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Original Research

The Environmental Status Assessment Model of Artificial Wetlands Based on Big Data Technology

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Abstract

With the strengthening of environmental protection awareness, constructed wetlands are an important part of urban ecosystems, and their environmental status assessment is paid more attention. This study aims to construct and validate a new model for the environmental state assessment of constructed wetlands, which integrates the analytic hierarchy process and backpropagation neural network to improve the accuracy and efficiency of assessment. This study collects a large amount of wetland environmental data, uses the analytic hierarchy process to determine the weights of key evaluation indicators, and then uses an improved backpropagation neural network to carry out in-depth learning and prediction to accurately assess the environmental state of constructed wetlands. An adaptive variation genetic algorithm was used to optimize the BP neural network model, along with L1 and L2 regularization techniques and Adam and RMSprop optimization algorithms were used to further improve the model performance. The results show that the model converges at the 20th iteration, the convergence speed is increased by 34%, 80% of the data falls within the error range of plus or minus 0.2, the R^2 value is as high as 0.99163, and the mean square error is close to zero, which shows that the model has significant advantages in improving the evaluation accuracy and efficiency. The comprehensive score shows that the overall environmental status of the constructed wetland is not ideal; there may be pollution problems, and improvement measures need to be taken. This model provides a scientific basis for wetland environmental protection and management, helps optimize protection measures, and realizes the sustainable development of wetland ecosystems. It is also of great significance for improving the efficiency and effect of wetland management.

Keywords: big data technology, analytic hierarchy process, BP neural network, artificial wetland environment, status evaluation model, GA

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Introduction

With the continuous expansion of human activities, the environmental status assessment and protection of constructed wetlands, as an important ecosystem, have attracted increasing attention. Traditional wetland environmental assessment methods are often limited by incomplete data collection and analysis method limitations, making it difficult to reflect the real state of wetlands accurately. Therefore, it is particularly important to use modern scientific and technological means, especially big data technology, to conduct a more comprehensive and in-depth assessment of the wetland environment [1, 2].

The development of big data technology provides a new perspective for wetland environmental assessment. Collecting and analyzing large wetland environmental data can reveal wetland ecosystems' complexity and dynamic changes. The application of big data technology can not only improve the comprehensiveness of data collection but also identify and predict the changing trend of wetland environments through advanced data analysis methods, such as machine learning and artificial intelligence [3, 4]. Although big data technology provides a powerful tool for wetland assessment, the environmental status assessment of constructed wetlands still faces many challenges. These challenges include the selection and quantification of evaluation indicators and the acquisition and processing of sample data. To overcome these challenges, researchers are beginning to explore new assessment models that combine traditional methods with modern techniques.

Analytic Hierarchy Processing (AHP) and Back Propagation Neural Network (BPNN) are two widely used methods in decision analysis and predictive modeling. AHP can decompose a complex decision problem into multiple levels and factors by constructing a hierarchical structure model and determining the weight of each factor by combining qualitative and quantitative methods. BPNN has strong learning and prediction ability, can extract useful information from a large amount of data, and can establish a nonlinear mapping relationship between input and output. This paper combines these two methods to construct a new type of environmental state assessment model of constructed wetlands to improve the accuracy and efficiency of assessment [5].

This study aims to construct and validate an environmental state assessment model of a constructed wetland based on AHP and BPNN to improve the accuracy and efficiency of the assessment. The research innovatively combines AHP and BPNN, fully utilizing the advantages of both to provide new ideas for assessing the environmental status of artificial wetlands. By constructing an evaluation model based on AHP and BPNN, a comprehensive and in-depth evaluation of wetland environmental status can be achieved, improving the accuracy and reliability of the evaluation. This evaluation model provides wetland managers with a scientific and objective decision-making basis, helps them better understand the environmental status of wetlands, and formulates more effective protection and management strategies. It also helps improve the efficiency and effectiveness of wetland management and promotes the sustainable use of wetlands.

The article is divided into four parts. The first discusses and analyzes the current research status of artificial wetland environmental status assessment models using big data technology AHP and BPNN at home and abroad. The second constructs an artificial wetland environmental status assessment model based on AHP and improved BPNN. The third verifies the performance of the algorithm model through experiments, and the fourth summarizes the research findings.

Literature Review

Recently, with the advancement of big data, researchers have utilized AHP, BPNN, and other manners in the field of evaluation. In response to the subjective judgment of individual risk criteria in current timber mining operations in China, which raises doubts about the credibility of evaluation results, Unver et al. adopted the AHP method to weight and rank the primary and secondary risk indicators, identify the major and sub-risks faced by logging operators, calculate the weights, and establish a prevention plan framework [6]. To accurately delineate the potential groundwater recharge zone, Dar et al. used GIS and AHP methods, combined with remote sensing data and other data sources, to determine the potential groundwater area northwest of the Himalayan Kashmir Valley. The research results showed that the method used had a very critical and reliable effect on the study area [7]. To seek an indicator method suitable for any location and water usage conditions, calculating the algorithm more conveniently, Sarkar et al. determined the weights of various alternative parameters through methods such as multi-indicator decision-making. They used classification-based evaluation techniques to measure their attractiveness. Experimental results showed that this algorithm has high accuracy and less workload, thus simplifying the process [8]. The evaluation of risk associated with knowledge fusion in the innovation ecosystem is linked to the success or failure of the ecosystem. Wang et al. constructed an innovation ecosystem knowledge fusion model based on BPNN and verified the effectiveness of this method through experiments [9]. Debris flow is a major disaster that endangers human survival and property, posing a great threat to the lives and property of surrounding people. Zhang et al. proposed a new method based on BPNN, which has a faster convergence speed and higher prediction accuracy than traditional BPNN models [10]. Structural health monitoring is crucial in preventing catastrophic failures in mechanical systems. Mousavi et al. introduced a novel deep neural network approach that is well-suited for detecting damage in mechanical systems despite modeling errors, measurement errors, and environmental noise uncertainties. Compared with other comparative methods, its detection accuracy was higher, providing strong technical support for the health monitoring of mechanical systems [11].

In recent years, researchers have proposed various models for evaluating the environmental status of artificial wetlands to protect the ecological environment. The symbiotic network of functional bacteria within the horizontal subsurface flow microbiota is diverse and complex, among which the cooperation and competition between bacteria are particularly significant. Zeng et al. adopted a partial least squares path model to investigate the microbial characteristics closely related to nitrogen, phosphorus, and Chemical Oxygen Demand (COD) removal in three pilot-constructed wetlands. Research revealed that high dissolved oxygen and redox potential create favorable conditions for bacterial community diversity, while the presence of noncritical bacteria reduces external pressure on functional bacteria and indirectly promotes nutrient removal efficiency [12]. Wetlands play a crucial role in urban ecosystems, and their environmental benefits cannot be ignored. Kumar et al. constructed a hybrid model that combines mature two-dimensional hydrodynamic models with physics-based one-dimensional distributed parameter models for simulating and drawing flood scenario maps. Through simulation of the water flow in the proposed artificial wetland, it was found that the overall flood near the waterway decreased by 23%, while the water depth of the return flow and drainage ditch also significantly decreased [13]. Pinninti et al. systematically evaluated the effectiveness of vertical flow constructed wetlands for treating domestic wastewater. The experimental data showed that Banana achieved high removal efficiencies of 87% for COD and 91% for biological oxygen demand. In addition, the removal rates of total nitrogen and total phosphorus were also high, reaching 97% and 98%, respectively [14]. Abdelhay et al. developed a regression-based nonlinear model to predict the BOD concentration in the system's effluent, given the increasing water scarcity problem in Jordan. This model conformed to the first-order dynamic law and provided an effective tool for predicting the effluent BOD value. Its R^2 value was 0.78, demonstrating good predictive performance [15]. To further enhance the removal efficiency of organic matter and nutrients in urban wastewater by tidal flow microbial fuel cells and tidal flow wetlands, Saeed et al. proposed a continuous stirred tank reactor model based on Monod kinetics to predict the removal rates of NH_3-N, TN, and COD in wetland systems. This dynamic model confirmed the important influence of matrix pollutants and environmental parameters on pollutant removal pathways [16]. Shukla et al. conducted a purification study on primarily treated domestic wastewater with a horizontal subsurface flow constructed wetland with a size of 10×3.5 m. By establishing and transforming different continuous wave systems, they found that all three continuous water treatment systems can effectively clean the primary treated wastewater, providing new ideas for designing and operating constructed wetlands [17]. In order to address the limitations of traditional wetland treatment systems in pollutant removal efficiency, Huang et al. proposed a method combined with ecological engineering landscape measures for wastewater treatment. By monitoring the water quality index of 4 typical wetland parks in Hangzhou City, the relationship between hydrological factors such as ground wetland, vertical flow wetland, free surface flow wetland, and pollutant removal contribution was analyzed. The research results show that a variety of geo-ecological factors, such as hydraulic conditions, plant types, and microbial microenvironments, have a heterogeneous impact on wastewater treatment, while water temperature significantly affects artificial water treatment performance in all seasons [18]. To solve the problem of water resource pollution, Soumyadeep B et al. proposed the technology of constructed wetlands coupled with microbial fuel cells, which combined the advantages of constructed wetlands and microbial fuel cells to achieve the dual goals of sewage treatment and electricity recovery. The research results show that the constructed wetland-coupled microbial fuel cell not only improves the sewage treatment efficiency but also improves the electricity generation performance, which has broad application prospects [19].

