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Evaluation of urban green space landscape planning scheme based on PSO-BP neural network model

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Abstract The evaluation simulation of urban green space landscape planning scheme based on PSO-BP neural network model is carried out in this paper. PSO-BP neural network can combine the principle of landscape ecology, integrate more evaluation indicators of ecology and urban development into the urban green space landscape planning scheme, and simply understand and predict human behavior, so as to make a more comprehensive evaluation and prediction of the urban green space landscape planning scheme. It not only has superior memory storage and learning ability, but also can simply understand and predict human behavior, so that more influencing factors that cannot be added in the past can be considered in the scheme evaluation and analysis, and the evaluation of urban green space landscape planning scheme is more comprehensive, scientific and reasonable. Experiments show that PSO-BP neural network has smaller error and better generalization ability than BP neural network. PSO-BP neural network rating model can analyze its more reasonable proportion according to the relationship between different types of green space and indicators, and give corresponding adjustment suggestions, which has guiding significance for the modification and adjustment of urban green space landscape planning scheme.

1. Introduction

With the continuous advancement of urbanization in China, more and more cities ignore the planning and development of urban landscape and the impact of urban green space landscape on the living standard and quality of urban residents,

With the continuous improvement of China's comprehensive strength and international status, the degree of urbanization in China has been greatly improved, and more and more urban construction is close to fashion cities. But at the same time, many cities ignore the planning and development of urban green space landscape and the impact of urban green space landscape on the living standards and quality of urban residents, resulting in the continuous reduction or even lack of urban green space landscape area, the simplification of urban landscape and the imbalance of ecological environment, Finally, it leads to the contradiction between the urban

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environment and the quality of life of urban residents [1–2]. Urban green space landscape planning has also become an important part of urban planning and development, and is an issue of increasing concern to urban residents [3]. With the improvement of China's economic level, the material life of urban residents has been basically met, the urban living environment has gradually become a problem of increasing concern to urban residents, and the urban green space landscape planning has also become an important part of urban planning and development [3].

In the composition of urban ecological environment, urban green space landscape system occupies a very important position and plays a core role in the maintenance and development of urban ecological functions. At present, it has also become one of the important indicators for the evaluation of urban development [4,5]. However, the concept of urban green space landscape planning in China started relatively late, and there is still a certain gap between the development level and the international level. Although urban green space landscape planning has exclusive planning in urban planning, its planning is still subordinate to the overall urban planning [6]. The sustainable development of the city needs to continuously deepen the content of urban green space landscape planning, and the urban green space landscape planning needs to be systematic, controllable and sustainable, which makes there is a certain requirement gap between the two, resulting in the lag of urban green space landscape planning. At the same time, the available land resources for urban planning and construction are limited. On the basis of meeting the actual functional needs, it is also necessary to meet the spiritual needs of urban residents. How to maximize the planning of urban green space landscape among different types of land and make it play an irreplaceable role has become the research direction of urban green space landscape planning [7,8]. How to determine the scope and quantity of urban green space landscape, green space plant diversity, type proportion, green space landscape location and pattern are all needed to be displayed in the urban green space landscape planning scheme. In the previous urban green space landscape planning scheme, there will be problems that the planning lags behind and cannot meet the needs of urban development after many years, or the new urban area cannot continue the green space landscape layout and historical context of the old urban area during the transformation of new and old urban areas [9,10]. This not only greatly limits the development of the city, but also reduces the quality of life and happiness index of urban residents.

Therefore, this paper proposes the evaluation of urban green space landscape planning scheme based on PSO-BP neural network model, uses the learning ability of BP neural network and the principle of landscape ecology to realize the relationship between urban green space landscape pattern and planning, and gives the corresponding effective analysis. At the same time, the uncertainty of particle swarm optimization algorithm conforms to the biological mechanism of nature, has good environmental interaction, and can obtain more opportunities to solve the global optimal solution. Therefore, this paper selects particle swarm optimization algorithm to optimize the performance of BP neural network model, so as to make it carry out overall ecological planning and quantitative planning evaluation and Analysis on urban green space landscape planning, Highlight the ecology of urban green space landscape planning and the comprehensive effect of the interaction of multiple ecological factors, so as to obtain the best scheme of urban landscape planning. This paper is mainly divided into three parts. The first part introduces the development and related technologies of urban green space landscape planning scheme evaluation. The second part is the construction of urban green space landscape planning scheme evaluation system based on PSO-BP neural network model. The third part is the training results and simulation results of urban green space landscape scheme evaluation system.

2. Related work

The planning of urban green space landscape is not scattered and separate, but an interconnected ecosystem. It is an important regulation mechanism for maintaining urban breathing. It mainly constitutes urban space function, ecological function, play and leisure function, cultural function, social function and urban protection and disaster reduction function in urban development [11,12]. Urban green space includes many types, different sizes and open urban special land with green vegetation as the main form. Planting water and soil are the basic elements of it and the landscape elements in the urban ecosystem. Urban landscape space is composed of urban green space patches, urban green space corridors, urban landscape matrix and urban landscape boundaries, and each part can be divided into urban landscapes of different types and sizes [13]. It can be seen that urban green space landscape planning is a systematic and complete ecological planning, which contains many ecological factors. The research on urban green space landscape system in China started relatively late, and it is still in the development stage in theory and practice. Some scholars early proposed to introduce computer technology into landscape architecture for auxiliary planning and management; Other scholars have proposed to carry out plant configuration of landscape architecture through artificial intelligence technology. These studies are inclined to plan landscape architecture and gardens with small urban scale [14]. Other scholars proposed to add remote sensing and corresponding computer technology to collect data of urban green space landscape on the basis of landscape ecology, so as to avoid large errors between the data in the planning scheme and the actual data [15]. Other scholars evaluated the urban green space landscape planning scheme from the perspective of Ecological Garden [16]. Or adopt the evaluation system combining expert evaluation and multi-level evaluation to evaluate the urban green space landscape planning scheme [17]. The above evaluation system lacks the predictability of the planning scheme, and the evaluation indicators in the system can not meet the actual situation of the city. With the development of artificial intelligence technology, the evaluation of urban green space landscape planning scheme is more humanized and scientific, and its evaluation index and system tend to be diversified and ecological, which is more in line with the humanistic environment of different cities and the needs of urban future development [18].

