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Research on Green Campus Evaluation in Cold Areas Based on AHP-BP Neural Networks

Mengqi Guo , Yiyun Zhu * and Aiyan Xu

School of Civil and Architectural Engineering, Xi'an University of Technology, Xi'an 710048, China; 2220721158@stu.xaut.edu.cn (M.G.); xuaiyan@stu.xaut.edu.cn (A.X.)
* Correspondence: zyyun@xaut.edu.cn

Abstract: The green campus agenda is a specific manifestation of sustainable development and China's basic strategy of developing the country through science and education. As a result of the differences in the climate environments and topographies of various places, the requisites for site planning and energy consumption by colleges and universities are different among regions, especially cold regions. However, China's current green campus evaluation standard, GB/T 51356-2019, does not refine the evaluation indicators according to the different regions. Therefore, it is important to develop a green campus evaluation system appropriate to the region. Firstly, based on the relevant literature and standards, this paper clarifies the four evaluation criteria of campus sustainable land use, resource utilization, healthy environment, and safety. Nine first-level evaluation indicators for campuses—master planning, energy utilization, indoor environment, etc.—and twenty-one second-level evaluation indicators for campus siting—such as the use of water-saving appliances and renewable energy—were determined. Secondly, expert scoring and hierarchical analysis (AHP) were utilized to calculate the weights of the evaluation indicators by inputting the experts' scores into the neural network model and testing the evaluation results using a back propagation neural network (BP) to finally establish a green campus evaluation model for cold regions based on an AHP-BP neural network. Finally, a university building in Xi'an, a cold region, was selected as a case study, and the errors in the green campus evaluation results were between 0.0001 and 0.001, which verifies the precision and practicability of the assessment system and the AHP-BP model. This paper's findings serve as significant references for the improvement in assessment criteria for green campuses in the future.

Keywords: green campus; evaluation system; neural network; analytic hierarchy process

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1. Introduction

The "Implementation Plan for the Construction of a National Education System for Green and Low-Carbon Development" was published by the Ministry of Education in October 2022, which urges green and low-carbon development to be incorporated into the national education system. Additionally, it proposes that concrete steps be taken to help the education sector achieve the goals of carbon neutrality and emissions reduction, as well as actively contributing to sustainable development [1]. Based on the Ministry of Education's statistics for 2023, there were 498,300 schools at all levels in China, with an area of 3.919 billion square meters, 291 million students, and 18.9178 million teachers. Colleges and universities accounted for as high as 48.5% of the overall education sector [2]. Colleges and universities are microcosms of cities, and their functions and social responsibilities affect the development of green campuses [3]. Therefore, they play a key role in promoting the green campus construction process [4].

In order to build a green campus, China has successively published the "Assessment Standard for Green Campus" CSUS/GBC 04-2013 [5], as well as the "Assessment Standard for Green Campus" GB/T 51356-2019 [6]. The latter is suitable for the evaluation of the design, construction, and operation of new and existing campuses. Because China is such a vast country, the climate varies significantly from region to region. However, this standard does not refine the evaluation indicators according to different regions. Compared with other regions, cold regions have obvious characteristics, such as winter heating and summer cooling requirements and less precipitation, as well as the insufficient utilization of nontraditional water sources [7], and using uniform standards for evaluations can result in higher campus construction costs and the waste of natural resources and energy. Therefore, based on current standards, the establishment of a green campus evaluation system in cold regions is the basis for achieving the low-carbon and sustainable development of green campuses.

In recent years, scholars have carried out relevant research concerning green campus evaluations to make positive contributions to the realization of green campus construction. These studies are mainly summarized in the following four categories:

(1) Partial Low-Carbon Design for Green Campuses. Kelly, O. [8] saw climate change awareness and campus greening methods as important parts of sustainable development strategies. Sun Bo [9] established a linkage between campus layout, the microclimate of the environment, and the comfort of activity areas in the improvement of outdoor comfort on campuses during cold winters. Hu Ying [10] constructed an ecological rainwater collection and comprehensive utilization system to achieve the goal of controlling runoff volume and pollution, as well as rainwater resource utilization. Some scholars [11,12] have proposed low-carbon technologies, such as using solar-based fresh air systems in dormitories and installing bidirectional reflective photovoltaic (BRPV) systems in campus buildings in order to reduce campus power consumption. Wenyu Wu [13] proposed a short-term linear forecast model (ARMA-LR) to evaluate everyday power on university campuses. Antônio [14] established a sustainable transportation evaluation index for campuses that considers the relevance of different environments. Zhang XuHao [15], based on real cases, provided optimization solutions for increasing traffic pressure as a result of pedestrian–vehicle interactions on campus. The above scholars have conducted studies on campus greening, transportation, energy consumption, and water resources, but all of the above studies are single-factor studies, and there is a lack of multi-factor systematic studies;

