	1.72%
3	0.366	0.380	3.83%	0.356	-2.73%
4	0.291	0.310	6.53%	0.279	-4.12%
5	0.498	0.472	-5.22%	0.521	4.62%
6	0.478	0.421	-12.13%	0.490	2.51%
7	0.266	0.261	-2.26%	0.271	1.50%
8	0.558	0.601	7.53%	0.571	2.15%
9	0.466	0.450	-3.43%	0.472	1.29%
10	0.366	0.351	-4.37%	0.377	3.01%
11	0.301	0.294	-2.33%	0.310	2.99%
12	0.466	0.477	2.36%	0.472	1.29%
13	0.433	0.411	-5.31%	0.421	-3.00%
14	0.511	0.566	10.76%	0.501	-2.15%
15	0.377	0.360	-4.51%	0.391	3.45%
16	0.648	0.662	2.16%	0.639	-1.39%
17	0.134	0.139	3.58%	0.130	-2.99%
18	0.629	0.655	4.13%	0.620	-1.43%
19	0.232	0.227	-2.31%	0.236	1.72%
20	0.262	0.270	3.05%	0.254	-3.05%

TABLE 5. Overall error of BP neural network and GA-BP neural network.

	BP Neural Network	GA-BP Neural Network
Relative Error	4.51%	2.48%

The analysis of the results shows that there are several serious errors in the results of the power grid investment risk evaluation model based on BP neural network. However, most of the errors are within 5%, and the overall effect is better. The experimental results of the power grid investment risk evaluation model based on GA-BP neural network have little deviation from the actual value, and the relative errors are kept within a small range (not more than 5%). The test data shows that both BP neural network and GA-BP neural network test results are in the same risk level as the actual value, and have good accuracy. However, the GA-BP neural network based evaluation model has better accuracy than the simple BP neural network evaluation model.

By analyzing the test results of GA-BP neural network and BP neural network, the overall error average value is obtained. As shown in Table 5.

TABLE 6. Comparison of BP neural network and GA-BP neural network.

	A		B		C	
	BP	GA-BP	BP	GA-BP	BP	GA-BP
1	10.11%	-6.47%	6.59%	1.75%	-4.55%	1.99%
2	6.67%	-2.99%	-1.66%	4.62%	-3.87%	-1.21%
3	-6.79%	3.85%	-1.57%	3.80%	1.34%	11.37%
4	6.74%	-3.98%	3.37%	-1.48%	10.93%	-1.58%
5	-1.87%	1.20%	2.39%	-3.64%	-5.66%	1.60%
6	-2.13%	1.33%	-1.78%	1.08%	5.04%	8.43%
7	3.63%	-2.19%	6.63%	-3.72%	3.49%	-1.87%
8	-2.71%	5.24%	15.31%	1.98%	-2.34%	1.99%
9	3.54%	3.67%	3.03%	-1.25%	-1.57%	1.40%
10	5.15%	-3.00%	-2.35%	2.40%	2.39%	4.02%
11	-6.15%	1.91%	5.85%	-2.84%	2.94%	1.75%
12	-1.90%	2.18%	2.70%	-1.64%	3.52%	-1.02%
13	-1.96%	1.60%	-3.15%	4.21%	3.15%	5.59%
14	-2.35%	-5.54%	-1.73%	1.96%	-1.33%	1.15%
15	-1.03%	2.83%	-3.18%	2.00%	-1.55%	3.52%
16	2.01%	-1.04%	-3.02%	-4.19%	1.60%	5.93%
17	1.48%	-2.41%	3.74%	8.86%	2.10%	-1.29%
18	1.27%	-4.31%	2.96%	-2.11%	2.10%	-3.82%
19	1.91%	-3.01%	1.50%	9.56%	-3.29%	6.58%
20	-4.76%	3.35%	-3.28%	6.82%	1.05%	-1.82%

It can be seen from the test results in Table 6 that BP neural network and GA-BP neural network have good accuracy, and BP neural network optimized by genetic algorithm has better performance. The experimental results show that for the multi-dimensional factor problem, the accuracy of the power grid investment risk evaluation model based on GA-BP neural network is greatly improved compared with the existing method, and the predicted volatility is also controlled.

The test results of the risk evaluation values of each sub-risk of power grid investment are shown in Table 6, including: policy risk A, economic development risk B and power grid development form risk C.

It can be seen from Table 6 that the test results of BP neural network and GA-BP neural network have some fluctuations, but the test results are in the same risk interval as the real values. At the same time, it can be observed that the power grid investment risk is not simply derived from the combination of policy risk, economic development risk and power grid development form risk, and there is a coupling relationship among the three sub-risks.

VI. CONCLUSION

A new method of power grid investment risk evaluation is proposed through incorporating the strength of BP neural networks modeling and global optimization capabilities on genetic algorithm. The grid investment risk evaluation model based on GA-BP neural network adapts to the characteristics of power grid investment, including multi-dimensional, strong nonlinear, high uncertainty and strong interaction. The model can be effectively applicable for evaluating the risk of power grid investment, with accuracy and convergence. Comparison of the results with the BP neural network and historical data obtained by expert scoring shows that GA-BP is an accurate, feasible and effective alternative. For the evaluation of multi-dimensional power grid investment risk, GA-BP has high accuracy, and the evaluation results have good stability without large fluctuations. This method can be applied to power grid risk evaluations of different regions and times by changing the input data. In addition, this paper not only evaluates the investment risk of the power grid, but also evaluates the risk of policy risk, economic development risk and power grid development form, which reflects the coupling effect between each sub-risk.

At the same time, the model has certain limitations: 1) the accuracy of the evaluation needs to be further improved; 2) the specific relationship between the impact factor and the power grid investment risk cannot be described. Therefore, future work will consider optimizing the genetic algorithm and adopting a variation on the crossover probability and the mutation probability. Then, based on the power grid investment risk assessment, the independence and coupling of various risk factors are explored, and dimension reduction and decoupling are carried out to simplify the risk analysis.

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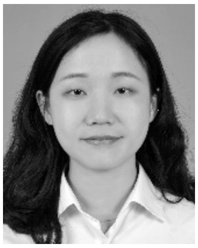

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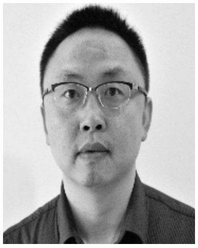

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