3. Evaluation system of urban green space landscape planning based on PSO-BP neural network model

3.1. Application feasibility and evaluation index of neural network in urban green space landscape planning scheme evaluation

Particle swarm optimization (PSO) is also translated into particle swarm optimization, particle swarm optimization, or particle swarm optimization. It is a random search algorithm based on group cooperation, which is developed by simulating the foraging behavior of birds. It is generally considered to be a kind of cluster intelligence. It can be incorporated into multi-agent optimization system. The advantage of evolutionary computing is that it can deal with some problems that cannot be handled by traditional methods. Examples include non differentiable node transfer functions or no gradient information. But the disadvantages are: 1. The performance is not particularly good on some problems. 2. The coding of network weight and the selection of genetic operator are sometimes troublesome.

From the perspective of value, it plays an important role in the urban construction system and plays an important and positive role in the construction of urban ecology, economy, society and modern civilization. Landscape is an indispensable part of modern urban planning, whether in the overall urban planning stage or in the detailed planning stage. The purpose of urban green space landscape planning is to redistribute, adjust and construct the urban green space landscape through human influence and planning, so as to restore the scattered ecosystem and environment [19]. There is a close and complex relationship between different landscape patterns in urban green space landscape planning, and this potential relationship can not be expressed by accurate equations or algorithms. Therefore, the artificial neural network with black box characteristics can reflect the relationship between urban green space landscape, as shown in Fig. 1.

Although there are many uncontrollable and unforeseen factors in urban green space landscape planning, the evaluation accuracy of the planning scheme can not reach 100%, but it can be achieved as sustainable and reasonable as possible for the green space landscape planning [20]. And the artificial neural network can be used as an important basis for urban green space landscape planning and evaluation by studying the changes of natural landscape, the psychological needs and behavioral characteristics of urban residents. In addition, the ecological of urban green space landscape changes and develops under the joint action of various factors with different weights. The process of influence in various aspects is complex and may overlap with each other. The training and learning purpose of artificial neural network is to determine the weights of these factors, so it can be considered that, The existing urban green space landscape and the planned green space landscape constitute input layer and output layer in structure, and the complex analysis and correction process in the middle constitute the hidden layer.

Artificial neural network is mainly used in three aspects, namely, resource evaluation, landscape ecology analysis and recreation analysis. Resource evaluation is to analyze and evaluate the quality, quantity and spatial distribution of green space landscape based on the results of the city field investigation, and to distinguish the different regional values. In the past, the quantitative analysis of urban green space landscape resources was carried out by using expert method and principal component analysis method. Artificial neural network can learn multiple professional standards and aesthetic standards by using super storage function and establish multiple expert analysis database for resource evaluation [21].

Landscape ecological analysis is to analyze the landscape characteristics, landscape pattern, ecological state and sensitivity of the city, so as to judge the suitable area for green space landscape construction and ecological sensitive areas for ecological protection, and further reasonably plan the distribution pattern of green space landscape [22,23]. At present, the survey data and actual situation error are often found in the process of landscape ecological analysis, which makes the accuracy and scientific of the analysis results decrease. The combination of artificial neural network and remote sensing technology can improve the accuracy and accuracy of image data, and the artificial neural network has certain advantages in image recognition. It can have a more scientific analysis of the pattern of green landscape planning, and can guide the layout and development of urban green landscape.

The analysis process of recreation is to predict and analyze the behavior of urban residents on the basis of simple understanding, so as to obtain the frequency of use of corresponding green space and the form of tourists using green space, and then classify and analyze the data to obtain the corresponding data model carrier [24,25]. Although it can predict and characterize the development trend of urban residents' behavior, the model can not be included in the analysis of human psychology and other factors. The difference between artificial neural network and traditional method is that it has no fixed mathematical model and can take into account the factors that can not be added in the past [26]. At the same time, we can learn and correct the errors constantly in the process of training and learning, and get the analysis results that are more consistent with the social behavior in the simulated space [27–32].

According to the actual situation of the sample selected in this paper, the output layer of the evaluation model of PSO-BP neural network is selected by four urban green space landscape pattern index, as shown in Fig. 2.

3.2. Network construction of urban green space landscape scheme evaluation system

BP neural network algorithm is a multilayer feedforward supervised artificial neural network, which continuously adjusts the connection weight and threshold between each neuron through the training process of forward propagation of input signal and back propagation of error signal, as shown in Fig. 3.

Suppose that the input of neurons from 1 to n in BP neural network is $x_1, x_2, ..., x_n$, and let the output of the $j-th$ neuron after being stimulated by the last neuron from 1 to n be expressed as $w_{j1}, w_{j2}, ..., w_{jn}$. As shown in formula (1), it is the net input value of the $j-th$ neuron:

$$S_j = \sum_{i=1}^{n} w_{ji} \cdot x_i + b_j = W_j X + b_j \tag{1}$$

Among them, $X = [x_1, x_2, ..., x_i, ..., x_n]^T$, $W_j = [w_{j1}, w_{j2}, ..., w_{ji}, ..., w_{jn}]$. If $x_0 = 1, w_{j0} = b_j$ is set, it is included in the input

