Research on Evaluation Method of Urban Human Settlement Environment Quality Based on Back Propagation Neural Network

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***Abstract*—In order to improve people's living experience, a method for evaluating the quality of urban human settlements based on back propagation neural network is proposed. Firstly, the initial evaluation index system is constructed, the initial evaluation index system is screened, and the final evaluation index system is constructed by using the remaining evaluation indexes. Then, the back propagation neural network is constructed to build an evaluation model, and the evaluation model is trained through the processes of network initialization, hidden layer output calculation and output layer output calculation. Finally, the improved genetic algorithm is used to optimize the back propagation neural network, improve the evaluation performance of the back propagation neural network, and realize the evaluation of human settlements quality. The experimental results show that the accuracy of the evaluation results of urban human settlements quality output by the trained back-propagation neural network model reaches 96.3%, which has a good effect.**

Keywords*—Back propagation; neural network; urban human settlements; quality evaluation; morbidity index; genetic algorithm

I. Introduction

The quality of the human settlement environment has consistently been a fundamental concern in urban research, as it directly impacts human well-being and urban development [1]. With the rapid growth of the global population in the 20th century, the degradation of the ecological environment resulting from industrial development has contributed to the widening regional disparities, and global scholars are increasingly concerned about the sustainable development of human settlements. The urban human settlement environment is a comprehensive regional concept. This refers to the dynamic interaction between the natural environment and human activities [2] and includes all fields of humanity, geography, economy and environment. It is the activity area of urban residents. Theoretically, the meaning of an urban residential environment should be the harmony between man and nature, the unity of material and spirit [3]. However, in civil engineering and geography, they have their own emphasis. In civil engineering, they tend to regard the urban residential environment as a small-scale operation object, which is more reflected in the study of urban architectural planning. In geography, the urban human settlement environment is more regarded as a large-scale geoinformation system [4], and urban structure is more discussed. Assessing urban human settlements holds great significance in terms of the survival and development of the population [5], as it offers essential parameters for the transformation of urban industrial structure and the optimization of human settlements.

Staats et al. [6], in the process of studying the environmental quality evaluation method, the number of parked cars and the number of street trees were taken as the evaluation criteria, and the former was divided into four levels: from no car to full capacity, and the latter was divided into three levels: from no tree to 50% density. The evaluation model is constructed using the neural network in the artificial intelligence method; the evaluation of environmental quality is achieved by analyzing two evaluation indicators. When utilizing this method, it has been observed that the neural network exhibits limited global search capability, making it susceptible to extreme local values and slow convergence. These factors consequently impact the computational efficiency and prediction accuracy of the neural network. Fomina et al. [7] analyzed the key factors and standards that have a significant impact on the quality of the living environment of the population in their research on urban environmental quality assessment methods and considered that ecological environment, urban planning, landscape and social factors are the main evaluation indicators, each set of factors are calculated quantitatively (based on a set of standards and indicators), at the same time, the category coefficient obtained according to the expert survey results is considered in the calculation process. In the application process of this method, some indicators have a weak impact on the evaluation results, which is only because the evaluators empirically think that these indicators are important, while subjective experience may not be objective and reliable, which leads to deviation in the final evaluation results. Longhini et al. [8], in the process of studying the environmental quality evaluation method, the evaluation index for the study is selected using the geochemical multi-index method, and the constructed evaluation model is used to achieve the purpose of environmental quality evaluation. Different indicators must be weighted according to the actual situation. In the process of using this method, the qualitative analysis method is used to obtain the evaluation results, which inevitably leads to a one-sided evaluation and cannot reflect the real situation. Sarkheil et al. [9] employed the fuzzy comprehensive evaluation method to construct the evaluation model. The research area selected for evaluating the environmental quality was the Pass economic energy Zone. It is worth noting that during the implementation of this method, there was a significant correlation observed among the evaluation indicators utilized; that is, the degree of information overlap between the indicators may be high. If this overlapping information is not processed, it will be emphasized repeatedly in the comprehensive evaluation, thus distorting the comprehensive evaluation results.

Although the above research has made some progress, there are still problems, such as the index system is not scientific and comprehensive, the differences in index selection and weight distribution in evaluation methods, and the lack of unified standards and systems. Therefore, this article studies the evaluation method of urban residential environment quality based on the back-propagation neural network and applies the back-propagation neural network to the evaluation process of urban residential environment quality. The significance of evaluating the quality of urban human settlements lies in evaluating and improving the living environment conditions of residents, providing scientific basis for urban planning, construction and management, and promoting the sustainable development of cities. By evaluating the quality of human settlements, the health of residents can be guaranteed, the influence of harmful factors on human body can be reduced and the quality of life can be improved. The evaluation results can also reveal the advantages and disadvantages of the city, provide decision-making basis for urban planning and construction, and promote the comprehensive development of the city. Evaluating and improving the quality of human settlements can enhance residents' happiness and satisfaction, and increase social stability and social harmony. Therefore, the quality evaluation of urban human settlements is of great significance to both cities and residents. Through the study of this method, it provides a reference for quantifying the quality of urban residential environments and monitoring the livability of cities. The overall structure of the article is as follows:

1) Build the initial evaluation index system, screen the initial evaluation index system, and use the remaining evaluation indexes to build the final evaluation index system.

2) Then, a back propagation neural network is constructed to build an evaluation model, and the evaluation model is trained through network initialization, hidden layer output calculation and output layer output calculation.

3) Using the improved genetic algorithm to optimize the back propagation neural network, improve the evaluation performance of the back propagation neural network, and realize the quality evaluation of human settlements.