(2) Analysis of Green Campus Evaluation Systems. Some scholars [16,17] compared and analyzed a variety of sustainable development assessment tools for universities, making the structure and contents of these tools easier to understand. Liao Xufeng [18] and Zhou Yue [19] conducted a cross-analysis of the evaluation criteria for green campuses in China and the US, and the research results provide useful insights for the construction of green campuses in China. In building sustainable development models, countries are following the trend of establishing sustainability assessment tools that are in line with their own [20–22]. The research by the above scholars provides favorable assistance for the development of green campus evaluation systems (GCES) that are locally appropriate and suitable for national-level conditions;

(3) Green Campus Evaluation Methodologies. Zhao Tai [23] and N. vanden Bogerd [24] used the OWA operator weighting method and the Delphi method to establish a green campus evaluation system to support the design and evaluation of green campuses, respectively. W. Na [25] proposed a system of evaluating indexes for low-carbon university campuses using hierarchical analysis and the entropy weighting method to quantify them. Hongmei Zhao [26] established an intelligent evaluation model based on dynamic Bayesian and adaptive fuzzy inference (DBN-ANFIS) to evaluate green campuses from four dimensions. Min Yu [27] established a neural network model based on a back propagation genetic algorithm for the ecological evaluation of small-sized buildings such as gardens. Wu Bo [28] established an assessment model for public building design proposals based on a BP neural network. Zhang Rongxin [29] established a new MADM model based on dynamic integrated time entropy and applied it to the study of green building project selection. Most studies on evaluation methods for green campuses used qualitative methods for

evaluation, which have excessive subjective factors and rough calculation processes that are not suitable for achieving high precision.

(4) Regional green campus evaluation. Gao Jinyi [30] used CAD-GIS-BIM (CGB) technology software integration for the simulation and suitability retrofitting of the existing campus buildings in areas with hot summers and cold winters. Yang Shuya [31] expanded the scope of hot-summer and cold-winter areas, selected the green campus evaluation systems of the East Asian and Southeast Asian countries for comparative analysis, and proposed amendments to regional indicators and supplementary suggestions. Yao Lu [32] summarized green campus technologies suitable for cold regions based on green campus case studies. The above research puts forward suitable green campus-relate suggestions based on the climate characteristics of different areas, and summarizes green campus technology. For cold regions, a suitable green campus evaluation system should also be established.

As can be seen from the above studies, most of the existing studies focus on the establishment of green and sustainable campuses and energy saving, as well as the integral comparison of evaluation systems, and a comprehensive, quantitative, and targeted evaluation system has not yet been established for green campuses in cold areas. Therefore, this paper takes colleges and universities in cold regions as the research object; the analytic hierarchy process and BP artificial neural network are used to evaluate the green campus, and then an evaluation model for green campuses in cold areas is established based on the BP neural network. We invite industry experts to score and use the analytic hierarchy process to determine the weights of evaluation indexes, input AHP evaluation scores into a neural network, and training the model with sufficient samples to meet the error requirements. Finally, it is verified by examples that the inaccuracies of the calculation results of the model are between 0.001 and 0.0001, which indicates that the model can reduce the defect of human subjective arbitrariness and can reasonably evaluate green campuses in cold areas.

2. Construction of Green Campus Evaluation System in Cold Areas

The scientific and rational selection of evaluation indicators is the first step in conducting an evaluation [33]. The appropriateness of the choice of evaluation indicators will have a direct impact on the conclusions of the synthesized assessment.