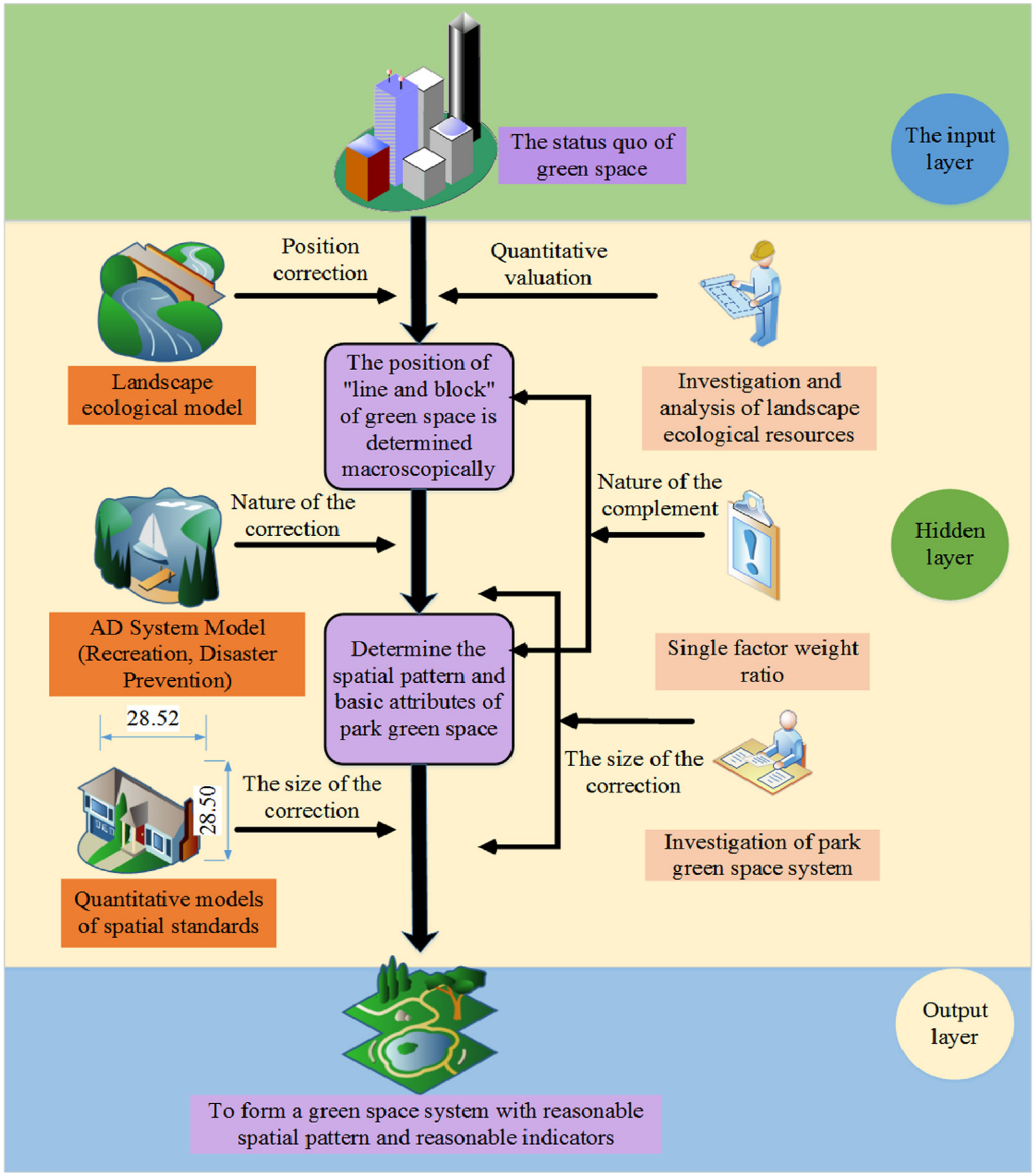

Fig. 1 Coupling of urban green space landscape planning and artificial neural network structure.

signal, and the input offset b_j becomes a weight element, then $X = [x_0, x_1, x_2, \ldots, x_i, \ldots, x_n]^T$, $W_j = [w_{j0}, w_{j1}, w_{j2}, \ldots, w_{ji}, \ldots, w_{jn}]$, As shown in formula (2), it is a simple expression of the output after the action of the excitation function:

$$y_i = f(s_j) = f(\sum_{i=1}^{n} w_{ji} \cdot x_i) = F(W_j X) \tag{2}$$

$$Net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{3}$$

θ_i is the bias vector of hidden layer, that is, $\theta = (\theta_1, \theta_2, \ldots, \theta_q)^T$.

Where $\phi(x)$ is the transfer function of the hidden layer.

The input and output expressions of the output layer are shown in formulas (5) and (6):

$$Net_k = \sum_{i=1}^{M} w_{ki} y_i + \alpha_k \tag{5}$$

$$O_k = \psi(Net_k) \tag{6}$$

Where α_k is the offset vector of the input layer, namely $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_L)^T$.

Where $O = (o_1, o_2, \ldots, o_L)$ is the output vector.

$$f = \frac{1}{1 + e^{-x}} \tag{7}$$

After the BP neural network obtains the output value, it compares with the ideal output value to obtain the prediction error e, as shown in formula (8)

$$e_k = Y_k - O_k \tag{8}$$

Index name	Exponential spatial representation	Value range	features	Practical significance
Patch density	Nonspatial component	PD>0	Landscape fragmentation	Reflecting human interference
Shannon diversity	Nonspatial component	SHDI=0	Spatial heterogeneity	The degree of structural and functional complexity
Ratio of plane perimeter area	Spatial configuration	AMPARA>0	Landscape spatial structure	The complexity of the shape
The spread of long	Spatial configuration	0<CONTAG=0	Optimal landscape pattern	Agglomeration degree or extension trend of different plaque types

Fig. 2 Landscape pattern index of output layer.

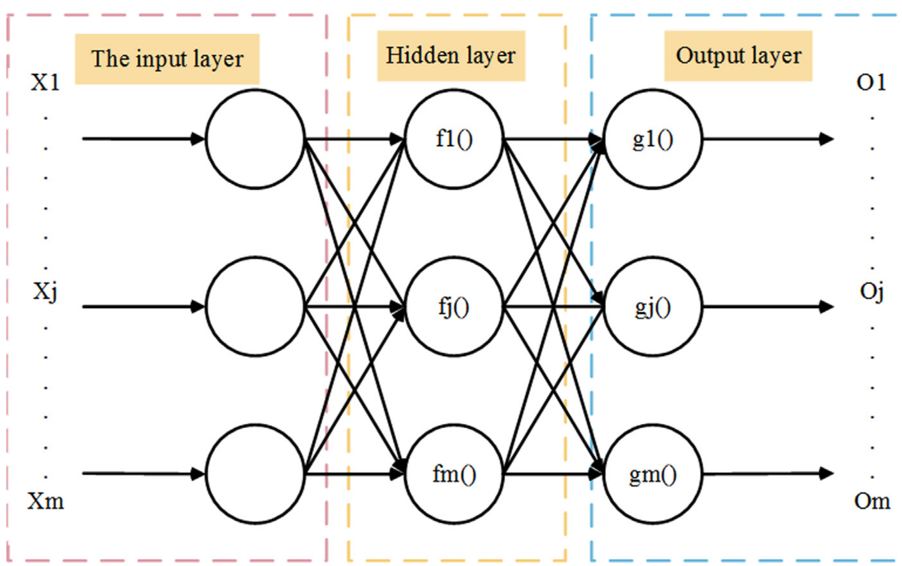

Fig. 3 BP neural network structure diagram.