In summary, the artificial wetland environmental status assessment model based on big data technology is an effective environmental assessment method. It can comprehensively and accurately reflect artificial wetlands' environmental status by comprehensively applying qualitative and quantitative analysis methods. However, there are still some challenges and shortcomings in current research in this field, such as the selection and quantification of evaluation indicators and the acquisition and processing of sample data. Therefore, the study proposes an artificial wetland environmental status assessment model based on AHP and improved BPNN, further exploring a more scientific and reasonable evaluation index system and providing more powerful support for designing, operating, and managing artificial wetlands.

Materials and Methods

Establishment of an Artificial Wetland Environmental Status Assessment Model Based on AHP and Improved BPNN

The study first uses the AHP to construct an indicator system for the operation status of artificial wetlands, establishes an evaluation indicator system framework, and finally constructs a BPNN model to apply to evaluate the operation status of artificial wetlands.

Construction of an AHP-based Evaluation Index System for the Operational Status of Artificial Wetlands

Artificial wetlands refer to comprehensive ecosystems that simulate the structure and function of natural wetlands. They achieve water quality purification and ecological improvement through the synergistic effects of physics, chemistry, and biology. They play an important role in improving the regional water ecological environment, ensuring water safety, and promoting water resource recycling. The operating system of artificial wetlands is shown in Fig. 1.

In Fig. 1, when the artificial wetland is well managed and maintained, it can effectively purify water quality and maintain ecological balance. At this point, plants, microorganisms, and substrates in the wetland are in good condition and can work together to remove pollutants from the wastewater. In some cases, artificial wetlands may be overloaded due to excessive wastewater treatment or pollutants. This may lead to the disruption of ecological balance within wetlands, a decrease in water purification function, and even the problem of effluent indicators being inferior to inflow indicators. Therefore, to improve the operational status and effectiveness of artificial wetlands, research is needed to establish an environmental status assessment model for artificial wetlands, monitor the wetland status in real-time, and promote the sustainable development of artificial wetlands. The AHP decomposes complex problems into various constituent elements based on data and evaluation criteria, grouping them into ordered hierarchical structures according to their dominant relationships. Next, based on a certain ratio calibration, the judgment is quantified through pairwise comparison, forming a comparative judgment matrix. Ultimately, this method boils down the system analysis to determine the relative importance weights of the lowest level relative to the overall goal or the sorting problem of the relative optimal order, thereby providing a basis for selecting decision-making options [20-22]. The architecture of the AHP is shown in Fig. 2.

Fig. 2 presents the architecture of the AHP, which is according to the problem's nature and the overall goal. The problem is broken down into individual factors,

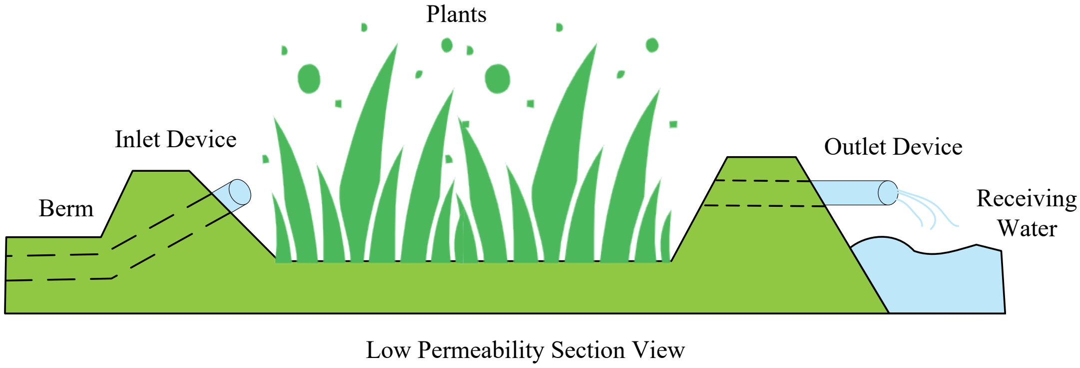

Fig. 1. Operation system of constructed wetland.

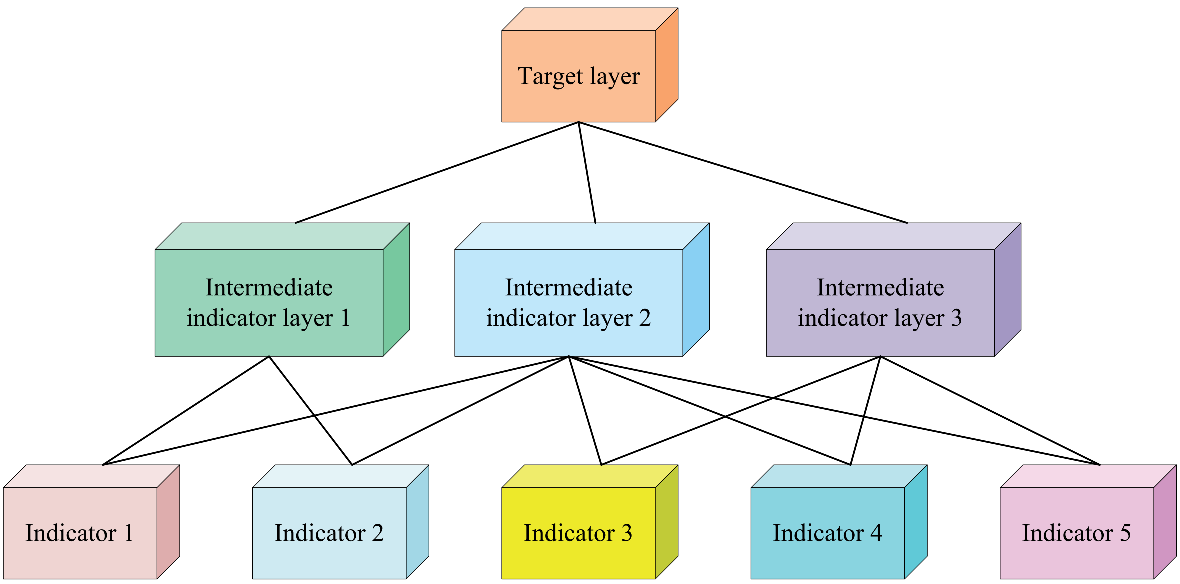

Fig. 2. Analytic hierarchy process architecture.

which are then combined and aggregated at various levels based on their interrelationships and membership relationships, creating a multi-level analytical structure model. The AHP method finds the eigenvector corresponding to its maximum eigenvalue, as indicated in Equation (1).

$$AP = \lambda_{\max} P \tag{1}$$

In Equation (1), $\lambda_{\max}$ represents the eigenvalues, A represents the corresponding eigenvectors, and P represents the matrix. Next, it normalizes A and uses the normalized values of A to represent the relative coefficients of different indicator weights. This study uses the sum product method to calculate the eigenvectors corresponding to the maximum eigenvalue of P, as indicated in Equation (2).