II. Quality Assessment of Urban Human Settlements

A. *Selection of Evaluation Indicators Based on Pathological Index Cycle Analysis*

There are many factors that affect the quality of urban human settlements, and these factors can be used as evaluation indicators of urban human settlements. However, these evaluation indicators are not only different from each other but also closely related. To accurately evaluate the quality of urban human settlements, it is necessary to choose suitable evaluation indicators to build a highly scientific, highly operational, qualitative and quantitative evaluation indicator system. These indicators were selected based on expert opinions and research findings from scholars in relevant fields. Among them, experts' opinions and researchers in related fields play an important role in the quality evaluation of urban human settlements. Experts and researchers in related fields can provide valuable opinions and suggestions to help determine the importance and applicability of evaluation indicators based on in-depth research on urban environment and accumulation of professional knowledge. When selecting the evaluation index of urban human settlements quality, expert opinions can be obtained through expert consultation, expert interview and expert evaluation. The experience and professional knowledge of experts and researchers in related fields are helpful to determine the evaluation index with high authority and credibility. They can evaluate different environmental factors, human settlement needs and socio-economic factors based on their understanding of environmental disciplines and related fields, so as to determine the appropriateness and importance of evaluation indicators.

Considering the potential presence of duplicate evaluation indicators in the initial system for assessing the environmental quality of urban human settlements, where there may be overlapping information among the indicators, it becomes necessary to employ the pathological index cycle analysis method to screen and refine the evaluation indicators in the system.

In order to prevent redundant evaluation indicators from being retained in the selection process of evaluation indicators, a set of urban human settlements environmental quality evaluation indicators $X_1, X_2, \cdots, X_n$, all are the remaining evaluation indicators after removing the indicators with poor criticality. The specific process of screening environmental qualitative assessment of people's urban habitation indicators on the basis of the pathological indicator cycle analysis is as follows:

1) Determine the matrix with Formula (1) X^Tcharacteristic value of $\phi_1, \phi_2, \cdots, \phi_n$:

$$|X^T - \phi_i \times D_n| = 0 \tag{1}$$

In Formula (1) X^T and D_n respectively represent the sample data matrix corresponding to the urban human settlements environmental quality evaluation indicator set transpose matrix and identity matrix of X.

2) C_{I_n} is used as a pathological index, which is determined by Formula (2) C_{I_n}:

$$C_{I_n} = \sqrt{\frac{\phi_1^*}{\phi_n^*}} \times X^T \tag{2}$$

In Formula (2), ϕ_1^* and ϕ_n^* respectively represent the matrix the upper and lower eigenvalues of X^T.

C_{I_n} describes the quality evaluation indicators of urban human settlements $X_1, X_2, \cdots, X_n$. The overall redundancy level is positively proportional to the overall redundancy level of the evaluation index.

3) Determine the indicator of clearing document X_i remaining after $n-1$ a pathological index of human settlements quality evaluation indicators in cities $C_{I_{(n-1)i}}$. Determine the residual according to the process of process (1) and process (2) $n-1$ pathological index of human settlements quality evaluation indicators in cities $C_{I_{(n-1)i}}$.

4) Use Formula (3) to determine the evaluation index of urban human settlement environment quality X_i overall redundancy contribution of C_{i1}:

$$C_{i1} = C_{I_n} - C_{I_{(n-1)i}} \tag{3}$$

C_{i1} describes the removal of urban residential environment quality assessment indicators X_i remaining after $n-1$ a conditioned index of evaluation indicators $C_{I_{(n-1)i}}$, the same as clearing X_i the pathological index of all previous evaluation indicators C_{I_n}. The value is the same as the evaluation index X_i the overall redundancy contribution to all evaluation indicators is positively proportional. The larger the C_{i1} is, the more it should be cleared of X_i.

5) Eliminate the indicators with the largest overall redundancy contribution in all urban human settlements' environmental quality evaluation indicators. If

$$C_{j1} = max\{C_{i1} | 1 \leq i \leq n\} \tag{4}$$

Indicate the evaluation indicators of the quality of human settlements in n cities $X_1, X_2, \cdots, X_n$ within X_j the largest contribution to the overall redundancy of the evaluation indicator set, X_j needs to be cleared.

For the convenience of description, the above process is defined as the first round of screening of redundant evaluation indicators. Cycle the above process to clear the remaining $n-1$ evaluation index with the largest overall redundancy contribution among the evaluation indexes. Thus, after several iterations, the evaluation indicators with the largest overall redundancy among the remaining evaluation indicators are removed in each iteration until the following termination conditions for the removal of redundant indicators are met.

The termination conditions for the removal of redundant indicators are as follows: if the morbidity index of all remaining urban human settlements' environmental quality assessment indicators is less than or equal to 10, the screening of redundant indicators will be terminated; On the contrary, the redundant evaluation indicators are continuously screened according to the above process until the morbidity index of the remaining evaluation indicators is less than or equal to 10.

Through the above process, the redundant evaluation indicators in the initial urban human settlements' environmental quality evaluation indicator system can be eliminated, and the final urban human settlements' environmental quality evaluation indicator system can be constructed.

B. *Construction of Evaluation Index System*

Following the implementation of the pathological index cycle analysis method, the evaluation indicators within the initial system for assessing the environmental quality of people's urban habitation have been screened, and the final evaluation index system is constructed, as shown in Table I.

TABLE I. INDEX SYSTEM FOR EVALUATING THE QUALITY OF URBAN RESIDENTIAL ENVIRONMENT

Target layer	Indicator layer
Quality of the urban living environment	Relief
	THI
	Vegetation Index
	Hydrological index
	Traffic accessibility
	Per Capita GDP

The calculation method of each evaluation index in the evaluation index system is as follows:

1) Topographic relief: As the foundation of human survival and development, the terrain changes and geomorphic characteristics on the surface will have a significant impact on the result of the qualitative assessment of people's habitation [10]. Referring to the research results of relevant scholars, the topographic relief is described by Formula (5):

$$R_{DLS} = (max\, H - min\, H) \times \frac{P(A)}{A} \times C_{j1} \tag{5}$$

In Formula (5), $max\, H$ and $min\, H$ are the upper and lower limits of regional altitude, $P(A)$ and A respectively represent the flat area and total area in the region.