2.1. Basis for Screening Evaluation Indicators

2.1.1. LEED, BREEAM

The subsystem "LEED BD + C: School in the American building evaluation system LEED V4.1" [34] is an evaluation standard specifically for campus buildings, which adds indicators for comprehensive design, the inhibition of mold growth, classroom acoustics, and site environment. The system includes eight categories of indicators for the integration process, siting and transportation, sustainable sites, water efficiency, energy and atmosphere, materials and resources, indoor environmental quality, innovative operations, and regional priorities, with energy and atmosphere having the highest weighting at 33% [35]. BREEAM Education for schools in BREEAM [36] covers the whole life cycle of a building project, including the following nine categories of indicators: management, physical and mental health, energy, transportation, water, materials, waste, land and ecology, and pollution, wherein the two indicators of energy and materials have a heavier weighting of 16% and 15%, respectively [37].

2.1.2. Assessment Standard for Green Campus GB/T 51356-2019

As a regional evaluation system, the criteria should be extracted from the current national standards, based on which climate suitability indicators should be constructed. The Green Campus Evaluation Criteria [38] includes five categories of indicators, including planning and ecology, energy and resources, environment and health, operation and management, and education and promotion, in primary and secondary schools, where energy and resources and environment and health account for the same proportion, 25%. In higher education institutions, planning and ecology and energy and resources account for the same proportion, 25%.

2.1.3. Evaluation Standard for Green Building GB/T 50378-2019 [38]

This standard contains the five categories of indicators of safety and durability, health and comfort, the convenience of life, resource conservation, and livability of the environment, of which resource conservation is weighted at 20% and the rest of the indicators are weighted at 10%. After summarizing and analyzing, regardless of the use of the building, energy and resources have a high weight.

2.1.4. Building Climate Zoning Standards GB 50178-93 [39]

In this paper, cold regions are chosen as the object of study, with a long, cold and dry winter, a hot and humid summer in the plains, a cooler summer in the highlands, and concentrated rainfall; the annual temperature gap is large and the sunlight is rich. Therefore, in winter, the buildings should meet the demands of anti-cold, heat, and frost protection, and anti-heat should be taken into account in some areas in summer.

2.1.5. Design Standard for Energy Efficiency of Residential Buildings in Severe Cold and Cold Zones JGJ 26-2010 [40]

This standard contains strict requirements for the green performance of all types of architecture in cold regions, and optimizes the selection of indicators for the climate characteristics of cold regions.

2.2. Construction of Evaluation Index System

By analyzing the above six standards and referring to the opinions of many experts in green building and low-carbon campus research, as well as consulting with relevant professionals, four evaluation guidelines, nine first-level evaluation indexes, and twenty-one second-level evaluation indexes have been identified, as shown in Table 1.

Table 1. The hierarchical model of green campus evaluation in cold regions.

Target Layer	Standardized Layer	Indicator Layer	Evaluation Layer
Green Campus Evaluation System in Cold Regions	Sustainable land A1	Campus Master Plan B1	Campus location C11 Campus plot ratio C12 Undergrounds space utilization C13
		Campus Transportation B2	Parking lots C21 Lane rationalization C22 Electric vehicle power supply equipment C23
	Campus Resource Utilization A2	Water Resources B3	Water-saving appliance use C31 Nontraditional water sources C32
		Material Resources B4	Local materials, use of green materials C41 Renewable, recyclable materials C42 Reduced full life cycle impacts C43
		Energy Utilization B5	Energy-saving equipment C51 Renewable energy utilization C52 Energy use monitoring system C53
	Campus Healthy Environment A3	Indoor Environment B6	Indoor light quality C61 Indoor thermal comfort C62 Indoor air quality C63
		Outdoor Environment B7	Outdoor sound quality C71 Campus green environment C72
	Campus Security A4	Fire Prevention B8	Smoke alarm system C81
		Emergency warning B9	Emergency measures C91

3. Constructing AHP-BP Neural Network Model for Green Campus Evaluation

Firstly, we utilize the analytic hierarchy process to calculate the weights of indicators at all levels. The AHP-BP neural network is built with the evaluation scores for each indicator as input and the total assessment scores as output. The constructed neural network model is then trained until it meets the anticipated accuracy requirements. Subsequently, the model is tested with another set of sample data. The relevant data are simulated using the trained network model, which ultimately results in the green campus's evaluation results.

