Rural Revitalization Evaluation using a Hybrid Method of BP Neural Network and Genetic Algorithm Based on Deep Learning Model

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***Abstract*—The rural revitalization strategy is a comprehensive plan for supporting rural revival in the new development stage while prioritizing agricultural and rural area development. Establishing a rural revitalization evaluation model will help monitor and guide the development of rural revitalization strategies and comprehensively deepen rural reforms. This research combines the benefits of the BP neural network with the genetic algorithm, introduces the genetic algorithm in optimizing the weights and thresholds of the BP neural network, and develops a GA-BP neural network model to evaluate and predict rural rejuvenation. The research findings demonstrated that the GA-BP neural network model possesses rapid convergence, accuracy, and stability in assessing and predicting rural revival and can evaluate and predict rural revitalization well.**

Keywords*—*The rural revitalization strategy; deep learning model; the GA-BP neural network; evaluation model

I. Introduction

The rural revitalization strategy marks that China has entered a new era in solving the “three rural” issues [1]. It will be significant for governments at all levels to understand the implementation process of rural revitalization, implement targeted policies, and give full play to the ingenuity, enthusiasm, and creativity of the country’s cadres and the masses [2].

The evaluation of rural revitalization might establish objectives and requirements. The general conditions for rural rejuvenation were described as “prosperous industries, livable ecology, civilized rural customs, effective government, and rich life” [3]. To make the general demands of the rural revitalization strategy and the “three-step” objective concrete and executable, an evaluation system for rural revitalization must be developed. Rural revitalization evaluation is conducive to an intuitive description of the overview of rural revitalization and construction, drawing a blueprint for the future vision of rural revitalization so that decision-makers, commanders, and builders of rural revitalization have a clear direction and goal of efforts and have a clear vision for rural revitalization [4]. Rural revitalization evaluation can keep track and make adjustments to the strategy’s progress. Using the rural revitalization evaluation model, it is possible to track the development of the rural revitalization strategy, including whether progress has been made in the five areas of “prosperous industry, livable ecological, civilized rural traditions, efficient governance, and prosperous life.” Through monitoring the rural revitalization process, the problems existing in the rural revitalization process can be found in time to implement targeted policies and correct the deviations in the development. Rural revitalization evaluation helps classify and guide rural revitalization strategies in various regions. The rural revitalization strategy must proceed from the actual situation of each region, and it needs to be promoted according to local conditions and classified. The rural revitalization evaluation can rank the existing rural conditions according to the index evaluation scores of various regions to scientifically measure the progress and grasp the actual situation of rural revitalization in various regions [5].

BP neural network, a multi-layer feedforward network trained through backpropagation algorithm, and genetic algorithm, a search algorithm that simulates natural selection and genetic mechanisms. This hybrid method can more effectively solve complex problems in rural revitalization evaluation. There are certain limitations in the evaluation of rural revitalization in existing research. Some studies may rely solely on traditional statistical methods or a single machine learning algorithm, which may not fully address the complexity and non-linear relationships in rural revitalization evaluation. By introducing a hybrid method of BP neural network and genetic algorithm, we can better capture these complexity and nonlinear relationships, thereby providing more accurate and comprehensive evaluation of rural revitalization.

II. Literature Review

A. Rural Revitalization Strategy

1) Rural revitalization strategy: The proposed and improved rural revitalization strategy is based on rural construction theory and practice [6]. Regarding national development, the stance of “agricultural, rural areas, and farmers” must be spelled out. The peasant masses are crucial to the process of national revolution, construction, and development, and peasant masses must constantly be taken into account in national development [7]. “Three Rural” work is not only related to rural areas’ development but also to social stability and the realization of national goals. The government should give political guarantees for the healthy growth of “agricultural, rural areas, and farmers” and should direct the development and construction of rural areas. The government should emphasize agricultural production and policy reform, promote agricultural and rural modernization, and improve the training of rural grassroots party groups and talent management [8].

2) The scientific connotation of a rural revitalization strategy: They were all development plans put forth by the state in reaction to the current domestic situation at the time, and the “rural revitalization strategy” was founded on “creating a new socialist countryside” [9]. The introduction of the rural revitalization plan is a necessary condition for the growth of the times, indicating that rural development has reached a new stage and that a new era based on the strategy is about to begin [10].

Rural revitalization is a three-dimensional security strategy that encompasses economic, ecological, cultural, social governance, and other components of the entire revitalization rather than just one or a few areas of revitalization [11]. First is adhering to the policy orientation of prioritizing the development of agriculture. Agricultural development must focus on high-quality development requirements, stabilize grain production, and ensure the absolute security of national rations. Agricultural development must adhere to the word “excellent” and quality first. Social development cannot simply pursue scale and speed but should seek sustainability. The level of development varies greatly in different regions. It is necessary to respect the differences, diversity, and regional characteristics of agricultural and rural development, implement classification, and adapt to local conditions [12]. Whether the prerequisites for the priority development of agriculture and rural regions can be accomplished in practice depends on whether the objectives of agricultural and rural modernization and national modernization can be achieved. Second, clarifying the general guidelines for the rural rejuvenation approach is the second step. Third, industrial revitalization is the focal point and critical component of rural revitalization. Developing modern agriculture, promoting the integrated growth of primary, secondary, and tertiary industries, and establishing a rural industrial system is crucial for the success of rural industries. The country needs to keep developing agriculture that is good for the environment now and in the future. Fourth, comprehensively deepening rural reforms are necessary for rural rejuvenation. Reform is necessary for rural revival to promote vitality. Further adjustments are required to ensure the agricultural structure is optimized and to assume the integrated growth of primary, secondary, and tertiary industries in rural areas.

B. Deep Learning Model

1) Deep learning: Deep learning, a machine learning algorithm, makes multiple multilayered, nonlinear modifications to data to abstract it [13]. A multi-level machine learning approach called “deep learning” is built on learning representations to model the intricate relationships between data [14].

Deep learning builds a hierarchical model structure matching the human brain (attribute categories or features) by modeling the brain's nervous system with a rich hierarchical structure and extracting the input data level by level to construct more abstract higher-level representations [15].

2) BP Neural Network Model

a) Structure and characteristics of BP neural network: A BP neural network is constructed with an input layer, several hidden layers, and an output layer [16]. The output signal from the second layer serves as the input signal for the third layer, the excitation mode unit of each node output by the input layer serves as the input for the first hidden layer, etc. [17]. Fig. 1 depicts a BP neural network with a three-layer design and one hidden layer.