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(AP)_i}{nA} \tag{2}$$

In Equation (2), $(AP)_i$ means the i-th element in the AP result. Consistency testing is an important method for evaluating the rationality of judgment matrices. The judgment matrix is usually used to decide the relative importance of each indicator and is an important component of decision analysis methods such as AHP. To determine whether the matrix is reasonable, a consistency test is conducted as shown in Equation (3).

$$C_1 = \frac{\lambda_{\max} - n}{n-1} \tag{3}$$

In Equation (3), C_1 represents the consistency index and n represents the order of the judgment matrix P. Research determines the weights of each evaluation indicator through AHP. Based on expert opinions and data analysis, a hierarchical structure is constructed, followed by the construction of pairwise judgment matrices, and the weights of each indicator are worked out using the feature vector method of AHP. The evaluation index system for the operational status of artificial wetlands is a comprehensive evaluation framework that comprehensively measures the operational efficiency and management effectiveness of artificial wetlands. This system integrates multiple key element layers for detailed analysis and evaluation of the overall performance of wetlands [23, 24].

The basic principles of constructing the evaluation index system of constructed wetlands include scientificity, systematicness, operability, dynamics, and comparability. The index selection has been carefully considered when constructing the wetland evaluation index system. First, a series of key indicators are identified based on wetland ecosystems' key functions and values, such as water purification, biodiversity conservation, flood regulation, etc. Secondly, through expert consultation, literature review, and field research, the existing knowledge and practical experience on wetland assessment were collected to ensure the rationality and validity of the selected indicators. In addition, the sensitivity and responsiveness of the indicators are also considered, that is, whether they can reflect the change of wetland environmental state in a timely manner. In order to ensure the scientific rationality of indicator selection, correlation analysis of indicators is also carried out to avoid selecting highly correlated indicators to reduce redundancy and improve the efficiency of the indicator system. At the same time, through pre-evaluation and pilot study, the preliminary selected indicators are tested and validated to evaluate their effectiveness and reliability in practical applications. Finally, according to the test results and feedback, the index system was optimized and adjusted to ensure its applicability and accuracy in the environmental state assessment of constructed wetlands. The specific evaluation index system for the operation status of artificial wetlands is shown in Fig. 3.

In Fig. 3, wetland indicators mainly focus on wetlands' physical and biological characteristics. Among them, the ponds' design involves the wetlands' layout,

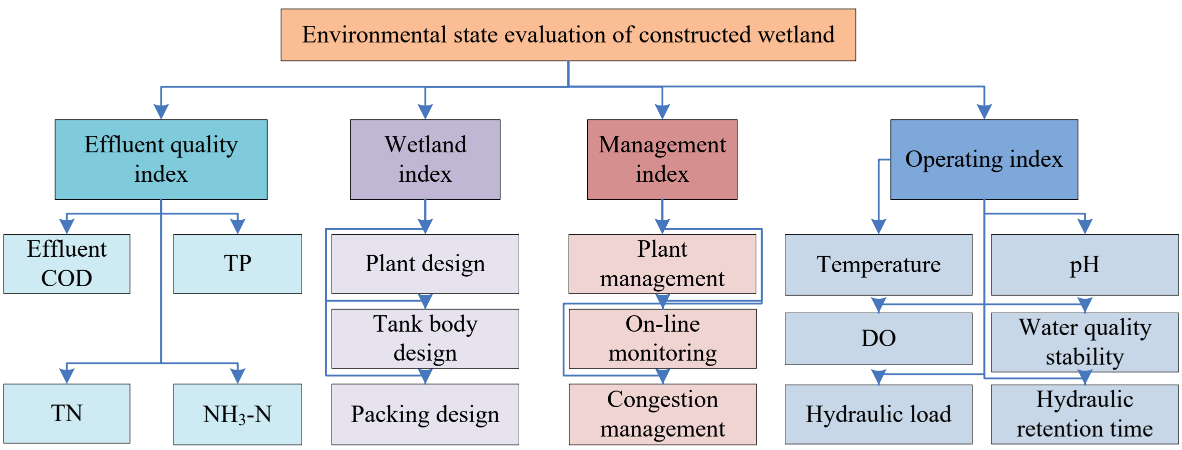

Fig. 3. Evaluation index system of operation state of constructed wetland.

size, and shape, directly affecting the wetlands' water flow pattern and purification capacity. Filler design focuses on wetland materials, significantly impacting the wetland's biodiversity and water purification efficiency. Plant design involves wetland plants' types, distribution, and density, which play important roles in wetland ecosystems, including providing habitat and absorbing pollutants. Operational indicators focus on the wetlands' various parameters and conditions during operation. Hydraulic load refers to the ability of wetlands to process water, which directly affects the purification effect of wetlands. The hydraulic retention time determines the flow rate and retention time of water in wetlands, which is crucial for the removal efficiency of pollutants. Temperature and pH are important factors affecting wetland biological activity and chemical reactions, while dissolved oxygen is related to the respiration and metabolism of microorganisms in wetlands. In addition, water quality stability is a critical indicator for evaluating wetland operational performance. The effluent quality indicators directly reflect the removal efficiency of pollutants by wetlands.

COD is a crucial indicator for measuring the degree of organic pollution in water, while ammonia nitrogen, total nitrogen, and total phosphorus are key parameters for assessing the risk of eutrophication in water bodies. Management indicators focus on the daily management and maintenance of wetlands. Online monitoring can provide real-time monitoring of the operational status of wetlands, enabling timely detection and resolution of issues. Plant management involves pruning and replanting wetland plants to ensure the health and stability of wetland ecosystems. Congestion management aims to prevent and address potential blockage issues in wetlands, ensuring their normal operation [25, 26]. The single-level ranking of indices for every level can be obtained through the judging matrix. This ranking is then used to calculate the overall ranking of the relative target layer. Table 1 shows the weight of index layer C relative to target layer A.

In Table 1, the weight values of 8 indicators, including filler design, plant design, hydraulic load, hydraulic retention time, water quality stability, effluent COD, TN, and TP, are above 0.05, which are relatively critical and have a significant influence on the operation status of artificial wetlands. When conducting hierarchical analysis, the dimensions and degree of variation of different indicators may lead to bias in the results. Therefore, standardization or dimensionless processing of data is crucial. Standardization can not only eliminate the influence of dimensionality but also make different variables numerically comparable, thus more accurately reflecting the relative importance between indicators. For qualitative data, it is usually necessary to assign values based on scoring criteria or expert scoring methods to convert them into numerical values that can be used for mathematical operations. For quantitative data, actual measured values can be directly used. A common method in data standardization is "minimum-maximum normalization", also called dispersion normalization. This method requires performing a linear transformation on the initial data,

Table 1. Weight coefficient of constructed wetland environmental state evaluation system.

Target layer A	Element layer B	Number	Weight	Index layer C	Number	Weight
Environmental state evaluation of constructed wetland	Effluent quality index	B1	0.4393	Effluent COD	C1	0.2336
				TP	C2	0.0814
				TN	C3	0.0814
				NH_3-N	C4	0.0427
	Wetland index	B2	0.1925	Plant design	C5	0.0825
				Tank body design	C6	0.0825
				Packing design	C7	0.0275
	Management index	B3	0.0738	Plant management	C8	0.0426
				On-line monitoring	C9	0.0060
				Congestion management	C10	0.0252
	Operating index	B4	0.2945	Temperature	C11	0.0134
				DO	C12	0.0297
				Hydraulic load	C13	0.0578
				pH	C14	0.0163
				Water quality stability	C15	0.0604
				Hydraulic retention time	C16	0.1170

mapping the resulting values to a range between 0 and 25. For the case where a larger indicator value is better, the conversion function is shown in Equation (4).

$$\hat{X}' = 0.1 + \frac{X_i - X^i_{\min}}{X^i_{\max} - X^i_{\min}} \times 0.9 \tag{4}$$

In Equation (4), X_i indicates the raw data, $X^i_{\min}$ and $X^i_{\max}$ are the minimum and max values in the data, and $\hat{X}'$ is the standardized data. For the case where a smaller indicator value is better, the conversion function is shown in Equation (5).

$$\hat{X}' = 0.1 + \frac{X^i_{\max} - X_i}{X^i_{\max} - X^i_{\min}} \times 0.9 \tag{5}$$

When conducting hierarchical analysis, the standardized data can be directly utilized to build a judgment matrix and then calculate the weights of each indicator. This method can eliminate the impact of dimensionality and degree of variation, making the analysis results more accurate and reliable.