3.1. Steps for Determining the Weights of the Indicators of the Hierarchical Analysis Method

Hierarchical analysis was first proposed by Saaty [41] in the 1970s as a relatively new and systematic approach to multi-objective decision-making, combining qualitative and quantitative approaches. First of all, the complex problem is gradually decomposed [42], forming several different levels of influencing factors, followed by the same level of influencing factors being compared with each other to determine the importance of the indicator layer, and constructing judgment matrices to objectively quantify the indicators using a scale of proportions. The weight values are then finalized for each indicator. The specific steps are as follows.

(1) Establish judgment matrix $A = [a_{ij}]_{n \times n}$: Pursuant to the 1–9 scale method (Table 2) used to evaluate the indicators in two-by-two comparisons and the assignment of value, construct a judgment matrix. See Formula (1) for the matrix's form.

$$A = \left(a_{ij}\right)_{n \times n} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{31} & a_{32} & \cdots & a_{nn} \end{bmatrix}, \tag{1}$$

Table 2. Meaning of judgment matrix assignment.

Scale	Meaning
1	Both have equal significance
3	The previous element is somewhat more significant than the latter
5	The previous element is significantly more significant than the latter
7	The previous element is more strongly significant than the latter
9	The previous element is more significant than the latter
2, 4, 6, 8	Intermediate values of the above adjacent judgments
Reciprocal	The latter has a higher importance scale than the former

(2) Calculate the eigenvalues: Depending on the judgment matrix, the eigenvalues and eigenvectors of the judgment matrix are solved by mathematical methods. After normalization, the relative weights of importance of the same layer's corresponding elements to an element in the preceding level are obtained [43], giving weights.

(3) Consistency test: The consistency test for the judgment matrix is conducted to guarantee the rationality of the analysis results. When the consistency ratio CR is less than 0.1, the consistency test is passed; when the test cannot be passed, the element value of the judgment matrix should be adapted, and then the calculation should be carried out according to the above steps.

3.2. Determine the Weights of Indicators Using AHP Hierarchical Analysis Method

According to the evaluation index level in the previous section, we invite multiple experts to participate in the evaluation, and the judgment matrix is constructed using average scores to improve the quality of the judgment matrix. We strive to explore the value of quantitative information and synthesize quantitative information with qualitative information to enhance the objectivity of the assessment process and ensure the comprehensiveness of the evaluation findings. The AHP was utilized to construct the matrix for criterion layer A, indicator layer B, and evaluation layer C, respectively, so that the relevant factors of different levels are evaluated in pairs in the matrix. Combined with the value of the importance scale in the previous article, the importance weight value is determined.

(1) The determination of the weights of the target layer requires a two-by-two evaluation of the four elements of sustainable land use A1, campus resource utilization A2, campus healthy environment A3, and campus safety A4 to form a comparison matrix (Table 3).

Table 3. Judgment matrix and results under the overall goal hierarchy.

Target Layer	A1	A2	A3	A4	Results
A1	1	1/2	2	3	0.2720
A2	2	1	3	5	0.4829
A3	1/2	1/3	1	2	0.1570
A4	1/3	1/5	1/2	1	0.0882
Consistency test	λ max: 4.0145; CR = 0.0054 < 0.1, Pass				

It can be seen from the above table that the utilization of campus resources A2 is the most important influencing factor in the assessment index system of green schools in cold regions; sustainable land A1 is the second most important influencing factor, followed by campus health environment A3 and campus resource security A4. Because of the climatic factors in cold regions, collective heating is required during the winter, and air conditioning is required during the summer in some areas, and the precipitation is relatively small. Therefore, a larger weight is set in terms of resource utilization.

(2) Determination of weights under the guideline tier level. Following the same method as above, the second-level indicators' judgment matrix and eigenvector concerning the first-level guideline tier, the maximum characteristic root, and the consistency test can be calculated, respectively. Tables 4–7 are shown below.

Table 4. Judgment matrix and results for sustainable land A1.

A1	B1	B2	Results
B1	1	1/2	0.3333
B2	2	1	0.6667
Consistency test	λ max: 2.0000; CR = 0.0000 < 0.1, Pass		

Table 5. Judgment matrix and results for campus resource utilization A2.

A2	B3	B4	B5	Results
B3	1	2	1/2	0.2970
B4	1/2	1	1/3	0.1634
B5	2	3	1	0.5396
Consistency test	λ max: 3.0092; CR = 0.0088 < 0.1, Pass			

Table 6. Judgment matrix and results for campus health environment A3.