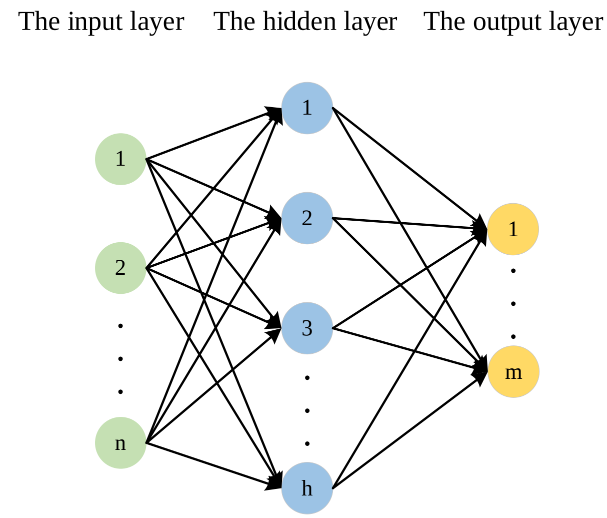


Fig. 1. Three-layer BP network model structure.

b) BP neural network learning algorithm: The mathematical relationship between signals of each layer is [18]:

$$o_k = f(net_k), k = 1,2,\dots,l \tag{1}$$

$$net_k = \sum_{j=0}^{m} w_{jk}\, y_j, k = 1,2,\dots,l \tag{2}$$

$$y_j = f(net_j), j = 1,2,\dots,l \tag{3}$$

$$net_j = \sum_{i=0}^{n} v_{ij}\, y_i \quad j = 1,2,\dots,m \tag{4}$$

The derivatives of *f(x)* in the above equations are all S-functions, and the derivatives of *f(x)* are:

$$f'(x) = f(x)[1 - f(x)] \tag{5}$$

The mean square error of the actual output of the network to the desired output is:

$$E = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2 \tag{6}$$

Then, the amount of weight adjustment in the output and hidden layers of the network is:

$$\Delta w_{jk} = \eta(d_k - o_k)o_k(1 - o_k)y_j \tag{7}$$

$$\Delta v_{ij} = \eta(\sum_{k=}^{l} \delta_k^o w_{jk})y_j\ (1 - y_j\ )x_i \tag{8}$$

$$\delta_k^o = (d_k - o_k)o_k(1 - o_k) \tag{9}$$

The η is the scaling factor, which represents the learning rate in the network training.

Supposing the BP network has *m* implicit layers. In that case, the number of nodes in the implicit layer is represented by m_1, m_2 ,..., m_h, and the output of the hidden layer is represented by y_1, y_2,..., y_h, then the amount of weight adjustment for each layer is:

Output layer: $\Delta w_{jk}^{h+1} = \eta(d_k - o_k)o_k(1 - o_k)y_j^h \quad j = 0,1,2,\dots,m_h; k = 1,2,\dots,l$; the h-th hidden layer: $\Delta v_{ij}^h = \eta(\sum_{k=1}^{l} \delta_k^o w_{jk}^{h+1}) y_j^h (1 - y_j^h) y_i^{h-1} \quad i = 0,1,2,\dots,m_{h-1}; j = 1,2,\dots,m_h$; first hidden layer: $\Delta v_{pq}^1 = \eta(\sum_{r=1}^{m_2} \delta_r^2 w_{qr}^2) y_q^1 (1 - y_q^1) x_p \quad p = 0,1,2,\dots,n; q = 1,2,\dots,m_1$

From the previous, it can be observed that in the BP learning algorithm, the input signal of each layer, the error signal of each layer's output, and the learning rate all influence how much the weights of each layer are adjusted [19].

C. Genetic Algorithm

1) Basic concept of genetic algorithm: A method for global optimization known as a "genetic algorithm" was developed by mimicking biological processes like genetic evolution [20]. It is characterized by group search and mutual exchange of information between groups. The genetic algorithm search does not depend on the gradient problem. So, it has excellent robustness and a capability for worldwide search. Additionally, complex nonlinear problems that are challenging to solve using conventional search techniques can be solved using evolutionary algorithms. Genetic algorithms use many concepts in biology, such as gene chain code, population, crossover, variation, fitness, and selection [21].

2) Flow of genetic algorithm: Like neural networks, genetic algorithms are capable of nonlinear mapping and can solve complex optimization problems, such as multi-objective and nonlinear optimization problems. In addition, a genetic algorithm is an approximation algorithm. The mathematical model of the genetic algorithm is shown in Fig. 2.

3) Design and implementation of genetic algorithm

a) Coding method: Genetic algorithms operate on individuals in a population to accomplish optimization, and they can only deal with individuals through gene chain codes [21]. Therefore, individuals need to be transformed into the form of gene chain codes before using the genetic algorithm. This process is called coding. When designing the encoding scheme, three issues are often considered.

Completeness: All points in the problem space can be found in the expression space, i.e., all possible solutions in the problem space can be transformed into gene chain codes. Soundness: all points in the expression space find their counterparts in the problem space, i.e., each gene chain code corresponds to a possible solution. Non-redundancy: there should be a one-to-one correspondence between the problem and expression spaces.

b) Design of fitness function: The fitness function's design is the foundation for the genetic algorithm's optimization search and directly impacts how well it works. The design of the fitness function is dictated by how the problem will be solved, and it must have a positive outcome. The following three aspects of the fitness function are explained from the fitness function's design method, the fitness function's adjustment, and the influence of the fitness function on the genetic algorithm [22].