Construction of Artificial Wetland Operation Status Model Based on BPNN

The study uses the evaluation results obtained from the previous section of the AHP method as the learning and training samples for the BPNN, takes the artificial wetland data reflecting various indicators as the inputting of the BPNN, and uses the corresponding evaluation results obtained from the AHP method as the outputting of the BPNN. In order to enhance the prediction ability of the model, more dimensions of environmental data are introduced. Integrating climate, land-use change, biodiversity, hydrology, water quality, and biological activity, data enables models to more accurately capture the complexity and dynamic changes in the environmental state of constructed wetlands, improve prediction accuracy, and provide scientific and real-time decision support for wetland management. Data preprocessing is a key step in building efficient and accurate models. In order to improve the performance of the model, wavelet transform technology is introduced, which is excellent in processing non-stationary signals and can effectively separate the trend and periodic components from the original data to reduce noise interference. In addition, using principal component analysis to reduce dimensionality, PCA helps simplify model complexity by extracting the major variation factors in the data while preserving the most critical information. This method not only reduces the computational burden of the model but also improves the robustness to outliers and noise. In order to further enhance the generalization ability of the model, the data enhancement technique is used to expand the training set. By applying various transformations, such as scaling, rotating, and adding slight noise, data enhancement techniques are able to generate new training samples without actually collecting more data. Combining these advanced data processing methods, the model can extract useful information from complex environmental data more effectively and maintain stable predictive performance under diverse environmental conditions.

BPNN is a supervised learning algorithm that utilizes gradient descent. It is a multi-layer feedforward neural network that typically includes inputting, hidden, and outputting layers. The training process of BPNN can be broken down into two sections: forward and backward propagation. During forward propagation, inputting samples are passed through the inputting layer of the network to the hidden layer (HL) and outputting layer, and the outputting value of each neuron is calculated. The outputting value is mapped nonlinearly through an activation function. Back propagation reduces errors by adjusting network parameters based on the error between the outputting and the actual values. Firstly, it calculates the outputting error and then uses the chain rule to calculate the error contribution of each neuron in the order from the outputting layer to the inputting layer and updates the weights and biases. The training of BPNN is an iterative process, which continuously adjusts weights and biases to make the network's outputting approximate the actual value [27-29]. It assumes that there are n nodes in the inputting layer, m nodes in the outputting layer, and l nodes in the HL. The excitation function is the functional relationship between the inputting and outputting of hidden and outputting layer nodes in a neural network, as shown in Equation (6).

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

In Equation (6), $g(x)$ represents the excitation function. The outputting of the HL is shown in Equation (7).

$$H_j = g\left(\sum_{i=1}^{n} w_{ij} x_i + a_j\right) \tag{7}$$

In Equation (7), w_{ij} indicates the weight from the inputting layer to the HL, H_j represents the HL's outputting, and a_j represents the biased term of the j-th neuron. The outputting of the outputting layer is indicated in Equation (8).

$$O_k = \sum_{j=1}^{l} H_j w_{jk} + b_k \tag{8}$$

In Equation (8), O_k represents the output value of the k-th output neuron, b_k represents the offset term of the k-th output neuron, w_{jk} represents the weight from the outputting layer to the HL. The error back propagation process of BPNN is actually a process in which the outputting error of the network is reversed layer by layer through the HL to the inputting layer in a certain form, and the error is distributed to the neurons and neural units of each layer. This process is carried out in a loop, and the weights are constantly adjusted until the error in the network outputting is reduced to an acceptable level or until the pre-set number of learning iterations is reached. In BPNNs, the error is determined by the difference between the actual outputting of the outputting layer and the expected outputting. To reduce this difference, the network will adjust the weights of each neuron layer by layer based on the path of error back propagation, to minimize the total error. This adjustment process is grounded on the gradient descent method, which calculates the gradient of the error function on the weight and adjusts the weight along the gradient descent direction to gradually reduce the error. In training, the network continuously learns the mapping relationship between inputting data and expected outputting and updates the weights through back propagation, gradually making the network's outputting approach the expected outputting. When the network reaches a certain number of training iterations or an acceptable level of error, the training process ends, and the network weights are fixed, which can be used for predicting new data [30]. The flowchart of the BPNN is shown in Fig. 4.

In Fig. 4, the inputting data is propagated through the network, and the outputting values of the HL and outputting layer are calculated. It calculates the error by comparing the predicted and actual values of the outputting layer and updates the weights and bias values using gradient descent. Forward propagation and backward propagation are repeated until the stop condition is arrived. The number of input layer nodes depends on the dimension of the inputting vector, and the optimal number of HL nodes can be determined, as denoted in Equation (9).

$$m' = \sqrt{n' + l} + a \tag{9}$$

In Equation (9), m', n', and l represent the amount of hidden, inputting, and outputting layer nodes, respectively. a is a constant from 1 to 10. However, the BPNN has some obvious drawbacks. The optimization of the BPNN relies on the gradient descent method, which is susceptible to becoming trapped in local minima while searching for the global optimal solution. This can cause the network to fail to find the true optimal solution. Therefore, the study adopts an adaptive mutation genetic algorithm (GA) to raise the BPNN model. GA is an optimization algorithm that simulates natural selection and genetic mechanisms. It can perform a global search in the search space and has a certain degree of adaptability and robustness. The adaptive mutation GA can dynamically adjust the mutation rate based on the problem's characteristics and the search's progress, thereby improving the algorithm's performance. In the search for the optimal global solution using GAs, the adaptability of each living organism is dynamically changing. Therefore, it is recommended that adaptive mutation probability (MP) be adopted. When the population's fitness is poor, MP should be enhanced to increase the population's diversity and increase the number of excellent individuals. Conversely, the MP should be lowered when the fitness is good, i.e., close to the globally optimal solution [31]. The calculation of adaptive MP P' is denoted in Equation (10).

$$\begin{aligned} P' = (P_1 + P_2)/2 = (P_0 - (P_0 - P_{\min}) * m''/M \\ + P_0 * \max_{X_K \in \Omega} F(X_K)/\bar{F})/2 \end{aligned} \tag{10}$$

In Equation (10), P_0 is the assumed initial MP, $P_{\min}$ is the MP range's min value, and $\bar{F}$ and $\max_{X_K \in \Omega} F(X_K)$ are the population's average and max fitness values, respectively. M is the max evolution generation and m'' is the current evolution generation. The research uses adaptive mutation GA to improve the BPNN model. There is a positive correlation between the amount of experimental samples and the accuracy of reaction

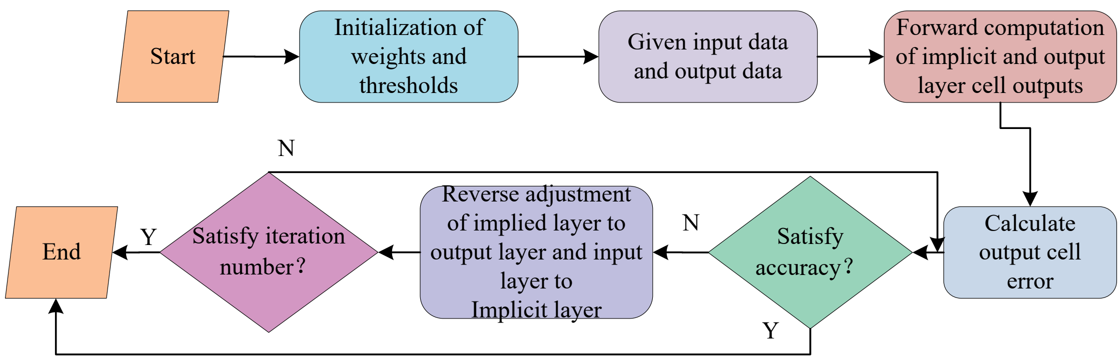

Fig. 4. BPNN flowchart.

results. However, when the sample size reaches a certain level, the accuracy will remain stable within a range, and no significant changes will occur. The larger the network size, the more complex the mapping relationship of the network. There are two common methods for selecting initial weights: one is to choose a sufficiently small initial weight, and the other is to make the number of initial weights equal to +1 and -1. Typically, several networks can be trained, and the most appropriate one can be chosen based on the analysis findings. In this study, a single HL neural network vector model was used in MATLAB, as depicted in Fig. 5.