Where Y_k is the ideal output value. Then the weight w_{jk}, w_{ij} and threshold a, b of BP neural network are adjusted, as shown in formula (9) to (12):

$$w_{ij} = w_{ij} + \eta y_j (1 - y_j) x(i) \sum w_{jk} e_k \tag{9}$$

$$w_{jk} = w_{jk} + \eta y_i e_k \tag{10}$$

$$a_j = a_j + \eta y_i (1 - y_j) \sum w_{jk} e_k \tag{11}$$

$$b_k = b_k + e_k \tag{12}$$

As shown in Fig. 4, the flow chart of BP neural network algorithm is shown.Fig. 5

The weight of BP neural network algorithm has a great influence in training. It is optimized by the method of additional momentum, as shown in formula (13):

$$\Delta W'(t+1) = \Delta W(t+1) + \partial^* \Delta W(t) \tag{13}$$

Where t denotes algebra and the previous generation influences the weight of the next generation, ∂ denotes the influence factor, namely additional momentum. In addition, the learning rate η of BP neural network is constant. If the value is too large, the BP neural network will have turbulence, and if the value is too small, the target effect cannot be achieved. Therefore, the adaptive learning rate is adopted, as shown in formula (14):

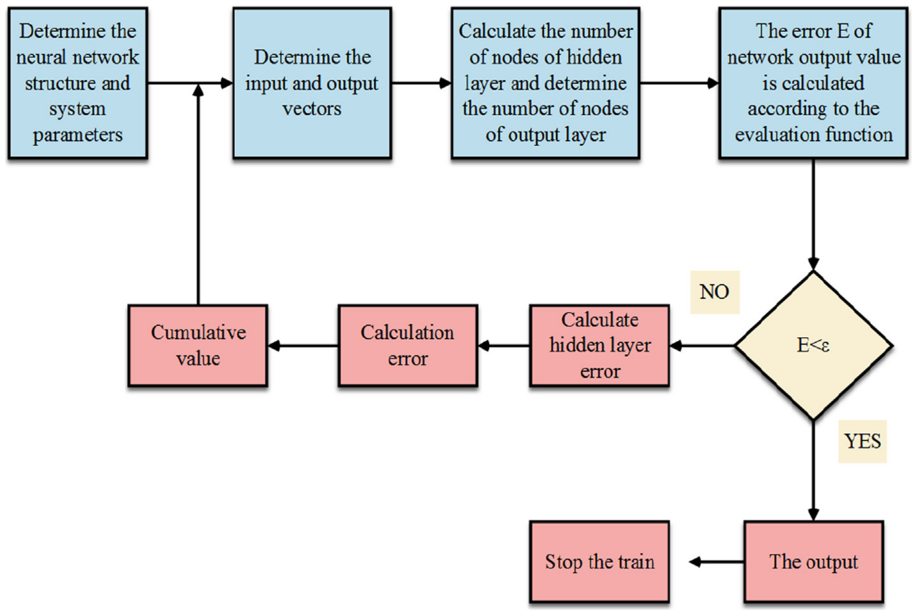

Fig. 4 Flow chart of BP neural network algorithm.

$$\eta(t+1)=\begin{cases}1.05\eta(t)E(t+1)>E(t)\\ 0.7\eta(t)E(t+1)<E(t)\\ \eta(t)other\end{cases} \tag{14}$$

3.3. Network optimization of urban green space landscape scheme evaluation system

Although BP neural network has good learning performance, the application effect in urban green space landscape scheme evaluation can not reach the ideal expectation. Therefore, this paper can achieve dynamic global search by iterating the global optimization through the search information shared by each particle in the collective population and the individual optimization of each particle, and each iteration will produce a better population to achieve the local optimal solution. In this process, it has a wider range of applications. Different from other algorithms, the population in particle optimization algorithm is composed of abstract particles without mass and volume. The population dimension is the number of individuals. If the dimension is n, the position of particles in the population can be expressed as vector $X_i=(x_1,x_2,...,x_n)$, and the velocity of particles can be expressed as vector $V_i=(v_1,v_2,...,v_n)$. The formula of particle optimization algorithm is shown in formulas (15) and (16):

$$v[k+1]=v[k]+c1*rand()*(pbest[k]-present[k])+c2*rand()*(gbest[k]-present[k]) \tag{15}$$

$$present[k+1]=present[k]+v[k+1] \tag{16}$$

Where $v[k]$ is the velocity expression of the particle after k iterations, $c1*rand()*(pbest[k]-present[k])$ is the individual income of the particle, $c2*rand()*(gbest[k]-present[k])$ is the overall income of the particle, $c1$ and $c2$ are the learning speed of the particle. If the particle optimization algorithm has a great speed at the beginning of iteration, it will narrow the search range in a short time, and then search the narrowed range in depth by reducing the particle speed, which will greatly improve the performance of particle optimization algorithm. Therefore, in terms of speed, a non negative inertia weight is added to control the particle speed, as shown in formula (17):

$$v[k+1]=w*v[k]+c1*rand()*(pbest[k]-present[k])+c2*rand()*(gbest[k]-present[k]) \tag{17}$$

Where w is the inertia weight, and its numerical value is positively related to the global optimization performance, and inversely related to the local optimization performance. The formula is shown in (18):

$$w(t)=\frac{(w_{ini}-w_{end})*(G_k-g)}{G_k}+w_{end} \tag{18}$$

Where G_k is the maximum number of iterations, w_{ini} is the initial value of inertia weight, w_{end} is the value of inertia weight caused by the maximum number of iterations.

After particle swarm optimization, the weights and thresholds of BP neural network exist as the position vector of particles in particle swarm optimization and are updated iteratively, so as to obtain the optimal weights and thresholds. Let the number of nodes in the input layer of BP neural network be expressed as n, the number of nodes in the hidden layer be expressed as l, and the number of nodes in the output layer be expressed as m, as shown in formula (19), the position of particles in the mass is as follows:

$$X_i=(x_{i1},x_{i2},...,x_{id})=(w_{l1},w_{l2},...,w_{lm},u_{l1},u_{l2},...,u_{nl},\beta_1,\beta_2,...,\beta_m,\partial_1,\partial_2,...,\partial_l) \tag{19}$$

$$v_{ik}(t+1)=w(t)v_{ik}(t)+c_1r_1(p_{ik}-x_{ik}(t))+c_2r_2(p_{gk}-x_{ik}(t)) \tag{20}$$