A3	B6	B7	Results
B6	1	2	0.6667
B7	1/2	1	0.3333
Consistency test	λ max: 2.0000; CR = 0.0000 < 0.1, Pass		

Table 7. Judgment matrix and results for campus security A4.

A4	B8	B9	Results
B8	1	1	0.5000
B9	1	1	0.5000
Consistency test	λ max: 2.0000; CR = 0.0000 < 0.1, Pass		

(3) On the basis of the individual calculation of the weights of each level, the total ranking of the indicator weights under the overall target level is carried out. The total weights calculated are shown in Table 8 below.

Table 8. Weights of green campus evaluation system in cold regions.

Target Layer	Standardized Layer	Weight	Indicator Layer	Weight	Evaluation Layer	Weight
Green Campus Evaluation System in Cold Regions	Sustainable land A1	0.2720	Campus Master Plan B1	0.0907	Campus location C11	0.0567
					Campus plot ratio C12	0.0216
					Underground space utilization C13	0.0124
			Campus Transportation B2	0.1813	Parking lots C21	0.0468
					Lane rationalization C22	0.1155
					Electric vehicle power supply equipment C23	0.0190
	Campus Resource Utilization A2	0.4829	Water Resources B3	0.1434	Water-saving appliance use C31	0.1195
					Nontraditional water sources C32	0.0239
			Material Resources B4	0.0789	Local materials, use of green materials C41	0.0593
					Renewable, recyclable materials C42	0.0288
					Reduced full life cycle impacts C43	0.0108
			Energy Utilization B5	0.2605	Energy-saving equipment C51	0.1660
					Renewable energy utilization C52	0.0273
					Energy use monitoring system C53	0.0673
	Campus Healthy Environment A3	0.1570	Indoor Environment B6	0.1047	Indoor light quality C61	0.0335
					Indoor thermal comfort C62	0.0584
					Indoor air quality C63	0.0328
			Outdoor Environment B7	0.0523	Outdoor sound quality C71	0.0262
					Campus green environment C72	0.0262
	Campus Security A4	0.0882	Fire Prevention B8	0.0441	Smoke alarm system C81	0.0240
			Emergency warning B9	0.0441	Emergency measures C91	0.0240

3.3. Steps of BP Neural Network Modeling

BP neural network was conceptualized in 1986 by scientists led by Rumelhart and McClelland. It creates autonomous learning rules by learning from the environment around it, emulating the structure of human neural networks [44]. Autonomous learning is capable of making adaptive decisions in response to changes in the environment by self-adjusting and optimizing decision-making strategies [45]. Artificial neural networks can model complex physical phenomena without explicit mathematical representation or detailed and expensive experiments [46]. The BP neural network is a type of multi-layer feedforward neural network that undergoes training through the process of error backpropagation, with ongoing adjustments made to the network weights for continuous improvement [47] and thresholds. It includes the input layer, the output layer, and the hidden layer. It is set according to the actual needs of accuracy, as shown in Figure 1.

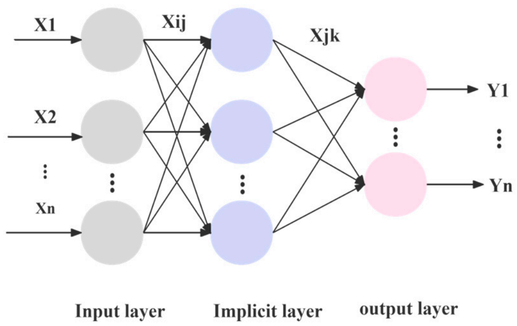

Figure 1. The structure of the BP neural network.

The core idea is to train a certain amount of samples after the process of correcting the weights and thresholds to minimize the error function, fit a more accurate nonlinear function [48], and finally output the corresponding predicted values. The specific procedure for learning is as follows.

Formula (2) depicts the relationship between BP neural network neurons' net activation and output, as follows:

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right), \tag{2}$$

In the formula, x_i is the input signal from other neurons, w_i is the connection weight of the i neuron, and θ is a threshold.