In Fig. 5, $\hat{P}$ is the inputting vector with a size of $R \times 1$, as denoted in Equation (11).

$$\hat{P} = [P_1, P_2, ..., P_R] \tag{11}$$

b_1 is the threshold vector of the inputting layer neurons, with a size of $S_1 \times 1$, as denoted in Equation (12).

$$b_1 = [b_1, b_2, ..., b_{S_1,1}] \tag{12}$$

IW_1 means the connection weight vector between the inputting layer neurons and the inputting vector, with a size of $S_1 \times R$, as denoted in Equation (13).

$$IW_1 = \begin{bmatrix} iw_{1,1}^{1,1} & iw_{1,2}^{1,1} & \ldots & iw_{1,R}^{1,1} \\ iw_{2,1}^{1,1} & iw_{2,2}^{1,1} & \ldots & iw_{2,R}^{1,1} \\ \ldots & \ldots & \ldots & \ldots \\ iw_{S_1,1}^{1,1} & iw_{S_1,2}^{1,1} & \ldots & iw_{S_1,R}^{1,1} \end{bmatrix} \tag{13}$$

n_1 is the intermediate calculation outcome of the first layer neuron, which is the weighted sum of the connection weight vector and threshold vector, with a size of $S_1 \times 1$, as denoted in Equation (14).

$$n_1 = IW_1 p + b_1 \tag{14}$$

a_1 means the outputting direction of the first layer neuron, with a size of $S_1 \times 1$, as denoted in Equation (15).

$$a_1 = f_1(IW_1 p + b_1) \tag{15}$$

The objective of the GA is to minimize the sum of squared errors in all evolutionary generations by obtaining the network weight and threshold. GA progresses towards higher fitness function values. Therefore, the fitness function is defined as the inverse of the individual's learning error, as shown in Equation (16). Therefore, the fitness function is defined as the inverse of the individual's learning error, as shown in Equation (16).

$$f_{fitness} = \frac{1}{E} \tag{16}$$

In Equation (16), $f_{fitness}$ stands for fitness and E represents the learning error. The model uses an adaptive MP mutation operation to strengthen the diversity of the GA population, enabling it to jump out of local optimal solutions and search for global optimal solutions in a timely manner, thereby avoiding the occurrence of premature convergence [32]. The algorithm model is shown in Fig. 6.

Fig. 6 illustrates that the optimal solution is searched by a GA and inputted into the BPNN as the initial weights and thresholds of the network. The model's data flow is as follows: Starting from the BPNN section, learning samples are determined using the data collected from the survey questionnaire, and the topological structure of the neural network is identified, including the number of network layers and neurons. Afterward, the initial population of the adaptive mutant GA is obtained. The adaptive mutation process in GA involves encoding, fitness calculation, and genetic operations to determine the optimal weight and threshold that satisfy the stopping conditions. The initial weights and thresholds obtained can then be utilized by the BPNN

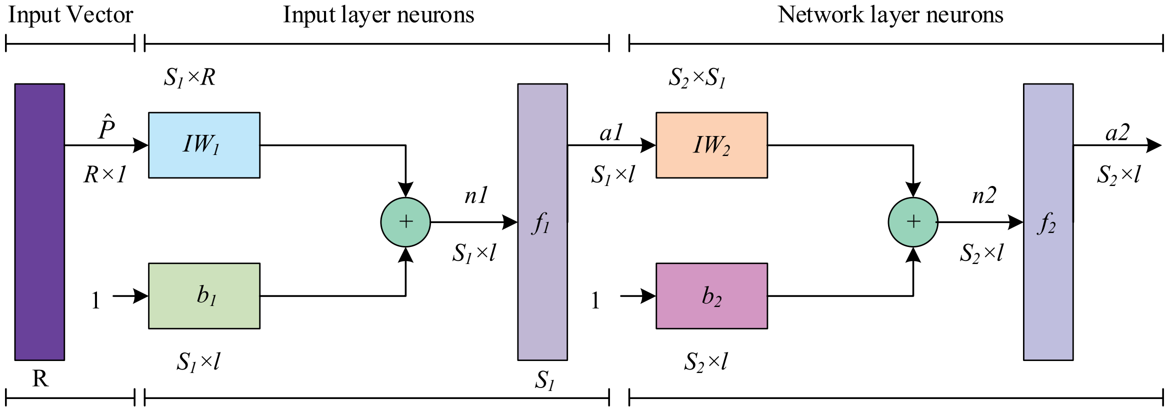

Fig. 5. Vector model of multilayer neural network.

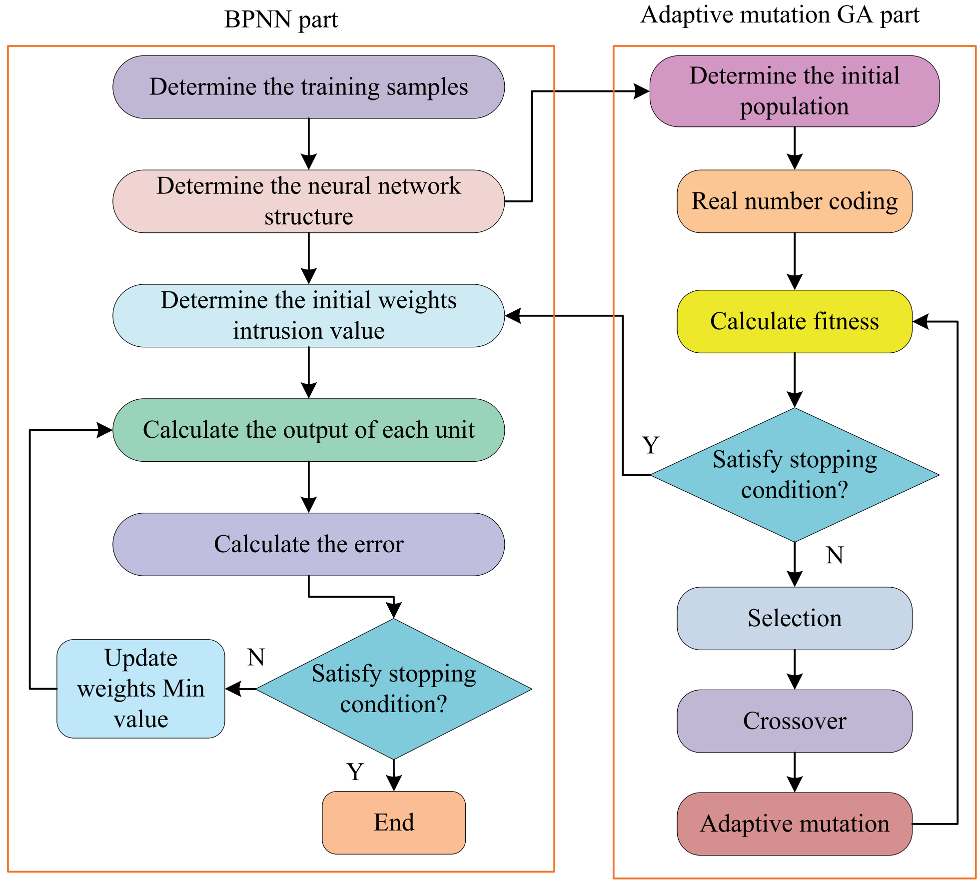

Fig. 6. Model of GA-BP algorithm.

to shorten the time required to find the optimal weights and thresholds, thereby speeding up the convergence speed of the network. After meeting the learning error or iteration requirements, an optimal GA-BP algorithm model can be generated. In order to further improve the training efficiency and performance of the model, L1 and L2 regularization techniques were first introduced to effectively control the complexity of the model and reduce the risk of overfitting. L1 regularization makes some unimportant weights zero by punishing the absolute value of weights, thus realizing the effect of feature selection. L2 regularization makes the weights tend to smaller values by punishing the sum of squares of the weights, increasing the model's stability. At the same time, Adam and RMSprop advanced optimization algorithms have been adopted to optimize the model. The Adam algorithm combines AdaGrad and RMSProp advantages, adaptively adjusts each parameter's learning rate, and makes the model converge more efficiently in the training process. The RMSprop algorithm provides a separate learning rate for each parameter by adjusting the cumulative average gradient square, which is especially suitable for dealing with non-stationary targets. Applying these optimization algorithms not only speeds up the convergence speed of the model but also improves the model's ability to find the optimal solution in the complex data distribution.

Results and Discussion

Performance Analysis of Artificial Wetland Environmental Status Assessment Model Based on AHP and BPNN

The study first conducted simulation experiments on the GA-BP algorithm model to test its performance indicators. Then, it analyzed the water quality of the artificial wetland's inflow and outflow through the evaluation model of its environmental status.