2) Temperature humidity index: Climate conditions have an important impact on human activities. The temperature and humidity index describes the degree of mugginess under windless conditions [11], and the formula is as shown below:

$$T_{HI} = t + R_{DLS} \times f \times 1.8t \tag{6}$$

In Formula (6), t stands for the average monthly temperature in Celsius; f stands for the average value of air relative humidity.

3) Vegetation index: The vegetation coverage within the region can not only be used as the main indicator to judge in the qualitative assessment of people's habitation but even as a ecological condition of human life [12]. The normalized vegetation index is calculated as follows:

$$N_{DVI} = (N_{IR} - R)(N_{IR} + R) \times T_{HI} \tag{7}$$

In Formula (7), N_{IR} and R respectively represent reflectance in a near-infrared band and red band.

4) Hydrological index: As the main resource for survival and development in the region [13], the quality of hydrological resources plays a crucial role in determining the quality of urban human settlements [14], and hydrological resources can be described by hydrological index:

$$W_{RI} = (\alpha \times P + \beta \times W_a) \times N_{DVI} \tag{8}$$

In Formula (8), P and α respectively represents the average annual precipitation and its weight in the region, W_a and β respectively represent the water area and its weight.

5) Traffic accessibility: The perfection of the traffic network within the region has a significant role in promoting the improvement of the quality of urban human settlements, so the traffic network has become the main indicator of the adaptability evaluation of regional human settlements, which can be described by the traffic accessibility within the region. The calculation formula is as follows:

$$D = \frac{L_i}{A_i} \times W_{RI} \tag{9}$$

In Formula (9), L_i and A_i respectively represent the total length of roads and the area of the region.

6) GDP per capita: The economic level within the region has a significant impact on the quality of urban human settlements, which can be described by the per capita GDP within the region. The calculation formula is as shown below:

$$P_{CCDP} = \frac{Z_{GDP}}{R_{pop}} \times D \tag{10}$$

In Formula (10), Z_{GDP} and R_{pop} respectively represent the gross domestic product and the total population within the region.

C. Construction of Evaluation Model Based on Back-Propagation Neural Network

1) Evaluation model of back-propagation neural network: An artificial neural network (ANN), referred to as a neural network (NN), is a mathematical model or computing model that imitates the structure and function of the biological neural network [15]. Its unique nonlinear adaptive information processing capability makes it particularly suitable for solving problems with complex internal mechanisms [16], prediction and other fields that have been successfully applied. The back-propagation (BP) neural network is a popular and extensively utilized model in the field of artificial neural networks. It typically consists of an input layer, one or more hidden layers, and an output layer. Fig. 1 shows the topology of a back-propagation neural network with a hidden layer.

The back-propagation neural network algorithm utilizes the gradient descent method as its underlying principle. During the learning process (training) of a neural network, back and forward propagation are utilized. Within the forward engendering stage, intake data is sequentially handled from the intake layer to the covered up one before being transferred to the outcome one. The neurons' state in each one specifically impacts the neurons' state within the subsequent one. Within the occasion that the outcome layer does not abdicate the required outcome, the back-propagation technique is employed. It recursively computes the difference (i.e., error) between the actual input and the expected input layer by layer [17]. The error signal is propagated back through the original connection pathway, and the weights between neurons in each layer are adjusted to minimize the error.

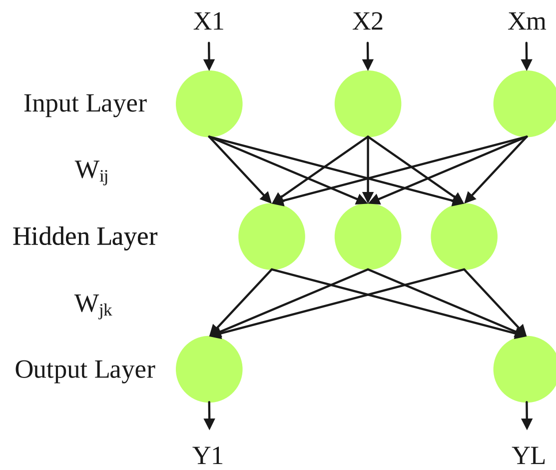


Fig. 1. Topological plan of the back-propagation neural system.

a) Foundation of preparing tests: Normalize the information within the evaluating measures (good quality, ordinary quality, light pollution and heavy pollution) of the six indicators listed in Table I, convert the specific values into [0,1] of the data in the interval, changes the absolute value of the physical system value into a relative value relationship. The urban residential environment quality grading metrics are used as training demos and intake to the network's intake hubs. Through the arbitrary number generation principles, 250 demos of every urban human settlement environmental quality index data were taken, and a total of 1000 samples were trained and modelled. MATLAB R2012b is used to establish the graphical user interface (GUI).

b) Neural network initialization: In the neural network model, we determine the hubs of the intake, hidden and outcome layers. Additionally, initializing the association weights among w_{ij} and w_{jk}; We also assign values to the hidden layer threshold a and output layer threshold b. These parameters are set along with the learning rate and neuron excitation function, select the input sequence (urban living environment quality evaluation index) and output sequence (urban living environment quality grading standard) of the system (X, Y) [18]. The hubs number within the covered up layer is evaluated utilizing an experimental equation.

$$Y_H = \sqrt{\theta_1 + \theta_2} \times P_{CCDP} \tag{11}$$

In Formula (11), θ_1 and θ_2 represent the number of neuron nodes in the input layer and the output layer, respectively.