The activation function is the function of mapping the net activation and the output. If the two are linear, the linear function is selected; see Formula (3). For the linear function, the output value can take any value.

$$f(x) = kx + b, \tag{3}$$

If the relationship is nonlinear, the activation function is generally a sigmoid function, as in Formula (4), as follows:

$$f(x) = \frac{A}{1 + e^{-x}}, \tag{4}$$

In the BP neural network, the error is back propagated. Assuming that all the results of the input layer are d_j, the error function E is given in Formula (5).

$$E(w,b) = \frac{1}{2}\sum_{j=0}^{n=1} (d_j - y_j)^2, \tag{5}$$

The neural network's training accuracy is significantly influenced by the number of neurons in the hidden layer of the network [48]. Experiments and experience typically determine the number of hidden layer neurons [49]. After several debugging sessions, the number of neurons in the hidden layer can be determined by applying one of three empirical formulas (see Equations (6)–(8)).

$$\sum_{i=0}^{n} c_{n_1}^{i} \geq k, \tag{6}$$

$$n_1 = \sqrt{m+n} + a, \tag{7}$$

$$n_1 = \log_2 n, \tag{8}$$

In the above equation, n is the input layer neuron, n_1 is the hidden layer neuron, m is the input layer neuron, k is the number of samples, and a is a constant between 1 and 10.

3.4. Establish BP Neural Network Model

A typical BP neural network has the following three layers: an input layer, a hidden layer, and an output layer. The prediction model is constructed with a single-hidden-layer BP neural network in this study. The number of nodes in the network input layer of the model in this paper n corresponds to the twenty-one-evaluation model index metric constructed. Since the output of the network has only one metric, the comprehensive green campus evaluation value, the number of output nodes $m = 1$. Based on Equation (6), the number of neurons in the hidden layer is calculated to be between 6 and 14. After 20 repetitions of debugging at each point, comparing the maximum values occurring for the correlation coefficient R^2, R^2 close to 1 is the best value. Table 9 shows that when there are eight hidden layer neurons, R^2 is 0.9612, and the sample data at this time have a good fitting degree. Therefore, in this paper, the finalized numbers of neurons are 21 for the input layer, 8 for the hidden layer, and 1 for the output layer. Figure 2 depicts the BP neural network algorithm's flow.

Table 9. Effect of testing the number of neurons in the hidden layer.

Number of Neurons in the Hidden Layer									
R^2 max	6 0.8426	7 0.8648	8 0.9612	9 0.8206	10 0.9261	11 0.8996	12 0.7644	13 0.7013	14 0.9169

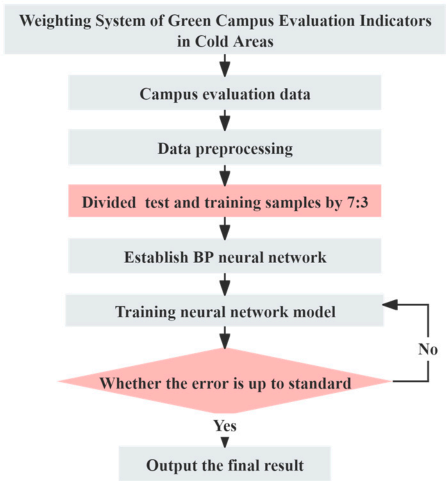

Figure 2. Flowchart of BP neural network construction.

A significant amount of data are required as a foundation for the development of a neural network model. In this paper, by analyzing relevant information and then conducting on-site visits and evidence collection, we designed a corresponding questionnaire and invited relevant experts to score the green campus situation of 20 college buildings in Xi'an, which will serve as the AHP-BP neural network model's learning sample. Each sub-indicator item in the evaluation index system is assessed and scored in five grades, which are categorized as excellent, good, medium, average and poor, as depicted in Table 10.

Table 10. Classification.

Grade Number	Level	Evaluation Score
1	Excellent	4–5
2	Good	3–4
3	Average	2–3
4	Fair	1–2
5	Poor	<1

The Matlab program is used to construct the structure of the neural network, which consists of the following four steps:

(1) Reading data. The sample data establish the connection with the neural network through the code "data=xlsread";

(2) Divide the test set and training set. The 21 evaluation indexes are used as inputs to the network, and the evaluation results are used as outputs. Here, 70% of the 20 sets of sample data were used as the training set and 30% were divided into the test set;

(3) Data normalization. Normalizing the sample data with the code "normalize" increases the effectiveness of neural network training and generalization capabilities;

(4) Create a neural network. The code "net=feed forwardnet (8)" is used to build the structure of the neural network. Select the S-type function "transig" as the hidden layer's activation function, a target error of 0.000001, 1500 training repetitions, and a learning rate of 0.01. The BP neural network is trained using the gradient descent method and "trainlm" function.