GA-BP Algorithm Model Performance

Research collected environmental status data of artificial wetlands, including indicators such as water quality, biodiversity, and soil conditions, and performed preprocessing and normalization. The optimized BPNN was used for training and testing, and a simulation experiment based on an improved GA-optimized BPNN for evaluating the environmental status of artificial wetlands was carried out using Matlab2013b. Combining GA-BPNN with BPNN, Extreme Learning Machine (ELM), Support Vector Machine (SVM), Random Forest (Random Forest RF), and Gradient Boosting Machine (GBM) for comparative analysis, the accuracy

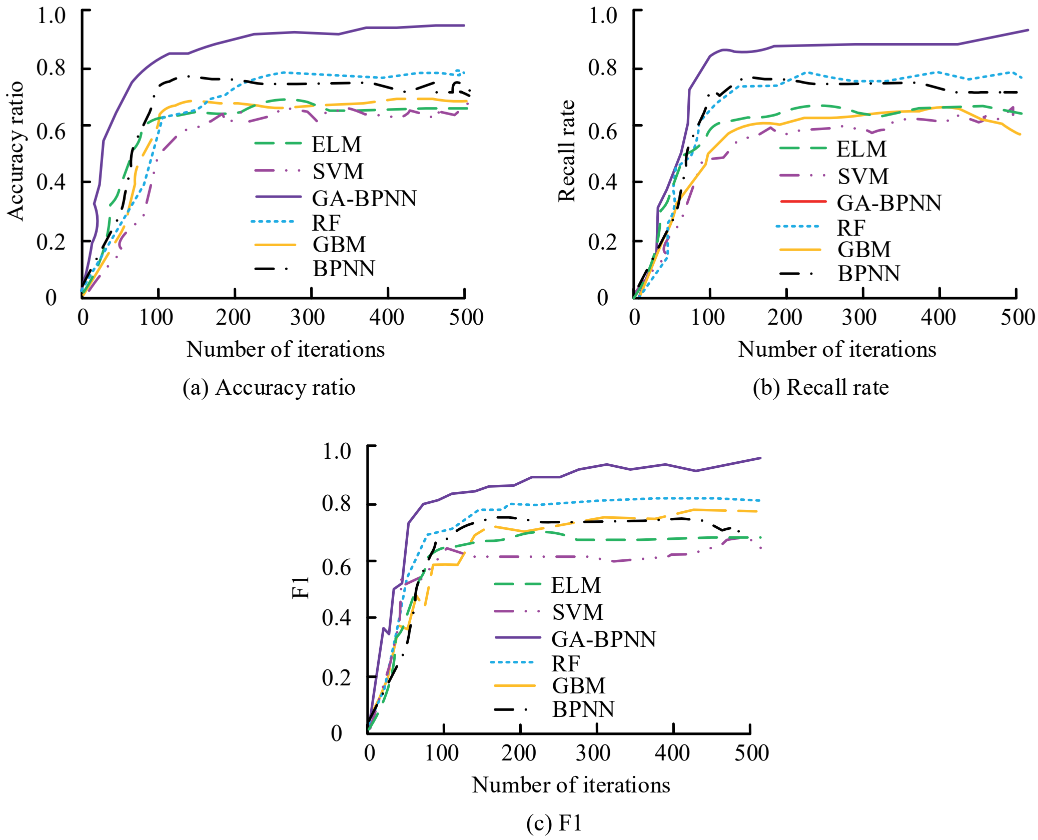

Fig. 7 The accuracy rate, recall rate, and F1 value of the six algorithms.

rate, recall rate, and F1 values of several algorithms are shown in Fig. 7.

In Fig. 7a), GA-BPNN and BPNN rise faster and quickly approach higher accuracy rates. With the increase in the number of iterations, the accuracy of GA-BPNN tends to be stable. It reaches a high accuracy of close to 1.0 after about 100 iterations, which shows its fast convergence characteristic during training. In contrast, the accuracy of other algorithms, such as ELM, SVM, RF, and GBM, increases gently, fluctuates greatly in the iterative process, and finally stabilizes between 0.6 and 0.8. This shows that GA-BPNN has better learning and generalization abilities when evaluating environmental states. In Fig. 7b), GA-BPNN also performs well in the recall rate, and its curve rises rapidly in the early iterations and stabilizes above 0.8 after about 100 iterations, showing its high efficiency in identifying positive samples. BPNN also had a higher recall rate but was slightly lower than GA-BPNN. The advantages of GA-BPNN in processing unbalanced data sets are confirmed, especially in improving the recognition rate of positive samples. In Fig. 7c), GA-BPNN also had an outstanding performance in the F1 score. Its curve rose rapidly in the early stages of iteration. It stabilized above 0.8 after about 100 iterations, showing its superiority in its comprehensive consideration of accuracy and recall rate, as well as its comprehensiveness and stability. To further prove the model's high accuracy of the raised model, the study analyzed and compared the training and learning results, as denoted in Fig. 8.

In Fig. 8a), the error of the BPNN model was relatively large, with some data falling outside the error range of plus or minus 0.2. In Fig. 8b), 80% of the data fell within the error range of plus or minus 0.2, indicating that the learning speed of the model has been greatly improved. That is to say, the model learned most of the data patterns in relatively few iterations. The study predicted the evaluation results of the last 20 sample data sets, as shown in Fig. 9.

In Fig. 9a), the prediction error of the BPNN model was relatively large. In Fig. 9b), the predicted results were basically consistent with the actual results, and the fitting degree reached over 90%. This indicated that GA optimization has played a critical role in improving the performance of BPNN models. The regression results could reflect the overall goodness of fit of the evaluation model, as indicated in Fig. 10.

In Fig. 10, regardless of the overall sample, training sample, or test sample, the regression results of the data showed excellent fit and avoided overfitting issues. This fully demonstrated that the model had an excellent ability to capture the inherent patterns and information of data, thereby being able to predict and interpret the dynamic behavior of data more accurately. The calculated R^2 value was as high as 0.99163, and the MSE was also approaching zero. The R^2 value was extremely close to 1, proving the effectiveness of the model-fitting effect.

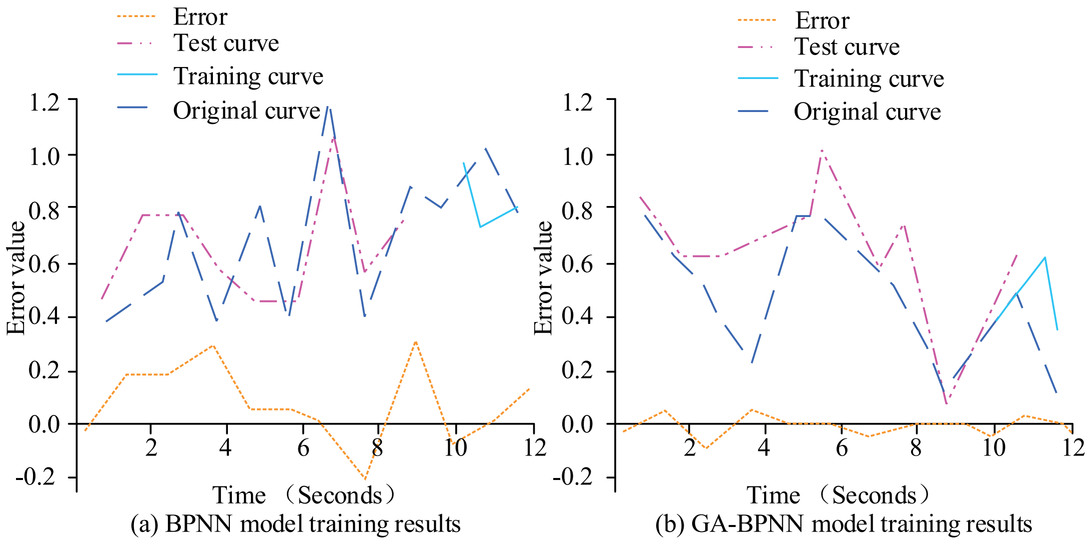

Fig. 8. Model training learning results.