c) Hidden layer output calculation: Using the input vector X, the association weights between the input layer w_{ij} and the hidden layer, as well as the hidden layer threshold a [19], we can compute the output of the hidden layer H; the calculation is shown in Formula (12), where f is the excitation function, and the excitation function is represented by the well-known Sigmoid function, as depicted in Formula (13).

$$H_j = Y_H \times f\left(\sum_{i=1}^{n} w_{ij}x_i - a_j\right), j = 1,2,\cdots,m \tag{12}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{13}$$

d) Output layer output calculation: Input according to the hidden layer H, hidden layer and output layer w_{jk} and output layer threshold b, calculate the predicted output of urban residential environment quality O, as shown in Formula (14).

$$O_k = f\left(\sum_{j=1}^{m} H_j \times w_{jk} - b_k\right), k = 1,2,\cdots,l \quad (14)$$

e) Error calculation: Considering the anticipated outcome O and desired outcome Y obtain estimation error e, as shown in Formula (15).

$$e_k = Y_k - O_k \quad (15)$$

f) Weight update: According to the prediction error$e$ to update connection weight w_{ij} and w_{jk}, the calculation formula is shown in Formula (16) and Formula (17). η is the learning rate.

$$w_{ij} = w_{ij} + \eta H_j\left(1 - H_j\right)x_i \sum_{k=1}^{l} w_{jk} e_k \quad (16)$$

$$w_{jk} = w_{jk} + \eta H_j e_k \quad (17)$$

g) Threshold update: According to the prediction error e to update threshold value a, b, the calculation formula is shown in Formula (18) and Formula (19), respectively.

$$a_j = a_j + \eta H_j\left(1 - H_j\right) \sum_{k=1}^{l} w_{jk} e_k \quad (18)$$

$$b_k = b_k + e_k \quad (19)$$

h) Judge whether the algorithm iteration ends: If the iteration is completed, it means that the training process of urban human settlements environmental quality assessment model based on back propagation neural network can be completed, and the show is established; In case the iteration isn't completed, return to the covered up layer yield evaluation part and begin a new preparing alteration procedure [20] until the method iteration is completed.

The evaluation model parameters mainly include the maximum number of training steps, performance parameters, the maximum number of confirmation failures, the number of hidden layer neuron nodes and other parameters [21]. These parameters can be manually modified as needed. At the same time, the initialization weight of the back-propagation neural network model is not unique. The final prediction result is the number of grades that appear most after the decision to repeat the training an odd number of times.

2) Optimization of back-propagation neural network algorithm: The back-propagation neural network exhibits robust capabilities in nonlinear mapping and complex logic operation ability, but the global search ability of the back-propagation neural network is relatively weak and is prone to local extreme values and slow convergence speed, which affects the backpropagation neural system's calculation efficiency and prediction accuracy. To enhance the global search capability of the back-propagation neural network within the assessment model for urban human settlement environmental quality, an improved genetic algorithm is employed for optimizing the network. Genetic algorithm is a search and optimization algorithm that simulates the natural evolution process. By simulating operations such as heredity, mutation and selection, the weight and structure of the network are gradually improved to make it better adapt to the evaluation task. In the process of optimization, the fitness function is defined, that is, the performance and fitness of the network are evaluated. By initializing the initial population composed of a group of genes, new individuals are generated by the operation of genetic algorithm, and they are evaluated according to the fitness function. Through iterative updating, individuals with high adaptability are gradually screened out. The improved genetic algorithm is used to optimize the back propagation neural network, which can improve the accuracy and generalization ability of the network by searching for better network weight and structure combination globally. The evaluation model of urban human settlement environmental quality can evaluate the urban environmental quality more accurately and provide a more scientific basis for urban planning, construction and management.

The conventional genetic algorithm often encounters challenges such as local optimization and slow convergence. To address this, an enhanced genetic algorithm with enhanced global search capability is proposed, building upon the traditional genetic algorithm. By employing an adaptive calculation strategy for crossover probability and mutation probability, the ability of the genetic algorithm to discover the global optimal solution is significantly improved. Compared with other evaluation methods, this improved genetic algorithm can overcome the problems that traditional genetic algorithm is easy to fall into local optimum and slow convergence, and has stronger global search ability. By adopting adaptive crossover probability and mutation probability calculation strategy, the improved genetic algorithm can flexibly adjust the parameters of genetic operation to adapt to the characteristics and difficulties of different problems. It can improve the extensive search ability of the algorithm in the solution space and reduce the dependence on the initial solution, thus effectively avoiding the problem of falling into the local optimal solution and being unable to find the global optimal solution.

a) Design of chromosome coding: The dimension of the chromosome gene vector in real coding is determined by the number of weights and thresholds present in the back-propagation neural network [22], and the formula is as follows:

$$X_i = (w_{11},\cdots,w_{ms},w_{11},\cdots,w_{sn},a_1,\cdots,a_s,b_1,\cdots,b_n) \quad (20)$$

b) Determination of fitness function: In the genetic algorithm, the fitness value of the individual is an important indicator to evaluate the excellent performance of the individual [23]; assuming that the fitness value of the ith individual is F_i, the back-propagation neural network yields a mean square error of $M_{SE}(X_i)$, the fitness function is taken as:

$$F_i = M_{SE}(X_i) \times a_j \times b_k \quad (21)$$

c) Select the design of the operation: Discarding the roulette wheel method in the traditional genetic algorithm, the formula of the probability of each individual being selected is:

$$p_i = \frac{\frac{l}{F_i}}{\frac{\sum_{i=1}^{N} l}{F_i}}, i = 1,2,\cdots,N \tag{22}$$

In Formula (22): $\frac{l}{F_i}$ represents the fitness value of the ith individual, l represents the adjustment factor.

d) Design of cross operation: An adaptive crossover probability is proposed for individuals with poor performance, appropriately increase the crossover probability of the individual to optimize its gene structure; For individuals with good performance, the crossover probability should be appropriately reduced to avoid damaging excellent genes. In addition, in order to ensure population diversity and the algorithm exhibits a fast search speed in the initial stage, followed by enhanced local search capability in the later stage, ultimately leading to convergence and avoiding oscillation at the extreme point [24]; this crossover probability should also be reduced with the iteration of the algorithm.