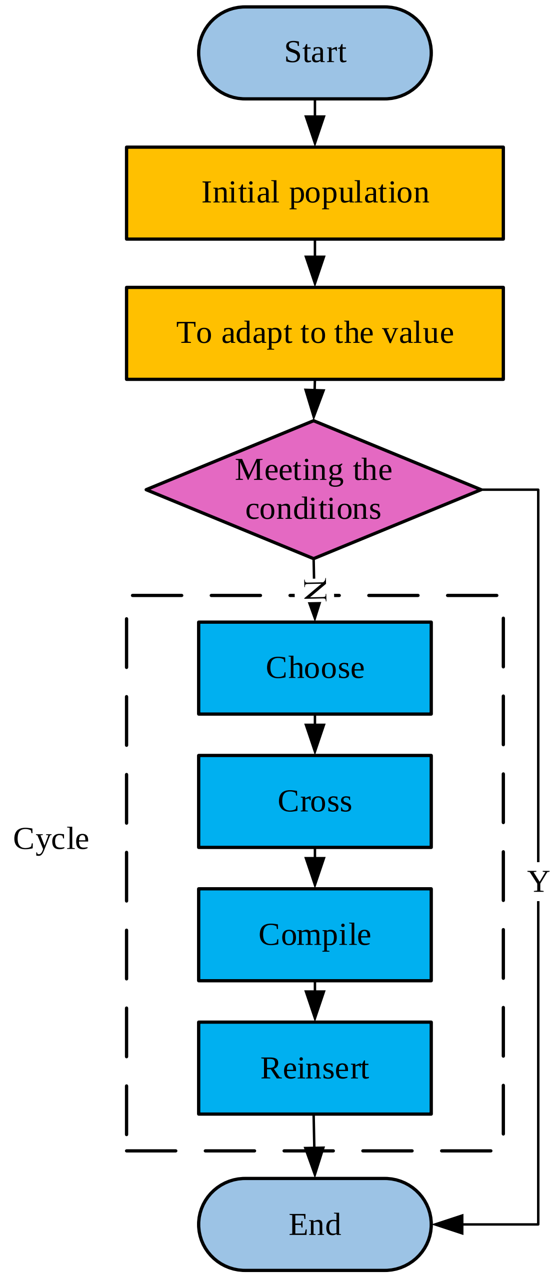


Fig. 2. Mathematical model of genetic algorithm.

i) The fitness function's design process. The fitness function's design must take into account two factors. First, the genetic algorithm seeks the smallest value rather than looking for the most significant value of the goal function of g(x). Second, the genetic algorithm ranks the individual's fitness based on this to determine the selection probability so that the fitness function must be positive. How to map the objective function into the maximum form and ensure the non-negativity of the fitness function is the key to the design of the fitness function. The function can be multiplied by -1 to transform the minimum value problem into a maximum value problem. However, this does not guarantee the non-negativity of the fitness function. For this case, the following approach can be taken to transform the objective function *g(x)*.

$$f(x) = \begin{cases} C_{max} - g(x), & g(x) < C_{max} \\ 0, & others \end{cases} \tag{10}$$

The C_{max} in the above formula is usually taken as the maximum value of *g(x)* in the process of evolution. If *g(x)* is a non-negative function, *f(x)=1/g(x)* conversion can also be used.

When the genetic algorithm finds the maximum value of the objective function *g(x)*, to ensure the non-negativity of the fitness function, the conversion can also be performed:

$$f(x) = \begin{cases} C_{min} + g(x), & C_{min} + g(x) > 0 \\ 0, & others \end{cases} \tag{11}$$

In the above formula, C_{min} is usually taken as the evolutionary process's minimum value of *g(x)*.

ii) Adjustment of the fitness function. Some abnormal individuals often appear when using the genetic algorithm to optimize the population. When the number of abnormal individuals is too much, the more competitive they will be, which will lead to the phenomenon of convergence before the optimization is full. Therefore, it is crucial to reduce the competitiveness of these abnormal individuals. Reducing the competitiveness of abnormal individuals can be achieved by deflating the fitness function, and this deflation becomes the adjustment of the fitness function. The adjustment of the fitness function is the key to ensuring that good individuals are selected, and the commonly used adjustment methods are linear adjustment and power function adjustment.

The following formula can express linear adjustment:

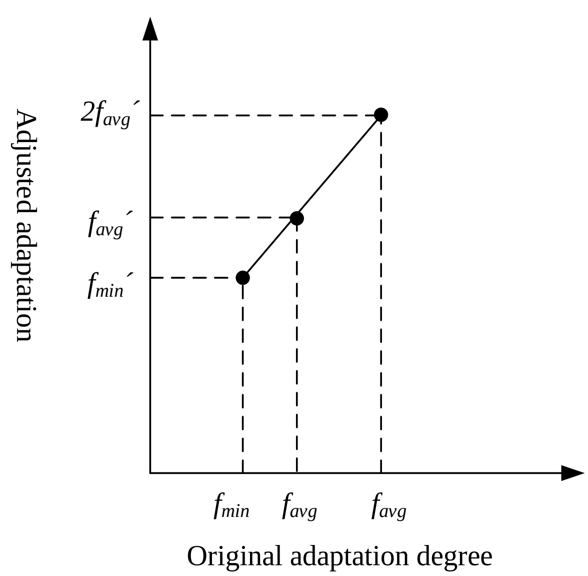
$$f(x)' = af(x) + b \tag{12}$$

In the formula above, *f(x)* represents the original fitness function, *f(x)'* represents the modified fitness function, and the coefficients a and b are selected to satisfy the following conditions: (1) The adjusted fitness must have the same mean value as the original fitness. (2) The highest value of the modified fitness function must be a predetermined multiple of the original fitness function's mean value. That is,

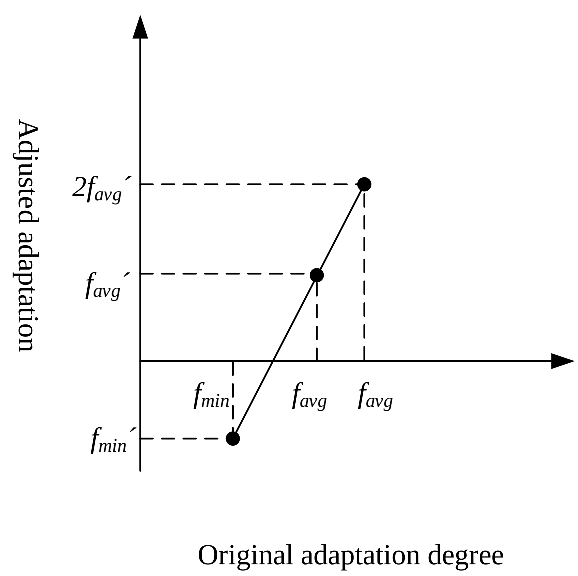
$$f_{max}(x)' = Cf_{avg}(x) \tag{13}$$

The *C* is a replication number set to obtain the optimal individual, and usually, *C* can take a value between 1.2 and 2.0.

Condition (1) is proposed to ensure that, on average, individuals in each population can produce the desired offspring in subsequent selection treatments. The proposed Condition (2) would limit the number of offspring generated by the person with the highest initial fitness. It should be noted that the adjusted fitness values may have negative values. The excessive scaling of coefficient C mainly causes the negative value to the original fitness function. Fig. 3(a) shows the result of the standard adjustment, in which the fitness values of a few abnormal individuals are scaled down, and the others are scaled up, and there are no negative fitness values. Fig. 3(b) shows the unreasonable adjustment. The fitness of abnormal persons is significantly lower than the mean value of fitness $f_{avg}(x)$ and the maximum value of fitness $f_{max}(x)$. When the linear adjustment is used to pull apart $f_{avg}(x)$ and $f_{max}(x)$, there will be negative fitness values. When the coefficient *C* cannot meet the requirement of fitness adjustment, the original fitness minimum $f_{min}(x)$ can be mapped to the adjusted fitness minimum and make $f_{min}(x)' = 0$, provided that $f_{avg}(x) = f_{avg}(x)'$ is still guaranteed.