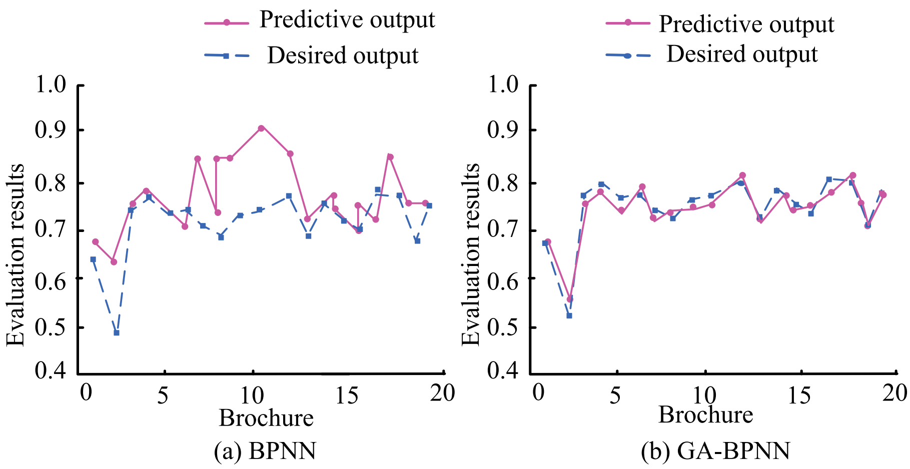

Fig. 9. Neural network model prediction results.

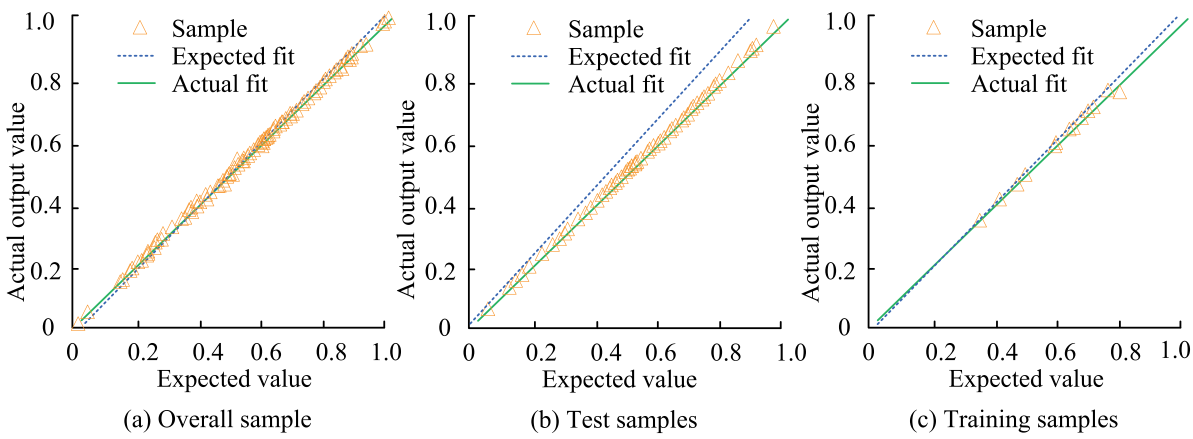

Fig. 10. Model regression result.

Example Analysis of Artificial Wetland Environmental Status Assessment Model

The study preprocessed qualitative and quantitative indicator data to conduct a comprehensive evaluation of the environmental status of artificial wetlands. It multiplied the processed data with the weights of various influencing factors to obtain comprehensive evaluation outcomes, as indicated in Table 2.

In Table 2, the comprehensive score of the established wetland was low, indicating that the overall environmental status of the wetland is not ideal and there may be a series of problems. The wetland may suffer from pollution from surrounding areas, and comprehensive measures need to be taken to raise the environmental status of the constructed wetland. Therefore, further analysis of the COD purification effect of pollutants was conducted, as shown in Fig. 11.

In Fig. 11a), the range of COD concentration in the influent of artificial wetland A was large, ranging from 25 mg/L to 142 mg/L, indicating significant fluctuations in influent water quality. The COD concentration range in the effluent was relatively narrow, ranging from 8 mg/L to 34 mg/L, and overall lower than

Table 2. Comprehensive evaluation of constructed wetland environmental status.

Serial number	/	1	2	3	4	5	6	7	8	9	10	11	12
C1	Effluent COD	0.42	0.42	0.76	0.90	0.85	1.00	0.76	0.42	0.51	0.90	0.90	0.42
C2	TP	0.59	0.35	0.10	0.13	0.68	0.52	0.68	0.95	0.52	0.67	0.47	0.43
C3	TN	0.75	0.52	0.60	0.59	0.81	0.83	0.69	0.65	0.66	0.64	0.60	0.59
C4	NH_3-N	0.77	1.00	0.96	0.97	0.70	0.94	0.93	0.92	0.92	0.91	0.80	0.72
C5	Plant design	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C6	Tank body design	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C7	Packing design	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C8	Plant management	0.10	1.00	1.00	1.00	0.10	0.10	1.00	1.00	1.00	0.55	0.33	0.33
C9	On-line monitoring	0.40	0.70	0.40	0.70	0.70	0.70	0.40	0.70	0.10	0.70	0.40	0.70
C11	Temperature	0.45	0.52	0.82	0.86	0.94	0.96	0.84	0.59	0.34	0.37	0.19	0.11
C12	DO	0.66	0.81	1.22	0.54	0.10	0.69	0.57	0.64	0.63	0.70	0.69	0.82
C13	Hydraulic load	0.10	0.10	0.10	1.00	1.00	1.00	0.10	0.10	0.10	0.10	0.10	1.00
C14	pH	0.94	1.00	0.73	0.63	0.78	0.92	0.57	0.55	0.92	1.14	0.71	1.14
C15	Water quality stability	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
C16	Hydraulic retention time	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
Overall rating	/	0.617	0.675	0.759	0.752	0.804	0.707	0.662	0.616	0.741	0.679	0.586	0.561

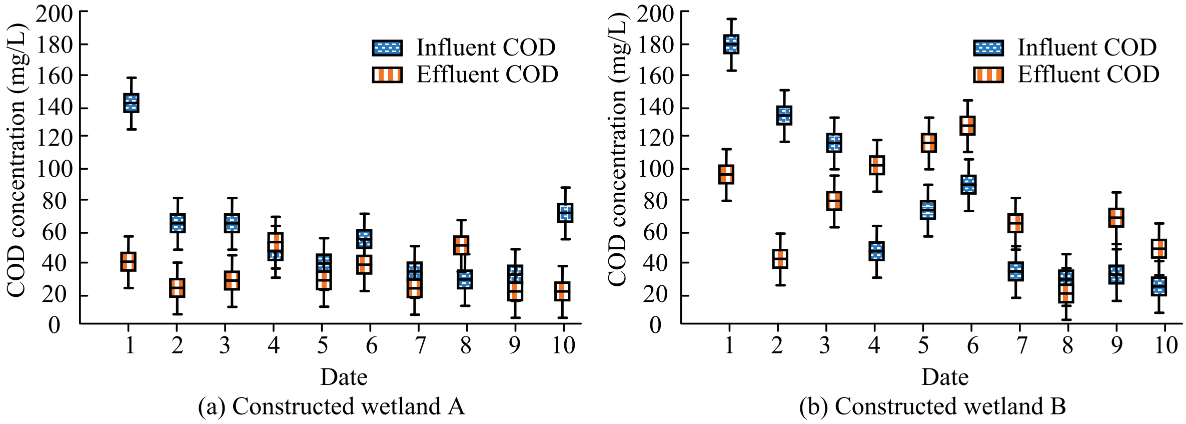

Fig. 11. Purification effect of pollutant COD.

that in the influent, indicating that the wetland system had a certain removal effect on COD. The average COD removal rate was 39%; although there was some removal effect, the removal rate was not high. The COD value of the effluent was lower than that of the inflow, indicating that the wetland system could play a certain role in COD removal most of the time. However, due to significant fluctuations in influent water quality and low removal rates, wetland systems may not fully meet water quality requirements in certain situations. In Fig. 11b), the COD concentration range of the influent in constructed wetland B ranged from 40 mg/L to 160 mg/L, with a slightly smaller fluctuation range compared to wetland A. The COD concentration range in the effluent was relatively large, ranging from 16 mg/L to 122 mg/L, indicating that the wetland system had an unstable COD removal effect. The average COD removal rate was 21%, which was lower than wetland A, indicating that wetland B had poor performance in COD removal. Further analysis was conducted on the purification effect of pollutants COD along the process, as shown in Fig. 12.