The calculation formula of individual crossover probability is:

$$p_{ci} = P\left(Pcmin_{cmax} \times \frac{t \times F_{min}}{T \times (F + F_{min}())}\right)_{cmax} \tag{23}$$

In Formula (23): t represents the current iteration number of the algorithm, T represents the total number of iterations of the algorithm, p_{ci} is the probability of the ith individual at the t-th crossing, F_{min} indicates the fitness value of the individual with the best performance of the population, P_{cmax} is the maximum crossing probability, which is 0.6, P_{cmin} represents the minimum crossing probability, which is 0.3.

Chromosome i X_i and the j chromosomes X_j on k and the bit crossing formula is:

$$\begin{cases} X_i^k = (1-\partial)X_i^k + \partial X_j^k \\ X_j^k = (1-\partial)X_j^k + \partial X_i^k \end{cases} \tag{24}$$

In Formula (24): ∂ represents a random number, and $0 \leq \partial \leq 1$.

e) Design of mutation operation: The mutation operation is implemented to preserve the global search capability in the initial iterations of the algorithm while also ensuring local search capability and stability during the later stages [25]. Consequently, the design assigns equal probabilities for individual mutation and crossover operations. These probabilities are determined based on the individual fitness value and the number of algorithm iterations [26]. The calculation formula is:

$$p_{mi} = P\left(Pmmin_{mmax} \times \frac{t \times F_{min}}{T \times (F_i + F_{min}())}\right)_{mmax} \tag{25}$$

In Formula (25): p_{mi} is the probability of the ith individual at the time of t variation, P_{mmax} represents the maximum probability of variation, 0.005, P_{mmin} represents the minimum probability of variation. Gene j on chromosome i X_i^j and the variation formula of is:

$$X_i^j = \begin{cases} X_i^j + \left(X_i^j - X_{i\max}^j\right) f(t), \lambda > 0.5 \\ X_i^j + \left(X_{i\min}^j - X_i^j\right) f(t), \lambda \leq 0.5 \end{cases} \tag{26}$$

In Formula (26): X_{imax}^j express the upper bound of gene X_i^j, X_{imin}^j express the lower bound of gene X_i^j, t represents the current number of iterations, λ represents a random number, and $-1 \leq \lambda \leq 1$.

f) Determination of population size and iteration number: Since there are many undetermined parameters in the back-propagation neural network, the selected population size is 100 to ensure global optimization; The number of iterations is 500 to ensure the complete convergence of the algorithm. Fig. 2 illustrates the flowchart of the back-propagation neural network model that incorporates an improved genetic algorithm.

The steps to optimize the back-propagation neural network using the improved genetic algorithm are as follows:

Step 1: Pre-process the urban human settlements' environmental quality evaluation index data, determine the network structure of the back-propagation neural network, and determine the coding method;

Step 2: Determine the fitness function and repeatedly select, cross, and mutate the initial population until the fitness value of a chromosome reaches the preset standard;

Step 3: Compute the output of each node in the hidden layer and the output layer sequentially, followed by the calculation of the output error for each node in the output layer.

Step 4: If the output error does not meet the accuracy requirements, update the weights and thresholds of each layer based on the error back-propagation process, and utilize the updated weights and thresholds to calculate the output error. Repeat this process iteratively till the output error satisfies the desired precision criteria, and then the teaching is over.