$$x_{ik}(t+1)=x_{ik}(t)+v_{ik}(t+1) \tag{21}$$

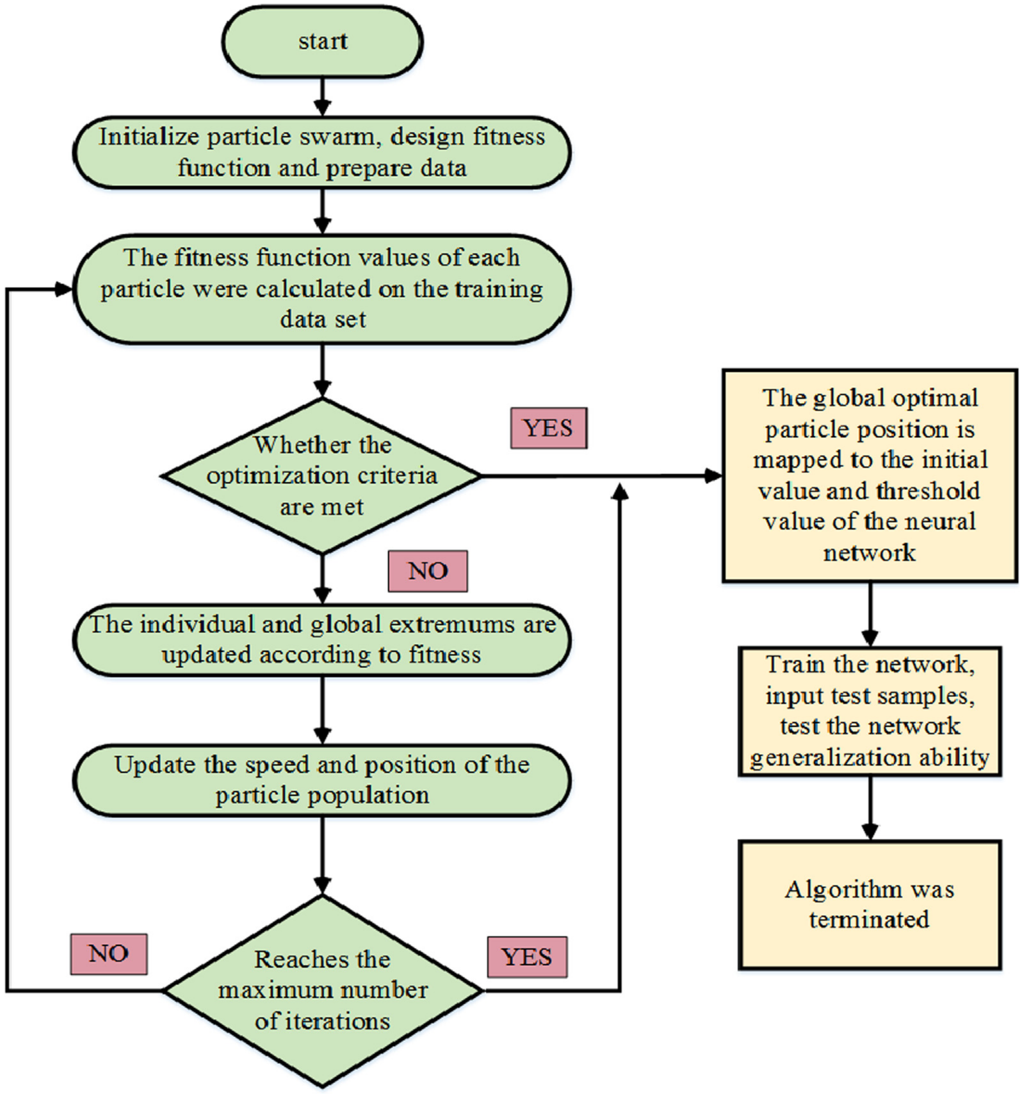

Fig. 5 PSO-BP neural network algorithm flow.

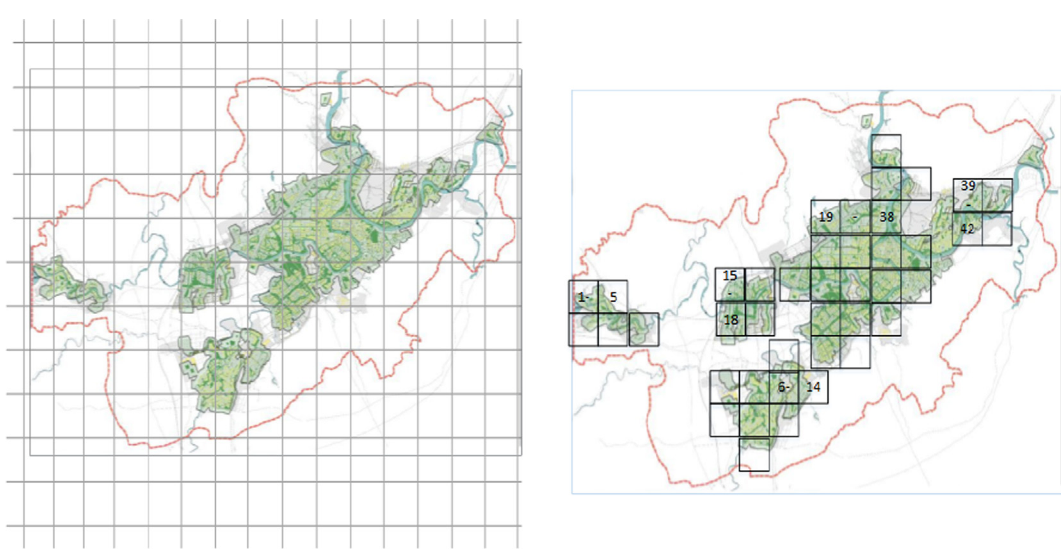

Fig. 6 Green space sample cutting map.

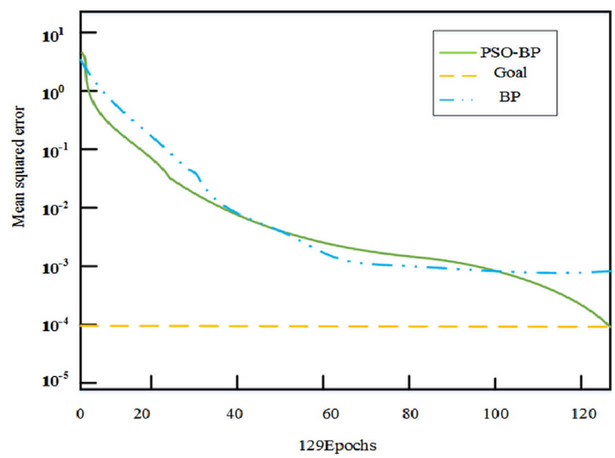

Fig. 7 Comparison of initial training error decline between PSO-BP neural network and simple BP neural network.