In Fig. 12a), artificial wetland A showed a slight increase in COD content in spring, mainly due to incomplete harvesting of plants in winter, resulting in residual plants starting to rot in spring. The decay of plant residues released organic matter into wetlands, thereby increasing the content of COD. In Fig. 12b), the secondary subsurface flow tank and the primary surface flow had poor performance in COD removal. Especially in winter and spring, the COD content in the effluent was even higher than that in the inflow, indicating that the water quality of the constructed wetland in this section has been polluted during these two seasons. The ecological and functional indicators of the constructed wetland environmental status evaluation model (Model 1) were compared with the wetland monitoring and evaluation model based on remote sensing technology

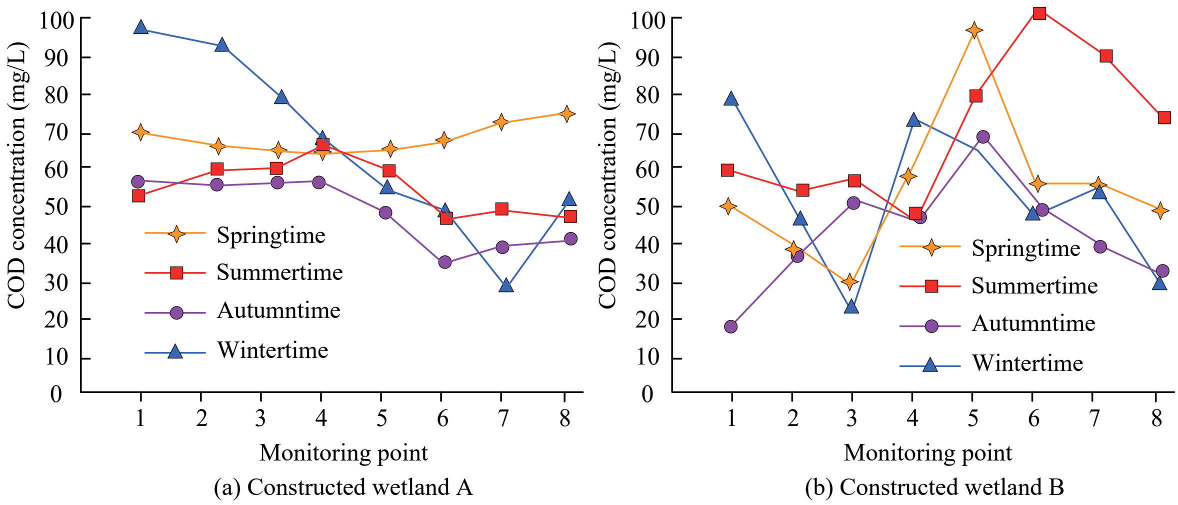

Fig. 12. Purifying effect of pollutant COD along the way.

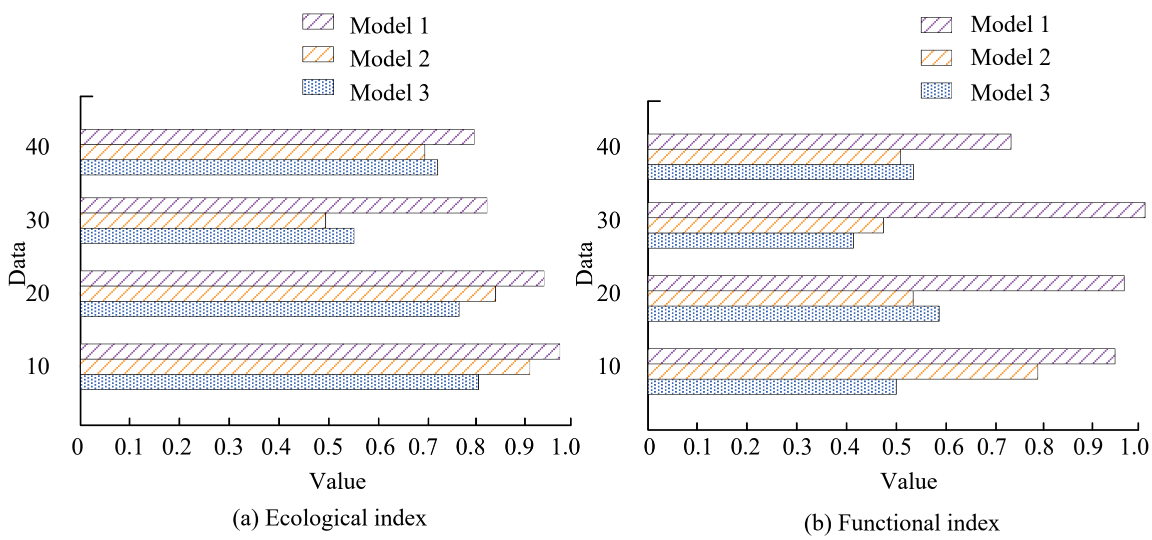

Fig. 13. Comparison of ecological index and functional index of three models.

Table 3. Comparison of comprehensive performance of different algorithms in environmental state assessment of constructed wetlands.

Algorithm	ELM	SVM	GA-BPNN	RF	GBM	BPNN
Stability index	0.855	0.780	0.915	0.865	0.845	0.875
Average prediction error (MSE)	0.011	0.014	0.004	0.008	0.007	0.009
Model complexity (number of parameters)	0.600	0.200	1.000	1.500	1.750	1.250
Interpretability	0.850	0.150	0.600	0.350	0.250	0.500
Prediction efficiency (ms/sample)	0.450	1.150	0.750	0.650	0.950	0.850
Training efficiency (normalized)	0.950	0.450	0.800	0.650	0.550	0.875
Noise resistance (normalized)	0.650	0.500	0.850	0.700	0.620	0.680
Cross-domain generalization ability (normalized)	0.550	0.400	0.700	0.600	0.520	0.580
Feature importance assessment (normalized)	0.750	0.250	0.650	0.500	0.420	0.480

(Model 2) and the wetland health evaluation model based on the comprehensive index method (Model 3), as shown in Fig. 13.

In Fig. 13a), Model 1 had the highest ecological index, averaging over 93%. In Fig. 13b), Model 1 had the highest functional indicators, averaging over 92%. Model 1 provides strong support for wetland protection and management and provides a reference for improving and optimizing other wetland models. A comprehensive performance comparison of different algorithms in the environmental state assessment of constructed wetlands is shown in Table 3.

In Table 3, from the stability index, the GA-BPNN algorithm leads with a score of 0.915, showing that it has the best stability under different test conditions. In terms of MSE, GA-BPNN also performs best with a low error value of 0.004, indicating its high prediction accuracy. The GA-BPNN algorithm performs well on several key performance indicators, especially in stability, prediction accuracy, anti-noise ability, and cross-domain generalization ability. This shows that GA-BPNN is a powerful tool for environmental assessment tasks that require high precision and efficiency. Despite its high model complexity, high scores on other performance metrics suggest that it is a comprehensive and effective choice.

Conclusions

With the strengthening of environmental protection awareness, artificial wetlands, as a crucial element of urban ecosystems, are increasingly valued for their environmental status assessment. The study used a combination of AHP and BPNN to construct a model for evaluating the environmental status of artificial wetlands. The AHP was applied to decide on the weight of each evaluation indicator, and a BPNN model was constructed with the evaluation index system and weight values. The research results indicated that the model's predicted outcomes were basically consistent with the actual outcomes, and the fitting degree reached over 90%. Whether it is the overall sample, training sample, or test sample, the regression results of the data showed excellent fit, with an R^2 value of 0.99163 and an MSE approaching zero, proving the effectiveness of the model's fitting effect. This model was superior to traditional methods in terms of evaluation accuracy and efficiency and could provide strong support for wetland environmental protection and management. The COD concentration in the inflow of artificial wetland A varied greatly, from 25 mg/L to 142 mg/L, reflecting significant fluctuations in water quality. The COD concentration in the effluent remained stable at 8 mg/L to 34 mg/L, generally lower than that in the influent, indicating that the wetland system had a certain ability to remove COD. Although the average removal rate was 39% and the wetland system could remove some COD most of the time, fluctuations in the inflow and insufficient removal rate may result in it not meeting specific water quality requirements. However, there are some shortcomings in the research, and the current data sources and collection methods still need further improvement. In the future, it can continue to deepen our research on applying big data technology and artificial neural networks in wetland environmental assessment. It needs to explore more diverse data collection and processing methods to raise the comprehensiveness and accuracy of data.

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Conflict of Interest

The authors declare no conflict of interest.

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