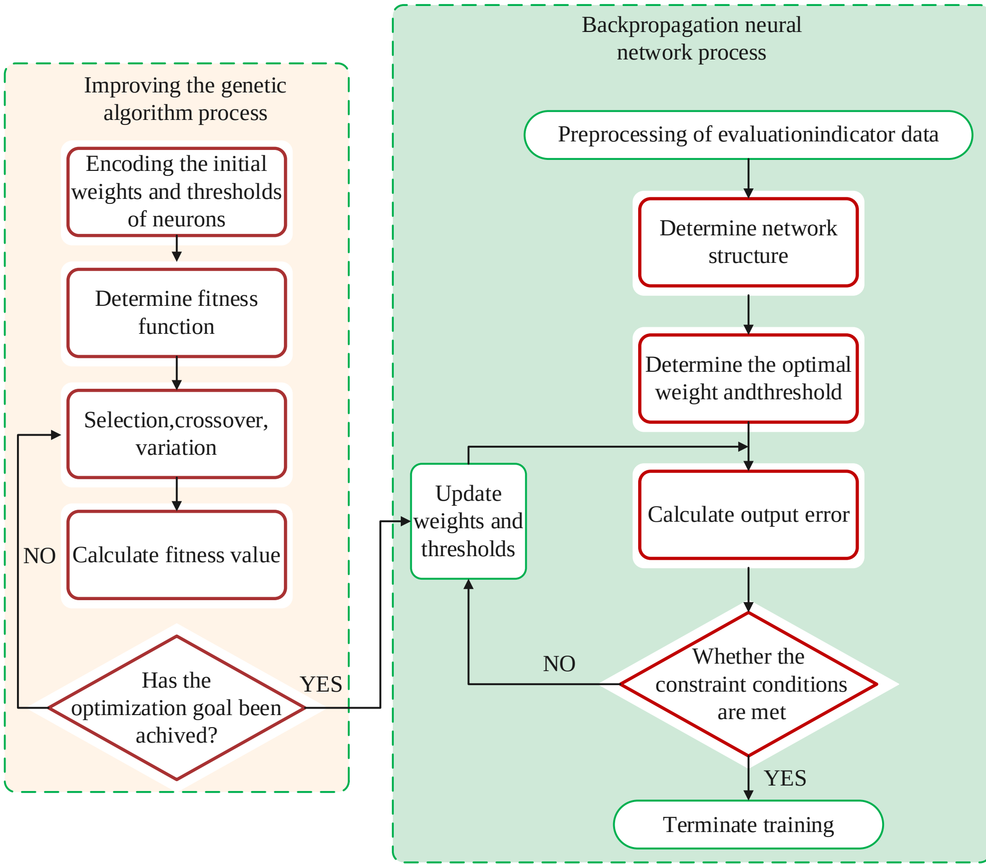


Fig. 2. Flow chart of back-propagation neural network model on the basis of improved genetic algorithm.

III. Experimental Results

This paper studies the urban residential environment quality assessment algorithm on the basis of the back-propagation neural network. In order to verify the application effect of this method in the urban residential environment quality assessment, a region is selected as the research object. The region contains nine cities, which are represented by A-I as shown in Fig. 3. The method in this paper is used to evaluate the urban residential environment quality in the study area. The results are as follows:

A. Data Source and Processing

The data used in the process of qualitative assessment of people's habitation of the research object using this method mainly include environmental data, population data, vector water network distribution data and basic geographic data. In the process of data collection, relevant data are obtained through various channels such as government statistics bureau, environmental monitoring department, professional research institutions and open data platforms. These data sources provide various indicators of urban environmental quality, such as air quality, water quality, noise level and green space coverage rate. In order to ensure the reliability and validity of the data, the data are verified and calibrated. Through data sampling and the integration of multiple data sources, the representativeness and reliability of data are improved, and residents' subjective feelings and evaluation on the quality of urban human settlements are obtained by means of field surveys and questionnaires, so as to increase the comprehensiveness and objectivity of the research. The data sources and corresponding processing processes are shown in Table II.

Based on the processing results of various types in Table II, the evaluation index data used in the process of urban human settlements' environmental quality assessment is obtained.

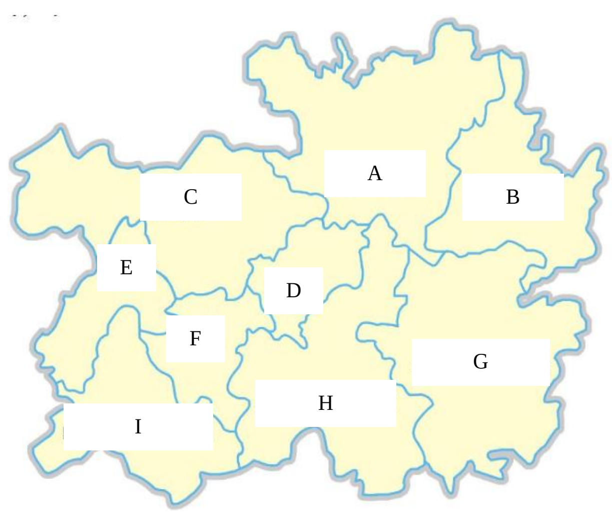


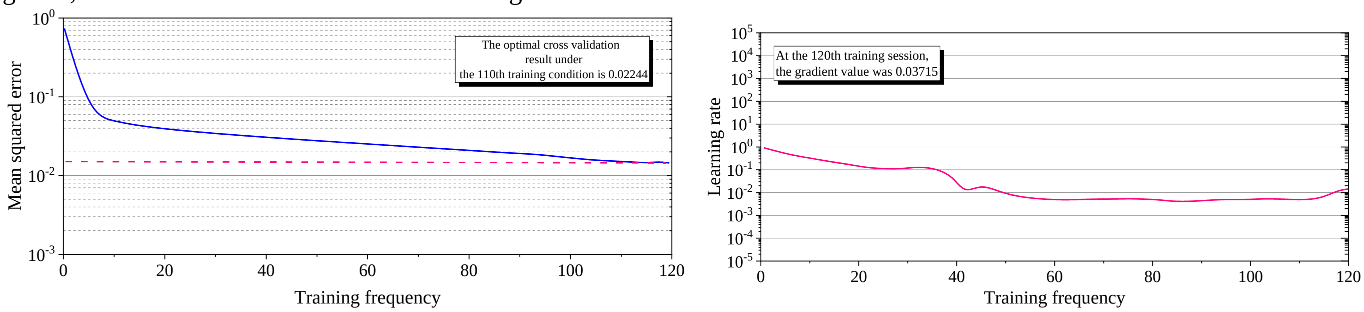
Fig. 3. Overview of the study area.