(a)



(b)

Fig. 3. (a) Result of standard adjustment. (b) Unreasonable adjustment.

Power adjustment: The adjustment is to do k times power treatment on the original fitness function *f(x)*, that is, $f(x)' = f_k(x)$, and the value of k is related to the solution of the problem to be solved, and it can be corrected on demand in the process of the algorithm.

iii) The influence of the fitness function on the genetic algorithm

First, the genetic algorithm's selection operation directly affects how the fitness function is designed. Second, the fitness function specifies the genetic algorithm's iteration stopping condition. There is no specific theory about the genetic algorithm iteration stopping condition. Generally, the iteration stopping condition is when the fitness function reaches the maximum or suboptimal value. However, the maximum and suboptimal values are uncertain in many optimization problems. In such cases, the algorithm iteration is usually terminated when the evolution of the population of individuals tends to a steady state.

c) Selection of genetic operators: The genetic algorithm makes up of three fundamental operators—selection, crossover, and mutation. The selection operator plays a crucial part in the genetic algorithm, with the fitness proportion technique and the expectation value method constituting the most overall selection strategies [23]. The most used selection algorithm is the fitness proportion technique. Each person's fitness in this approach relates to how likely they will be chosen. If the starting population size is n and each individual's fitness score is f_i, the likelihood that an individual will be chosen is P_i.

$$P_i = \frac{f_i}{\sum_{j=1}^{n} f_i} \tag{14}$$

The expectation ratio method calculates the number of individuals' next generation expected to survive based on their fitness values. This method can avoid the phenomenon that good individuals are eliminated and abnormal individuals are selected in the fitness proportion method. The following formula can describe the expected value proportion method.

$$M = \frac{f_i}{\bar{f}} = \frac{n f_i}{\sum f_i} \tag{15}$$

The *f* is the fitness function's average value.

D. Optimization of Neural Networks by Genetic Algorithm

1) Optimizing network connectivity: The BP learning method is the most traditional way to gain the connection rights of the BP neural network. This algorithm's drawbacks include sluggish training speed and frequent slips into local minima. This issue can be significantly resolved by employing the genetic algorithm. The steps of the genetic algorithm to improve the connection rights of the BP neural network are as follows.

a) Determining the encoding scheme. The encoding method has binary encoding and real encoding. Binary coding is simple but not intuitive, and the accuracy is not high; Real coding is very intuitive and accurate. Therefore, the real coding method is commonly used to encode the connection weights.

b) Determining the fitness function. In genetic algorithms, fitness functions can be defined as f= C-e, where C is a constant and e is the sum of the squares of errors. There are many ways to select the fitness function, including the relationship with energy function, evolution time, and network complexity, as long as the fitness function is non-negative.

c) Genetic manipulation. In a genetic algorithm, genetic operation mainly refers to selection, crossover, and variation. The advantage of genetic operation is that it can realize a global search for complex nonlinear functions. However, when gradient functions are easy to obtain, they should be used as much as possible. The local optimization capability of the BP algorithm is relatively robust. Thus, adding a genetic algorithm with global optimization capability can modify the BP algorithm's flaws.

2) Optimizing network structure: The connection patterns and weights between the nodes are the two primary components of a neural network's structure. The following are the main steps in the genetic algorithm optimization of the neural network structure.

a) Randomly generate n different structures and encode each structure. Different codes correspond to different structures.

b) Training the structures in the individual set with different initial weights.

c) Determining the fitness of individuals with the results of training.

d) Selecting the individuals with higher fitness for the next generation.

e) Crossover and mutation of the population to produce a new generation.

f) Repeat the process of (2)-(5) until the network structure meets the requirements.

E. Establishment of the GA-BP Model

Optimizing BP networks with genetic algorithms mainly includes three aspects: optimizing connection weights, optimizing network structure, and optimizing learning rules [24]. However, the theory of network structure optimization and learning rule optimization is still immature and difficult to implement. This paper focuses mainly on the research and implementation of genetic algorithms to improve the weights and thresholds of BP networks [25].

A genetic algorithm encodes the connection weights and thresholds in the BP network in order to maximize the neural network's connection weights. Finally, genetic operators are employed, including selection, crossover, and variation [26]. The genetic output results are utilized as the initial weights and thresholds of the BP network to generate the GA-BP prediction model, and the GA-BP model is trained to attain the needed level of accuracy [27]. The specific operation flow is shown in Fig. 4.