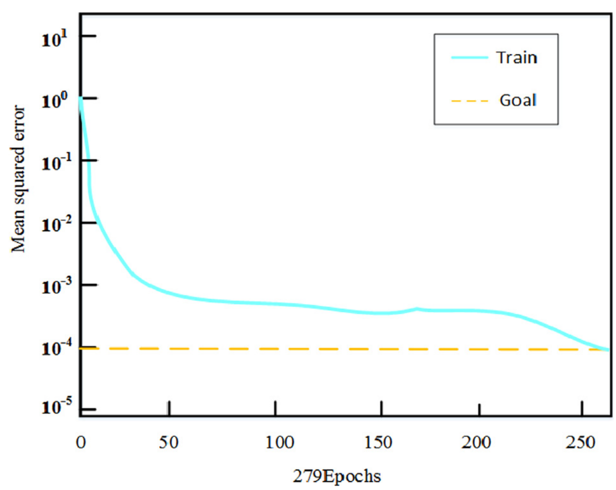

Fig. 8 Iteration error decline curve.

The learning factors are c_1 and c_2, the random values are r_1 and r_2, and the number of particles in the population is k. As shown in formula (22), it is the expression of inertia weight update

$$w(t) = w_{\max} - t * \frac{w_{\max} - w_{\min}}{T_{\max}} \tag{22}$$

The flow chart of PSO-BP neural network algorithm is shown in Fig. 6.

4. Training results and simulation results of urban green space landscape scheme evaluation system

4.1. Training results of PSO-BP neural network system for urban green space landscape scheme evaluation

This paper selects the green space landscape planning system plan of Wanning district as the experimental basis, extracts the corresponding patches and carries on the sample grid, and selects 42 samples from the grid for the following test, as shown in Fig. 6.

The 42 samples include different urban green space landscapes such as protective green space, ecological green space and comprehensive park. Before the experiment, the area and percentage of different green space need to be extracted. In addition, the data of patch density, average perimeter area ratio, spreading degree and Shanno diversity index need to be processed. After the sample data is collected and classified, the similarity of samples 15 and 23, 30 and 37 is very high. Therefore, it is meaningless to learn PSO-BP neural network at the same time, which will reduce the learning speed of the system. In addition, the plaque types of samples 8, 10, 14, 16, 28, 33 and 34 are unitary, which belong to abnormal samples and are not representative. If they are added into the sample learning.

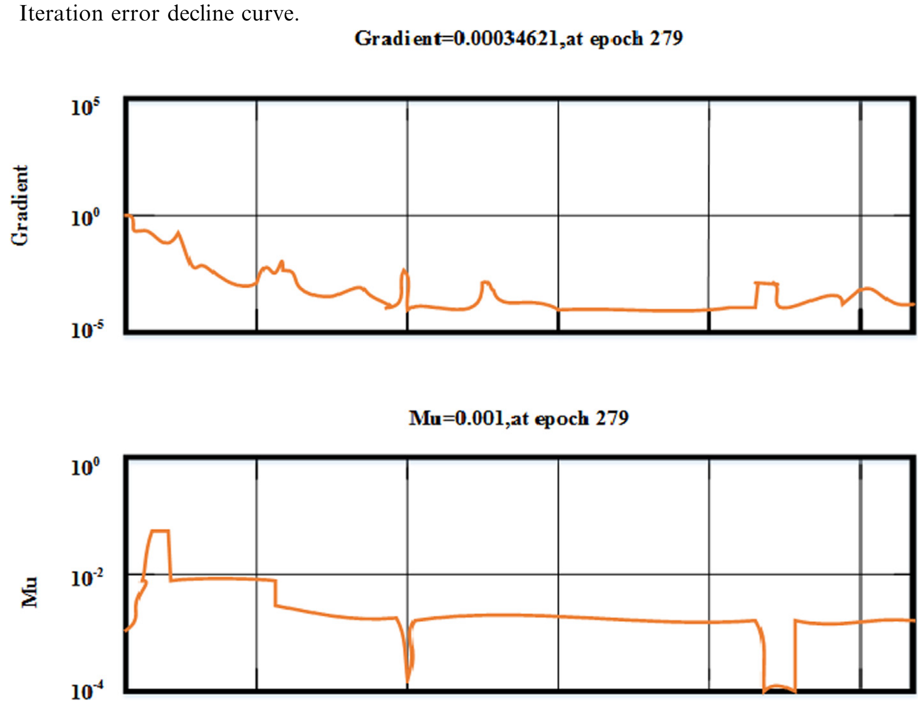

Fig. 9 Iteration error gradient change.