TABLE II. DATA SOURCES AND CORRESPONDING PROCESSING

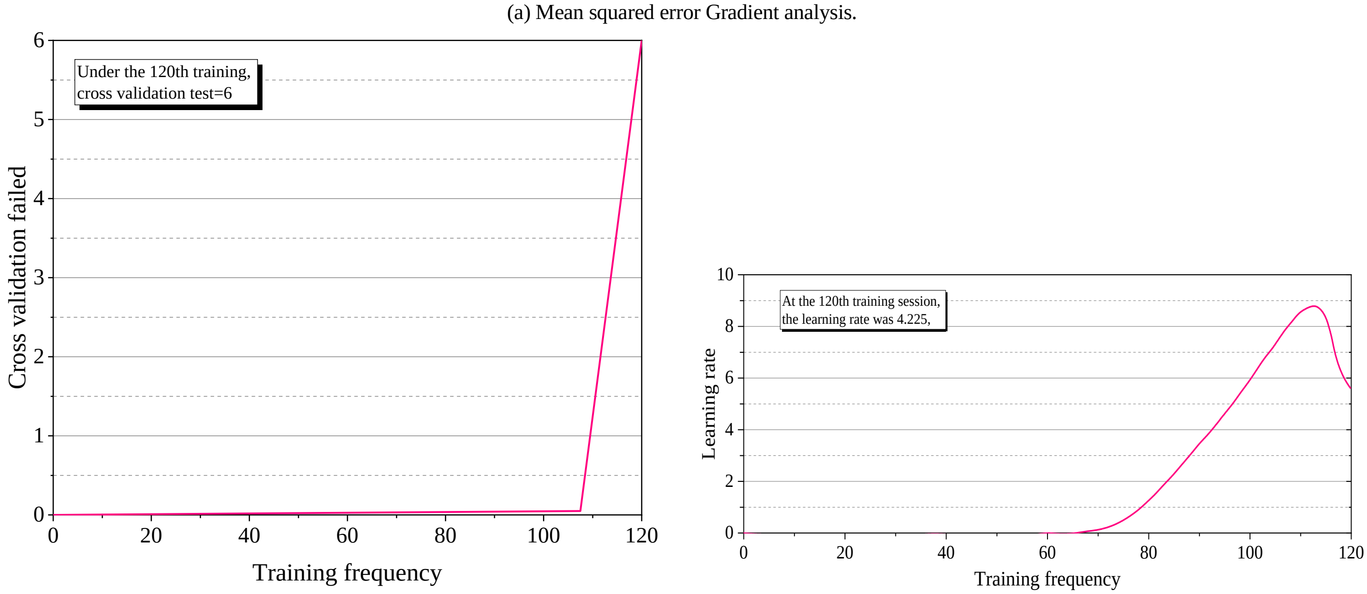
Data type	Relevant content	Main sources	Processing technology
Environmental data	Temperature, relative humidity, precipitation, etc	Regional Meteorological Station Resource Library	For various types of data, the Kriging method, spline method, and inverse gradient distance square method are used for interpolation processing to obtain regional meteorological element layers
	Digital Elevation Model	Global GTO-PO30	Adopting the conic projection of double standard weft lines with positive axis area to obtain 0.5km × Digital elevation model map of 0.5km area
	NDVI	Earth Science Data Sharing Center	-
Demographic data	Demographics	Regional Statistical Yearbook	-
Basic geographic data	Traffic distribution vector data	Data Center of the Chinese Academy of Sciences	Build a 0.5km × 0.5km grid, determine the water network density of the grid through spatial analysis, and convert it to a 0.5 km × Grid scale of 0.5 km
	Distribution data of social settlements	Earth Science Data Sharing Center	On the basis of the data gathered using the sharing centre and combined with the latest map implementation comparison and optimization
Economic data	Various economic data within the region	Regional Statistical Yearbook	-

B. *Training and Parameter Adjustment*

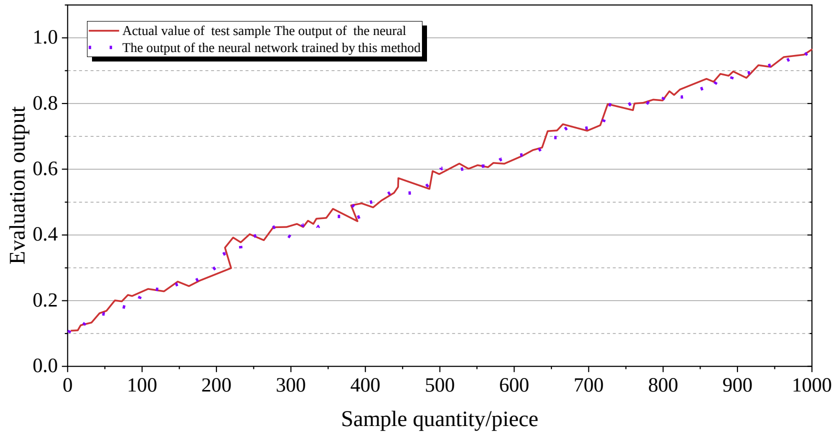
By utilizing the Nprtool toolbox in MATLAB R2012b software, the neural network is trained and evaluated, the data import, data pre-processing, establishment and training of neural networks, and the use of error mean square and confusion matrix are automatically completed to analyze the modelling effect of back-propagation neural networks used in this evaluation method. The back-propagation neural network is constructed with two-layer feedforward architecture. The transmision function employed in the covered up one is the sigmoid, while the entire network is trained using the variable gradient algorithm. 1000 training demos are consumed for training and learning. In which, the training set consists of 700 samples, the verification set comprises 150 samples, and the rest 150 demos are allocated to the set of test. After several iterations, the optimal number of neurons in the hidden layer for the back-propagation neural network is determined as 10, with a training target error set to 0. To mitigate overfitting, the maximum number of training iterations for the neural network is set at 1000. The maximum number of validation set failures is set to 6. The training process and parameters are shown in Fig. 4.



(a) Mean squared error Gradient analysis.



(b) Cross-validation failed learning rate.



(c) Output accuracy.

Fig. 4. Parameter adjustment process of back-propagation neural network training set.

It can be seen from Fig. 4 that the back-propagation neural network used in this method can stop training after 110 times of training, and the error is 0.02244. Among them, it can be seen that the gradient of the back-propagation neural network is declining in the training process, which conforms to the characteristics of back-propagation neural network error back-propagation. The accuracy of the evaluation results obtained by substituting the training data back into the neural network model is 96.3%.

C. Evaluation Results

The trained back-propagation neural system is for evaluating the quality of urban human settlements in nine cities within the study object, and the evaluation results are shown in Table III.