Finally, the network structure model's fitting effect is then examined. The network structure model fits better the closer the correlation coefficient is to 1. Figure 3's regression curves demonstrate that, for the training sample, the correlation coefficient Rs among the predicted and actual values of the sample data are R = 0.9947, R = 1 for the validation and test samples, and R = 0.992 for the overall sample.

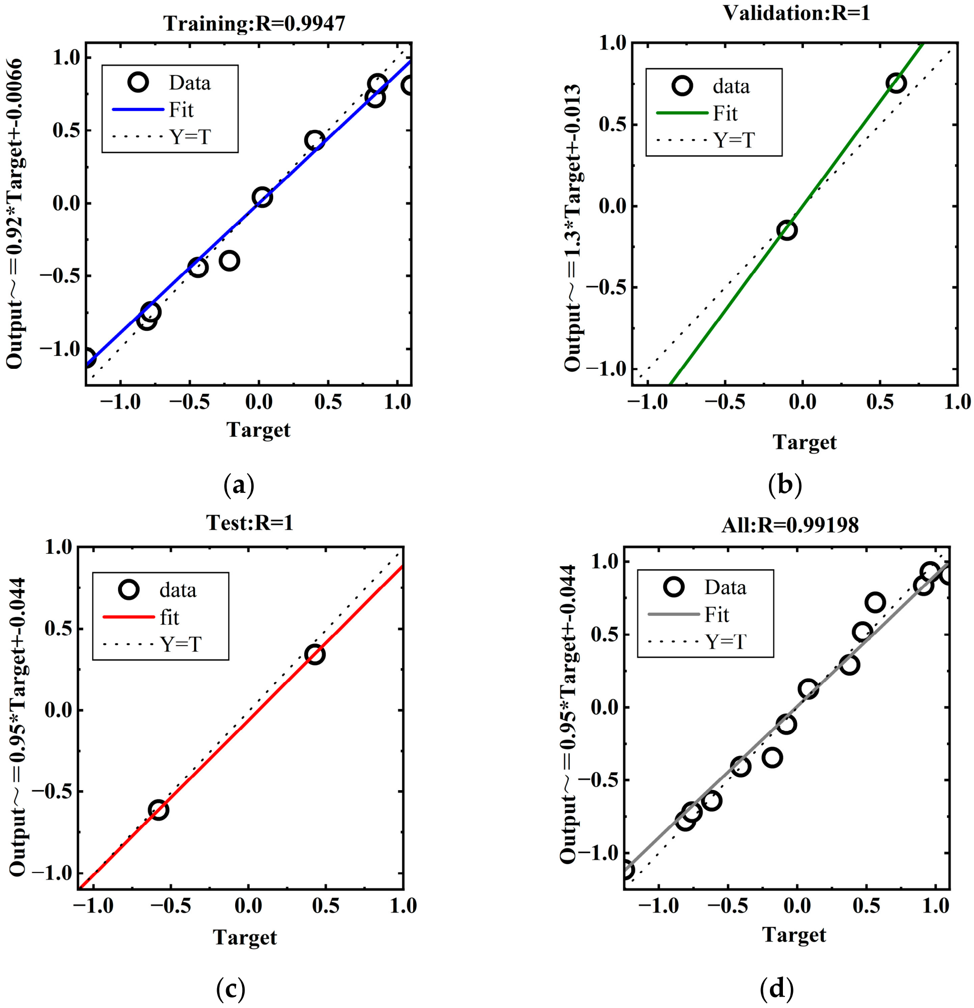

Figure 3. Correlation analysis of BP neural network. (**a**) Training. (**b**) Validation. (**c**) Testing. (**d**) All.

According to the execution of the Matlab program, the simulation value after network training is very close to the experts' initial evaluation data, as depicted in Figure 4. This demonstrates that the network performs exceptionally well. In Figure 4a, the actual curve of the training set as a whole overlaps with the predicted curve, with a high degree of fit. It is evident from Figure 4b that the actual curve of the test set deviates very little from the predicted curve, with a high degree of fit.