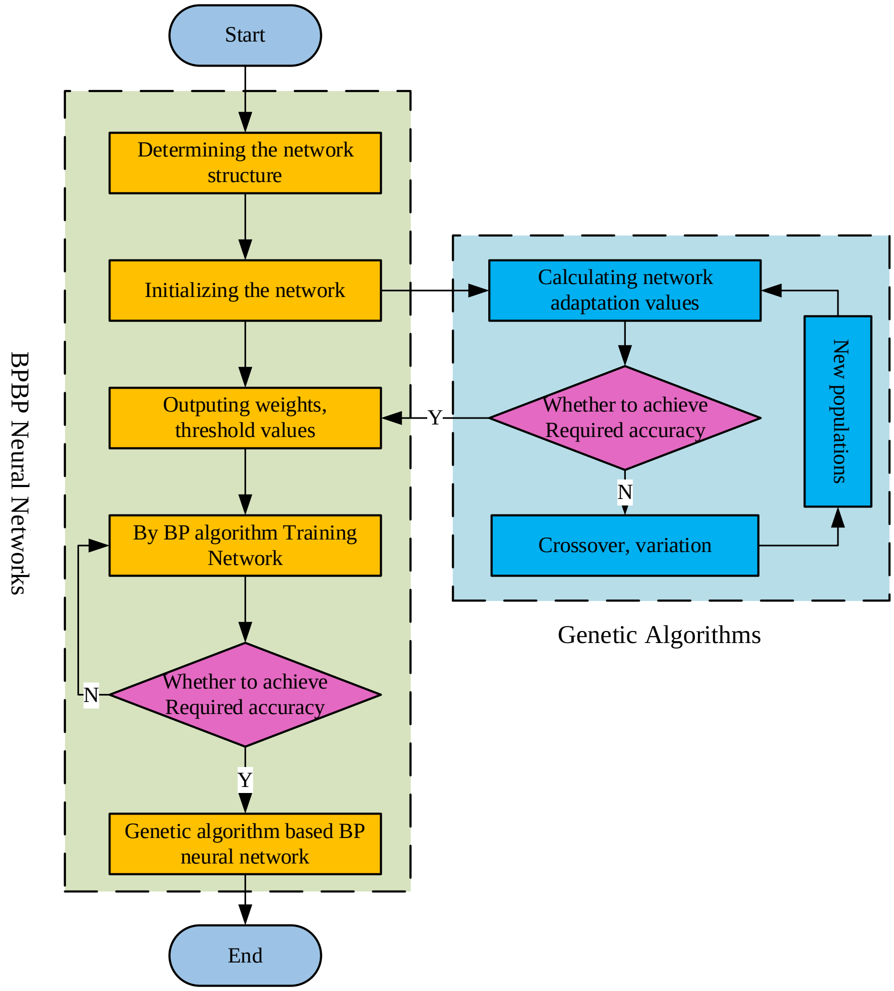


Fig. 4. GA-BP model.

III. Method

A. Establishment of Rural Revitalization Evaluation Index System

This paper establishes the following evaluation index system based on the Specification for the Construction of Beautiful Countryside in the New Era. There are four primary indicators and 15 secondary indicators. The primary indicators are the basis of industrial development, ecological environment, civilization management, and living standards.

B. Determination of the Evaluation Level of Rural Revitalization

This paper uses the Delphi technique to measure how rural revitalization has affected the research object to measure the situation accurately. The Delphi technique is simply a confidential letter consultation process. Generally, it involves gathering expert opinions on the problems that need to be forecasted, sorting, induction, and statistics, followed by anonymous feedback to the experts. This process is repeated until all expert opinions are in agreement.

C. Construction of GA-BP neural network model

1) Determination of the number of neurons in the input and output layers: The contribution of the BP network to this experiment is the second indicator of the rural revitalization evaluation index. Therefore, there are fifteen neurons in the input layer and one neuron in the output layer, which reflect the assessment value of the results of rural revitalization.

2) Determination of the number of hidden layers and the number of neurons: Nonlinear recognition capabilities of the BP network are caused mainly by the existence of one or more hidden layers between the input and output layers. Through the addition of more hidden layers, accuracy can be enhanced and error reduced. However, it also increases the network's complexity and training time, as well as the training error of the network weights. Consequently, there are two methods for improving accuracy: increasing the number of hidden layers and the number of hidden layer neurons. The optimal number of neurons for the buried layer cannot be calculated with absolute confidence on a theoretical level. The selection of the number of inferred layer neurons is also compatible with specific empirical formulations, such as Formula (16). The estimated number of implied layer neurons derived from the formula can serve as the starting point for the trial-and-error process.

$$m = \sqrt{n+1} + \alpha \tag{16}$$

Fig. 5 shows the correlation coefficients and mean square error (MSE) obtained by training the three-layer BP neural network with the number of neurons in the hidden layer ranging from 5 to 15.

According to this study, when there are 12 neurons in the hidden layer of a three-layer BP network, the correlation coefficient is at its highest, and the MSE is at a more desired level. The correlation coefficient is at its lowest when the number of neurons in the hidden layer is 13, and the correlation coefficient is even negative during training. Theoretical investigation indicates that the average number of neurons in the buried layer is between 1 and 2. After repeated training, two BP number neural networks were initially identified: BP networks with one hidden layer and two hidden layers. Fig. 6 depicts the output of the correlation coefficients and mean square error (MSE) after training these two networks ten times.

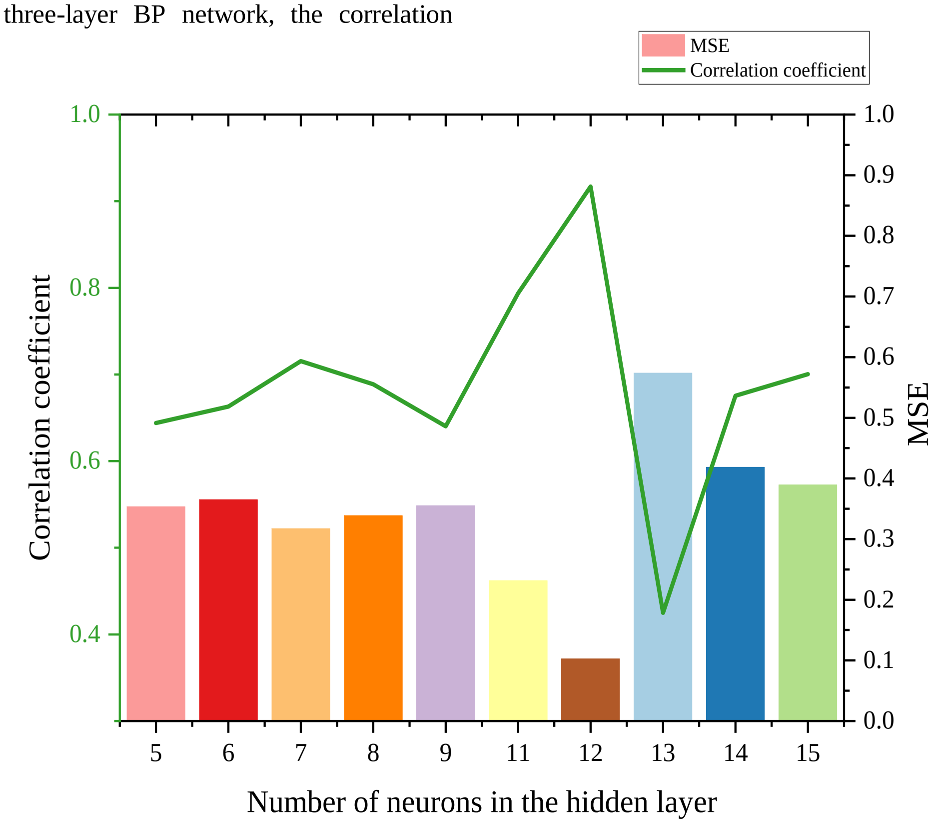


Fig. 5. Training of three-layer BP neural network.