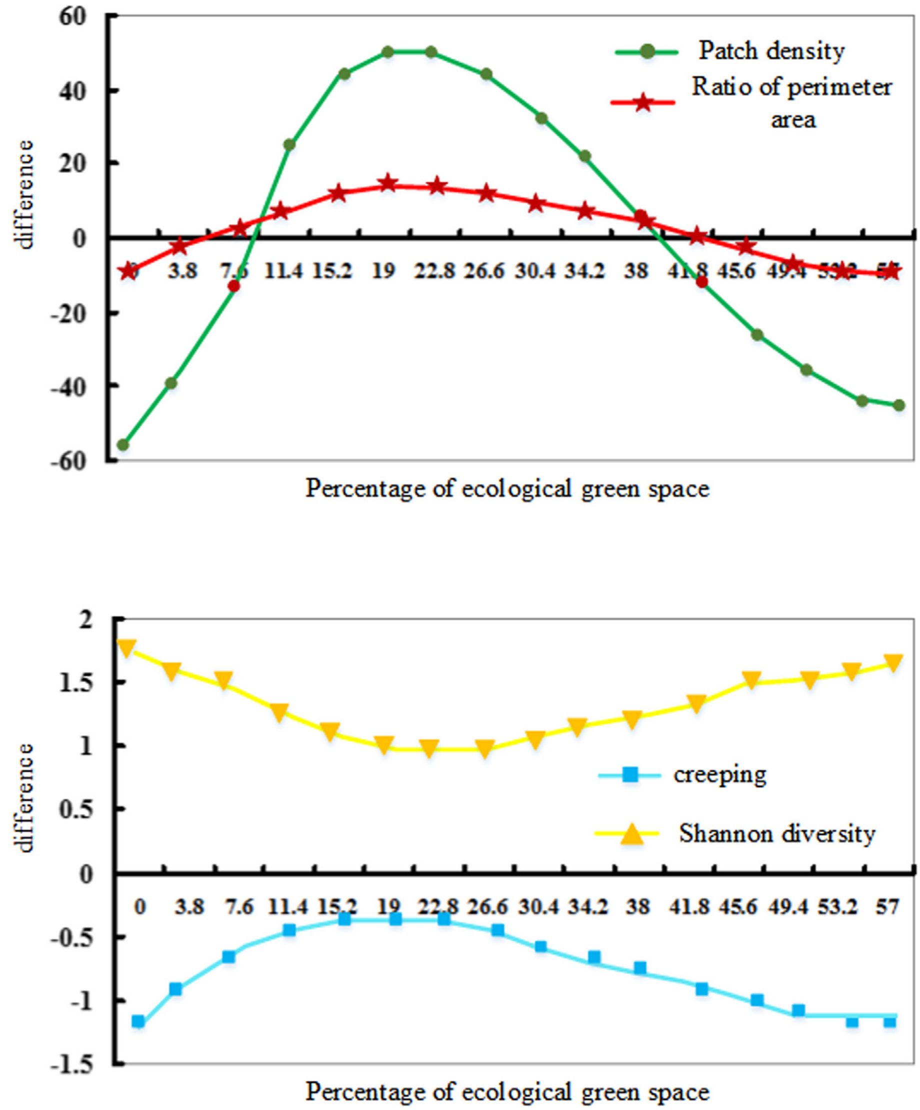

Fig. 10 Ecological green space and four index curves.

The problem of vanishing gradient exists in the BP neural network model. This paper avoids this problem by confirming the number of neurons in the hidden layer. PSO is to find the optimal solution through cooperation and information sharing among individuals in the group. The advantage is that it is simple and easy to implement, and there is no adjustment of many parameters. At present, it has been widely used in function optimization, neural network training, fuzzy system control and other application fields of genetic algorithm. Thus, PSO algorithm is used to control parameter adjustment in this paper. After testing, it is concluded that when the number of neurons in the hidden layer is 12, it can not only ensure its accuracy, but also improve its generalization ability. As shown in Fig. 7, it is a comparison diagram of initial training error reduction of PSO-BP neural network and simplified BP neural network. It can be seen from the figure that the error of PSO-BP neural network and BP neural network in the first 25 training and learning decreases greatly, and after 25 training and learning, the error decreases and tends to be stable gradually. After 129 times of learning, PSO-BP neural network began to converge and the error value reached the ideal value. After 83 times of learning, the error of BP neural network remains stable, but there is still a certain distance from the ideal error value, which shows that there is a problem of local optimal solution. The initial training error reduction of PSO-BP neural network and simple BP neural network is compared experimentally. It can be seen from the experiment that the error of PSO-BP neural network and BP neural network in the first 25 training and learning is small. After many training and learning, the error decreases and gradually tends to be stable. The error of BP neural network remains stable, but there is still a certain distance from the ideal error value, indicating that there is a local optimal solution problem. It can be seen that the optimized PSO-BP neural network has faster learning speed, avoids the problem of local optimal solution and reduces the error. It can be seen that the optimized PSO-BP neural network has faster learning speed, avoids the problem of local optimal solution and reduces the error.

After the above error test, PSO-BP neural network algorithm can maintain the error in a very small state, but there

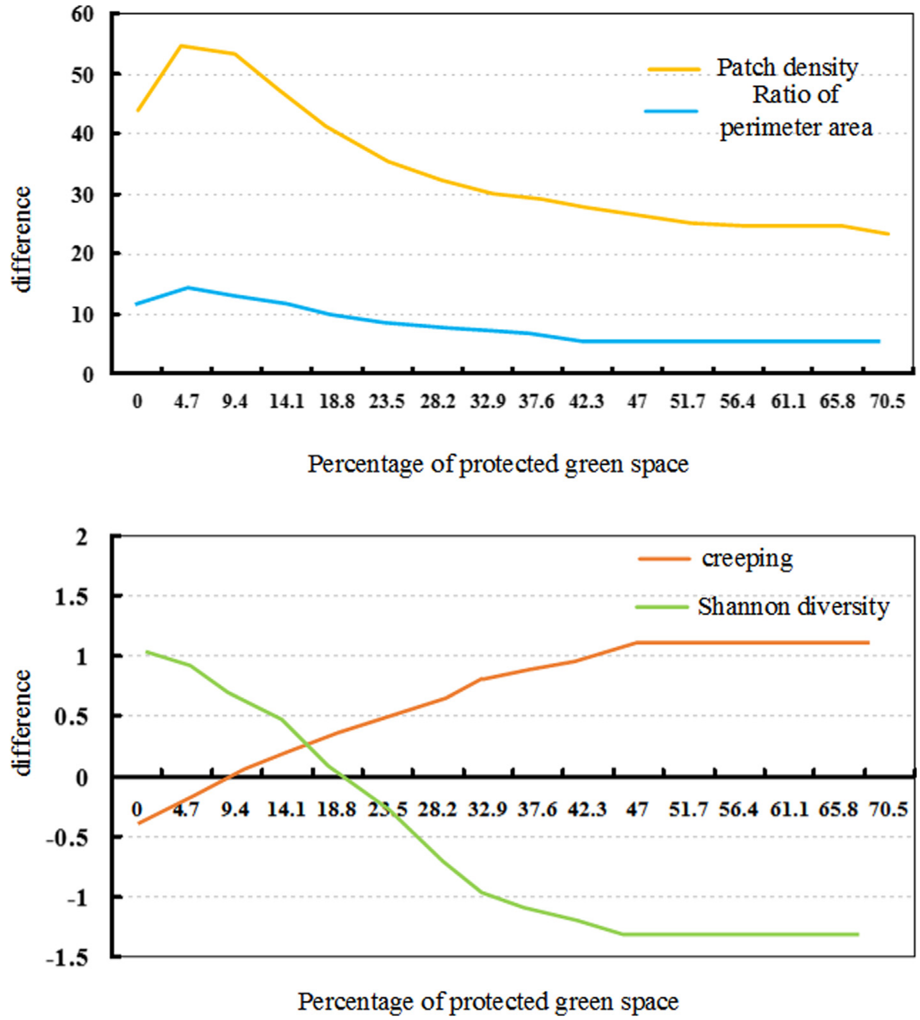

Fig. 11 The curves of protective green space and four indicators.

is still a certain distance between the number of samples above and the actual number of green landscape to be evaluated. Therefore, iterative training test is also needed, as shown in Figs. 8 and 9.