According to the analysis of Table III, the urban residential environment quality of nine cities in the study object was evaluated using the method in this paper, and the results showed that the quality of the urban residential environment in G city was excellent; The qualitative assessment of people's habitations in cities A, D, E and F is average; However, the qualitative assessment of people's habitations in cities B, C, H and I is slightly polluted. At the same time, the obtained results from this approach align perfectly with the actual conditions of each city, indicating the method's capability to complete the qualitative assessment of people's urban habitations accurately.

TABLE III. EVALUATION RESULTS OF THE STUDY OBJECT

City number	Evaluate Results	Actual situation
A	Average quality	Average quality
B	Slightly polluted	Slightly polluted
C	Slightly polluted	Slightly polluted
D	Average quality	Average quality
E	Average quality	Average quality
F	Average quality	Average quality
G	Superior in quality	Superior in quality
H	Slightly polluted	Slightly polluted
I	Slightly polluted	Slightly polluted

D. Analysis of the Improvement Effect of Urban Residential Environment Quality

This method is used to complete the qualitative assessment of people's habitations in all cities within the study object. The assessment outcomes gathered from the algorithm are utilized to optimize the quality of human settlements in various cities. Compare the fluctuation of human settlements' environmental quality assessment grades in different cities before and after the assessment using this method, and the results are shown in Fig. 5.

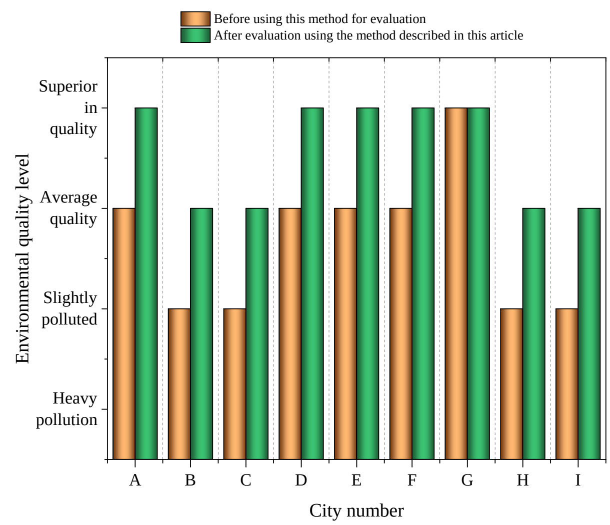


Fig. 5. Fluctuation of the assessment levels of people's habitations quality in different cities.

From the results in Fig. 5, it can be seen that after evaluating the quality of human settlements in different cities using this method, most cities have shown a certain degree of improvement after environmental optimization, further verifying the effectiveness and feasibility of this method in evaluating the quality of urban human settlements. Specifically, except for the relatively high initial evaluation results of City G, which do not require environmental optimization, all eight other cities have achieved further improvement after environmental optimization. This means that using the method presented in this article can accurately identify areas that need improvement and provide corresponding optimization strategies, thereby improving the quality of urban living environment. This result further demonstrates that the method proposed in this paper has good evaluation performance and provides effective solutions for the quality of human settlements in different cities. It helps urban planners and policy makers to better understand the current state of human settlements in cities and take corresponding measures to improve their quality of life.

IV. Discussion

In the study of the evaluation method of urban human settlements based on back propagation neural network, this method is applied to evaluate and improve the urban environmental quality. By constructing an appropriate index system and training a back propagation neural network evaluation model with good generalization ability, the situation of urban human settlements can be accurately evaluated and scientific basis can be provided for urban planning and management.

Through this study, it is found that the evaluation method of urban human settlements quality based on back propagation neural network has some remarkable advantages. Firstly, this method can integrate multiple environmental factors and socio-economic factors, and comprehensively consider the comprehensiveness and complexity of urban human settlements. Secondly, the back propagation neural network has strong fitting ability and generalization ability, and performs well in dealing with nonlinear relations and predicting future trends. Finally, this method can be flexibly adjusted and optimized according to the actual needs and data, and has high operability and adaptability.

V. Conclusion

This research focuses on the qualitative assessment of people's urban habitations through a backpropagation neural system method. An assessment model is constructed using the back-propagation neural network, and an improved genetic algorithm is introduced to address the issues of local optimization and slow convergence commonly associated with the back-propagation neural network. Additionally, the optimization of the initial weights and thresholds of the network is addressed, ensuring the stability of the algorithm and overcoming the shortcomings of the back-propagation neural network algorithm. Through experiments, the following conclusions are obtained:

1) After 110 times of training, the BP neural network used in this method can stop training, and the error is 0.02244. According to the characteristics of back propagation neural network, the accuracy of evaluation results obtained by substituting training data into neural network model is 96.3%.

2) This method can accurately evaluate the quality of urban human settlements.

3) The method in this paper has good evaluation performance for the quality of human settlements, which can effectively promote the improvement of the quality of urban human settlements.

There are some limitations in the study of this method in practice, such as the lack of availability and completeness of data. Although there are many data sources to choose from, the data of some urban environmental indicators may be lacking or incomplete, which affects the accuracy and reliability of the evaluation model. Future research can solve this problem by improving the coverage and quality of data collection and monitoring systems, or by integrating multiple data sources. At the same time, the construction of evaluation index system is still a challenge. At present, there are still subjectivity and limitations in the selection of evaluation indicators and the distribution of weights, and there is still a lack of unified standards and systems. Further research can explore a more scientific, comprehensive and objective evaluation index system, taking into account social and economic factors, residents' subjective feelings and other factors, so as to evaluate the quality of urban human settlements more comprehensively.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation."

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work."

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Competing of Interests

The authors declare no competing of interests.

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Conceptualization, Supervision, Project administration.

Wenbo Song: Language review, Methodology, Software.

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