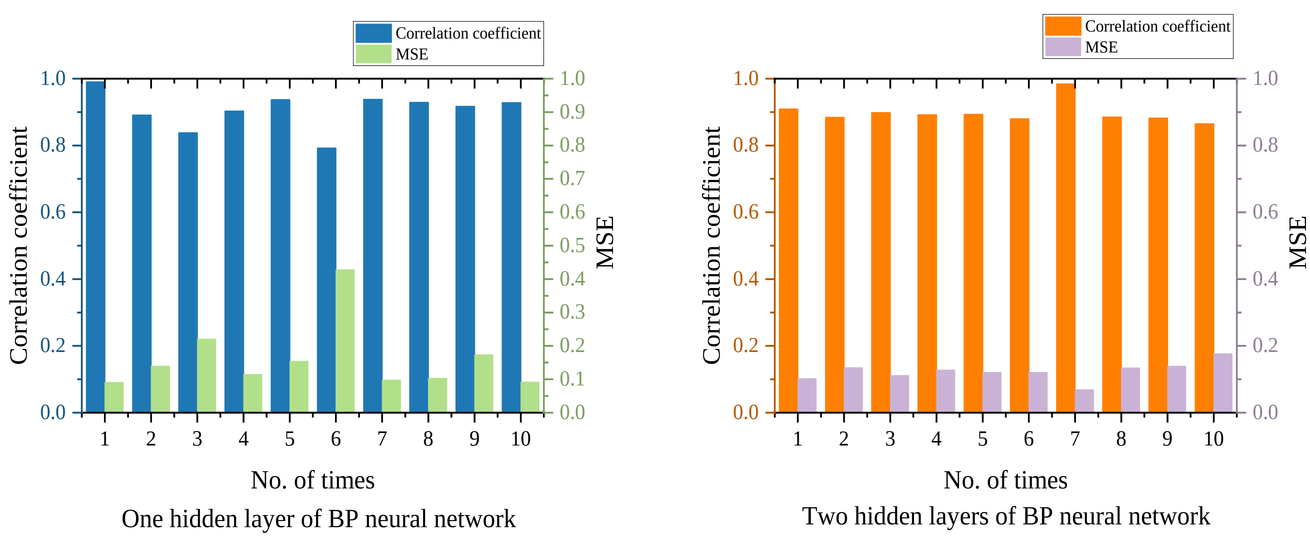


Fig. 6. Correlation coefficients and MSEs of BP networks with different numbers of hidden layers.

The unpredictability of the BP network's initial weights is evident in the fact that the outcomes of each training are not the same and that there is a significant amount of variability in the training results. It is found that the differences in training error, correlation coefficient, and MSE between the BP network with one hidden layer and the BP network with two hidden layers are not much. Moreover, compared with the BP network with one hidden layer, the network structure with two hidden layers is more complex and takes longer to train. The fact that the results of each training are different and that there is a sizable level of variability in the training results shows how unpredictable the starting weights of the BP network are.

D. Optimization of Weights and Thresholds by Genetic Algorithm

1) Determining the genetic algorithm population: In genetic algorithms, the size of the population directly affects the global optimization characteristics of the genetic algorithm. In general, the larger the population size, the higher the diversity of the population, and the less likely the algorithm will fall into local minima during optimization. The population size is generally set between tens and hundreds. The calculation speed is also considered in the selection of population size. Combining these two factors, in this experiment, the number of genetic algorithm populations is 40.

2) Determining the genetic algorithm variation probability: In the genetic algorithm, the variation probability's size directly affects the algorithm's convergence and the final solution's performance. The larger the variation probability, the higher the diversity of individuals, but an increase in the variation probability reduces the convergence of the network, leading to a reduction in the final solution's performance. In engineering applications, the variation probability size usually ranges from 0.001 to 0.1. In this experiment, the probability of the genetic algorithm was determined to be 0.05.

3) Training of the genetic algorithm: The fact that each training produces a new set of outcomes and a considerable degree of variability in the training results demonstrates how unpredictable the BP network's beginning weights are. The genetic algorithm of this experiment is selected 100 times, and the MATLAB genetic algorithm toolbox is applied to train the samples. The error sum of the squares curve and fitness value curve during training are shown in Fig. 7. With the increase in training times, the sum of error squares becomes smaller and smaller, and the fitness value increases gradually. The larger the fitness value, the higher the sample's fitness to the environment is.