Comparing Figs. 8, 9 and Fig. 7, it is found stability of PSO-BP neural network has obvious changes after adding the number of new samples on the basis of the number of initial training samples. The error of PSO-BP neural network begins to decline steadily and slowly, and tends to converge at about 220 times, Finally, the expected error effect is achieved at 279 times. This shows that the increase of the number of samples will make the PSO-BP neural network improve its complexity level, thus increasing the change of network structure.

4.2. Evaluation and analysis of PSO-BP neural network system for urban green space landscape scheme evaluation

Human activities are one of the important factors in urban green space landscape planning. Therefore, four indicators will be analyzed when the urban green space landscape planning scheme is simulated and evaluated. As shown in Fig. 10, the ecological green space and four indicators are shown in the curve.

It can be seen from the curve in the figure that the impact of ecological green space on urban green space landscape pattern planning is relatively simple. There is only a large fluctuation in the trend of patch density or average perimeter area ratio. When the maximum peak value appears, it is the time when the proportion of ecological green space is the most inconsistent with the two indexes, that is to say, the landscape planning of urban green space is in the most fragmented state at this time. In addition, there are two intersections between the ecological green space curve and the two indexes, which means that the values of the two indexes are consistent with the planning values. The curve of spread degree and diversity is relatively flat, which is in a relatively balanced value from 15% to 26%. To sum up, on the basis of keeping other green space conditions unaffected, the proportion of ecological green space can be appropriately increased, so that the ecological pattern of the whole urban green space landscape can be better developed.

As shown in Fig. 11, it is the curve chart of protective green space and four indexes. It can be seen from the figure that the

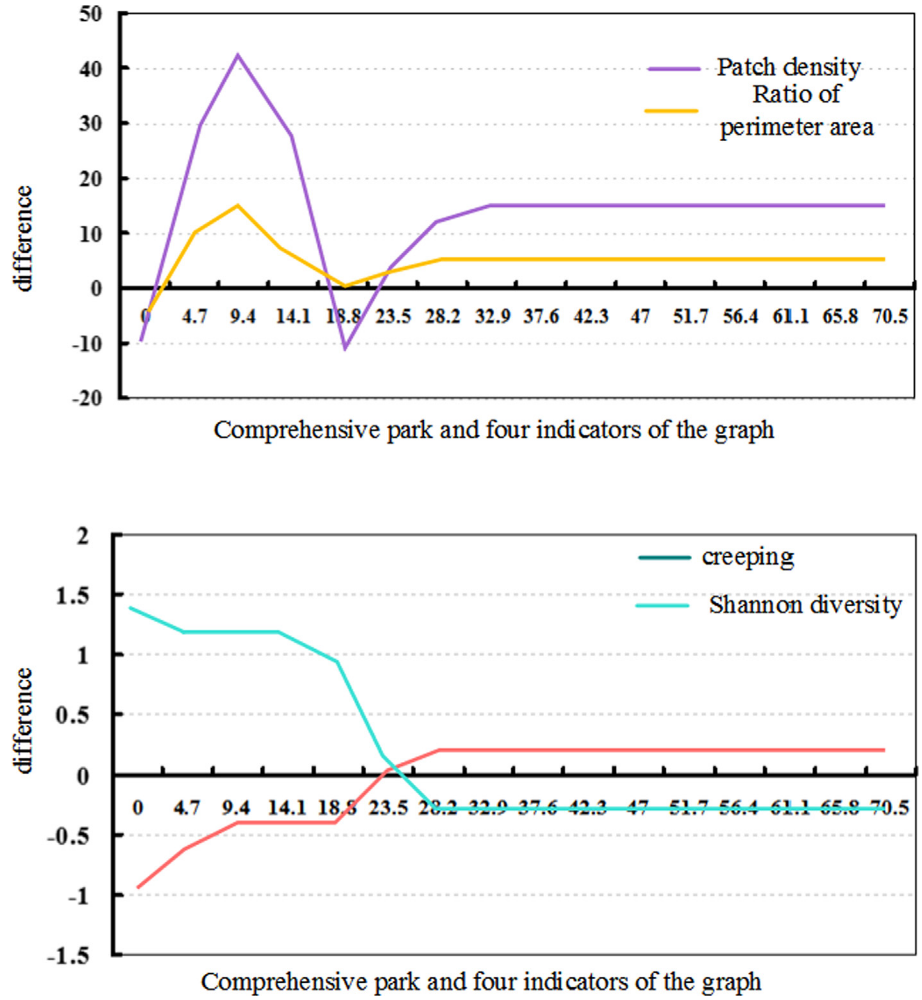

Fig. 12 Comprehensive park and four indicators of the graph.

three indexes, namely patch density, average perimeter area ratio and diversity, have reached a higher value at the initial value. In addition to the diversity index, the other two indexes showed a small increase in the proportion of 3%, and then began to decline. Among the four indexes, only the spread degree is in a state of slow increase. Therefore, the protective green space has little influence on the landscape ecological planning of urban green space. It can be seen from the intersection of the spread degree and diversity curve that when the proportion reaches about 17%, both values are higher than the expected value, so the proportion of protective green space can be controlled at about 17%, so as to maintain the stability of the diversity and spread of the overall urban green space landscape planning.

As shown in Fig. 12 is a graph of comprehensive park and four indexes. It can be seen from the curve in the figure that the change in the top 30% proportion has a great impact on the urban green space landscape planning. After 30%, the curve tends to be stable, and the influence does not change with the increase of the proportion. The curve of diversity index was at the maximum value at the initial value, then began to decline in a small range, and began to stabilize when the proportion reached about 28%. According to the two indices, the proportion of comprehensive park is reasonable in the range of 10% to 25%.

5. Conclusion

This paper constructs the evaluation model system of urban green space landscape planning scheme based on PSO-BP neural network. Through the simulation test, the reasonable proportion of green space can be analyzed according to the relationship between different types of urban green space and the four indicators, and the corresponding pattern adjustment suggestions can be given according to the original situation, which makes the urban green space landscape planning more in line with the behavior and needs of urban residents and contribute to the future development of urban green space landscape planning. Compared with the traditional evaluation system, PSO-BP neural network evaluation model can improve the accuracy of urban green space landscape planning data. On this basis, multiple expert evaluation databases are established at the same time. Through training and learning, the analysis error is greatly reduced, so as to obtain scientific and reasonable evaluation and analysis results in a short time. In the previous urban green space landscape planning scheme, the problems such as the data obtained is far from the actual situation and the scheme analysis is unreasonable are solved. However, the research of this paper still lacks the destructive investigation of the existing green landscape ecology of the city. Therefore, it needs further improvement in the future research.

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Declaration of Competing 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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