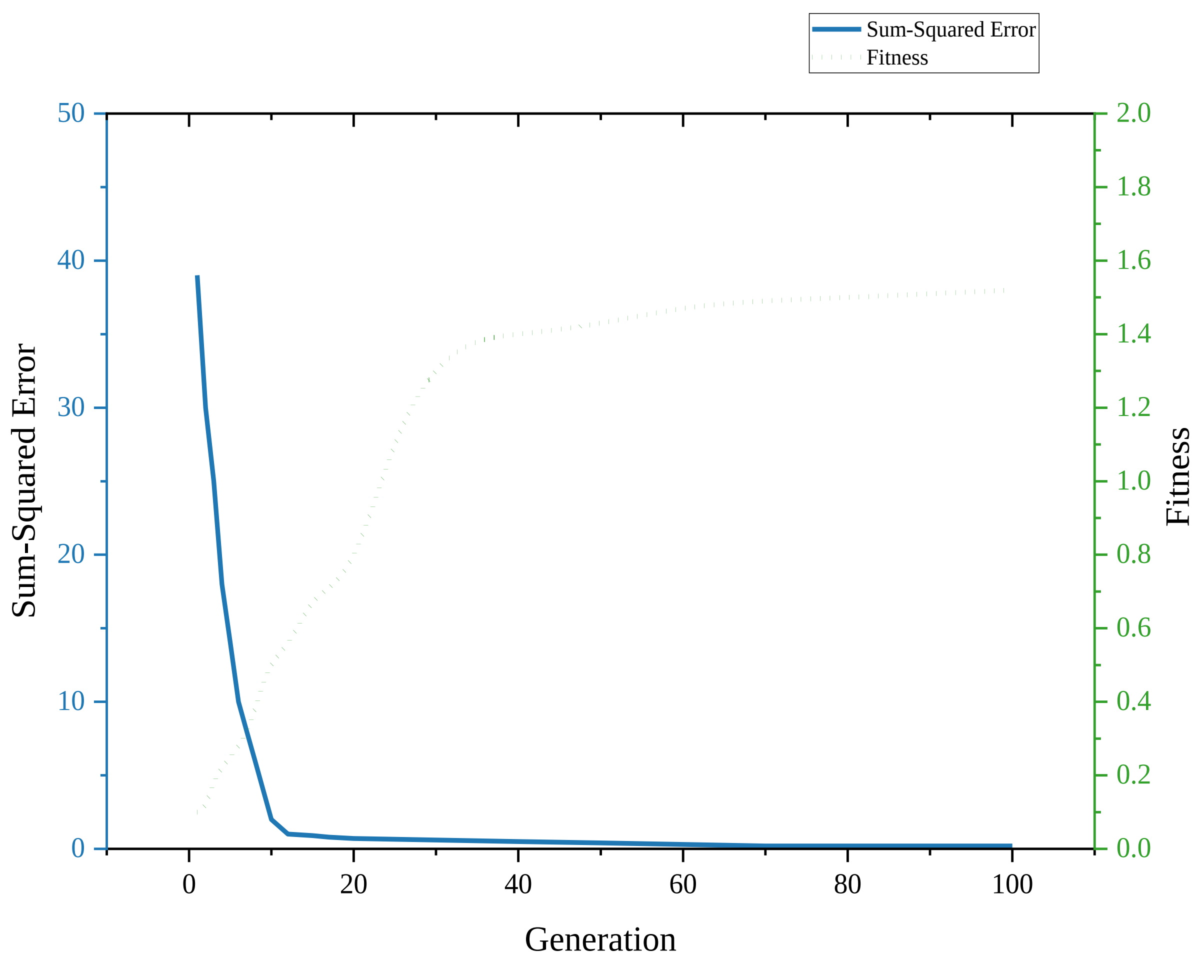


Fig. 7. Error sum-of-squares curve and fitness curve.

IV. Results

A. Selection of Training Samples

In this work, 30 samples were selected: 20 were used for training the GA-BP model, and 10 were used as test samples. The evaluation indexes in the samples were used as the input of the GA-BP model, and the model's output was the prediction of the rural revitalization evaluation at this time. Finally, the prediction accuracy of the GA-BP model could be obtained by comparing the predicted value with the actual value.

B. Evaluation of GA-BP Prediction Model

This paper used three indicators of convergence, accuracy, and stability. Convergence was judged based on the number of Epochs of steps in the network training process to determine the convergence speed. Different networks converge faster with fewer steps when they reach the same training goal; conversely, convergence is slower with more steps. Accuracy was determined by the relative error between the test simulation output value and the desired output value of different networks to determine the accuracy of the output results obtained by testing the trained network. Where, relative error = (test simulation output value - desired output) / desired output × 100%. The stability of the network was further judged from the macroscopic point of view by calculating the mean square error (MSE) of the test output of different networks based on the error between the test simulation output and the expected output.

The convergence curves of the GA-BP prediction model are shown in Fig. 8. It can be found that the loss function of the GA-BP prediction model converges to stability and achieves the training goal after 400 times of training.

In this article, the GA-BP network model was evaluated, and the test simulation output results are depicted in Fig. 9. It can be seen that the GA-BP prediction model can reduce the percentage error of predicted samples to less than 4% and that the prediction error of some samples is nearly zero.

The GA-BP prediction model was trained ten times, and the percentage error, correlation coefficient, and mean square error (MSE) of the test samples are output, as shown in Fig. 10.

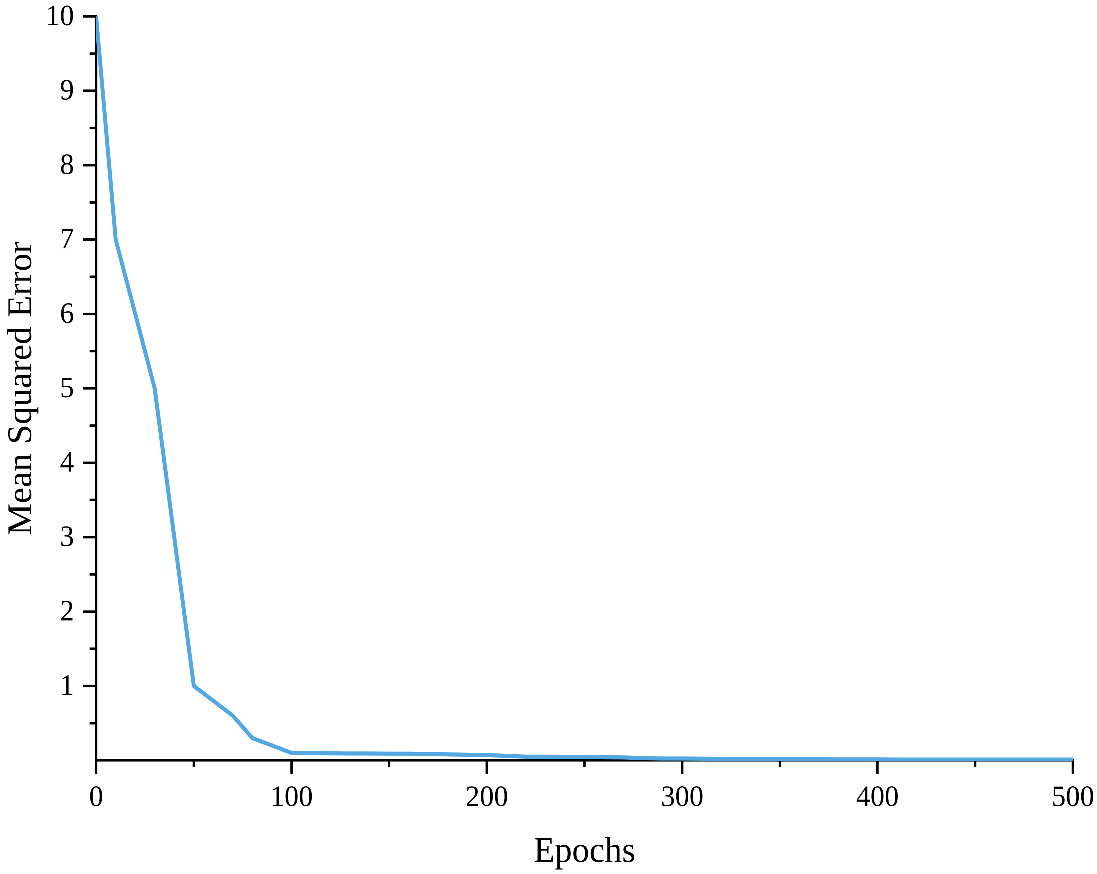


Fig. 8. Convergence of the GA-BP prediction model.

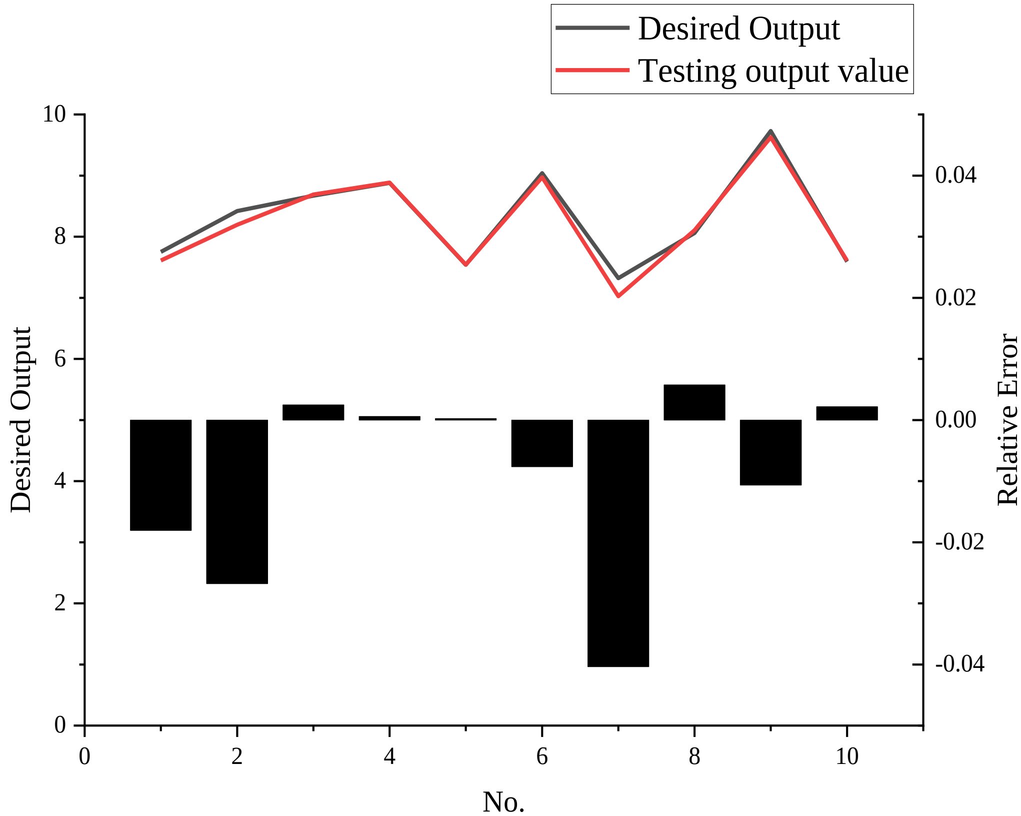


Fig. 9. Simulation results of GA-BP neural network for test sample data.

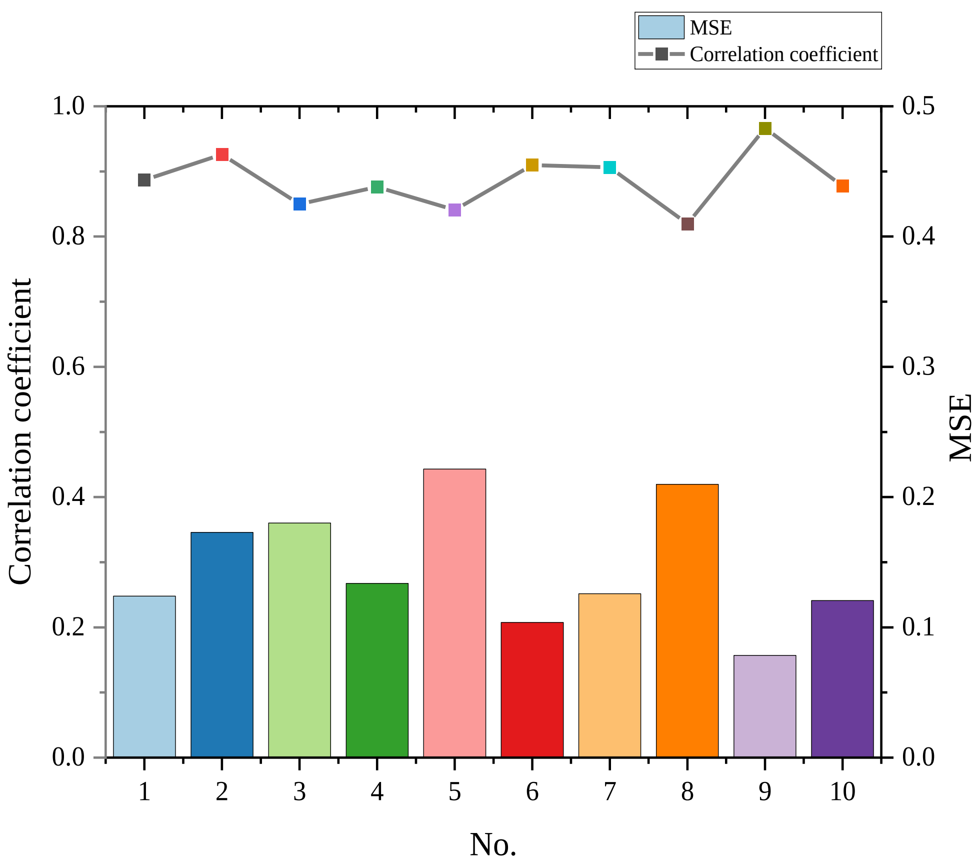


Fig. 10. Prediction of samples by GA-BP model.

V. Discussion

There are many factors affecting rural revitalization, and this paper only designs the evaluation index system based on the existing policy situation and literature research in China. The relevance and applicability of the evaluation indexes and the allocation of index weights are issues that need further study in evaluating rural revitalization. In addition, due to the difficulty of obtaining evaluation data, this paper only selects relevant subjective evaluation data obtained in actual work to train and test the neural network, which is insufficient in the sample data. The information reflected by the sample is not comprehensive enough. Further research is needed to find a general, efficient, or accurate parameter setting method; for the shortcomings of the traditional genetic algorithm, which is prone to premature maturity and slow convergence, other methods can be used to improve the traditional genetic algorithm.

VI. Conclusion

This research conducted an extensive and systematic study on the evaluation of rural revitalization by the consultation of several pieces of literature, given the circumstances of rural revitalization strategy. This article established the rural revitalization evaluation index system according to pertinent policies and documents. The GA-BP neural network model was built using deep learning theory. The GA-BP neural network model addressed the BP neural network's training process drawbacks, including its slow pace, ease of dipping below the local minimum value, and reliance on the initial weight. The rural revival was assessed and predicted using the GA-BP neural network model. The findings demonstrated that the GA-BP neural network model had rapid convergence, accuracy, and stability in rural rejuvenation's evaluation and prediction abilities, demonstrating its high applicability in these areas.

Competing of Interests

The authors declare no competing of interests.

Authorship Contribution Statement

Songmei Wang: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Min Han: Methodology, Software, Validation.

Data Availability

On Request

Declarations

Not applicable

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