From Tables 11 and 12 of the error analysis, it is evident that the largest relative error in training between the output value obtained by the neural network and the anticipated value is 3.02%, and the biggest test relative error is 4.08%. This margin of error is perfectly acceptable when evaluating green campuses in cold regions. In the end, the trained BP neural network is saved in the file. When evaluating and analyzing the green campus in the actual cold area, entering the values of the 21 metrics for model training in the Matlab 2022a training environment, the "sim (net, 21 indicators)" simulation training is performed. The value predicted during green campus evaluation can be obtained, and the final evaluation result can be obtained according to the comparison between the predicted test and the score table.

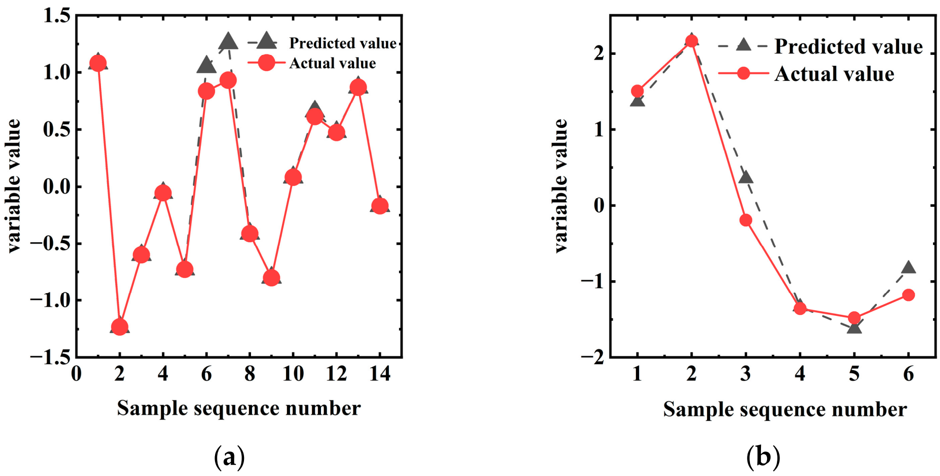

Figure 4. Comparison of true value and predicted value. (**a**) Training set. (**b**) Test set.

Table 11. Error analysis of training results.

Serial Number	Expected Output	Training Results	Absolute Error	Relative Error
1	4.2331	4.2331	0	0.00%
2	3.7503	3.7503	0	0.00%
3	3.8798	3.880	0.0002	0.00%
4	3.9917	3.9922	0.0005	0.00%
5	3.8513	3.8513	0	0.00%
6	4.1033	4.2263	0.124	3.02%
7	4.2024	4.2685	0.0061	0.00%
8	3.9235	3.9234	0.0001	0.00%
9	3.8405	3.8405	0	0.00%
10	4.0153	4.0152	0.0001	0.00%
11	4.1159	4.1469	0.031	0.00%
12	4.0788	4.0787	−0.0001	0.00%
13	4.1865	4.186	0.0005	0.00%
14	3.9669	3.9699	0.003	0.00%

Table 12. Error analysis of test results.

Serial Number	Expected Output	Training Results	Absolute Error	Relative Error
1	4.3307	4.2186	−0.1121	2.59%
2	4.4578	4.4569	0.0009	0.00%
3	3.9484	4.1095	0.1611	4.08%
4	3.7265	3.7718	0.0453	1.22%
5	3.7296	3.6997	−0.0299	1.10%
6	3.7445	3.8959	0.1514	4.04%

3.5. AHP-BP Neural Network Model Analysis and Discussion

Utilizing the current standards and related literature at home and abroad, an AHP-BP neural network evaluation model and a green campus evaluation system with regional suitability are constructed in this paper for cold regions. The BP neural network's training and testing results indicate that this model can accurately and quickly provide a green campus assessment. In practical application, when using this evaluation system for the green campus evaluation of campuses in cold regions, the problem of inaccurate and unreasonable evaluation scores caused by geographical differences can be avoided. The detailed division of evaluation indicators can quickly find the "point of loss", carry out targeted green campus design, save construction costs, and lessen the amount of energy and natural resources wasted.

In this paper, attention needs to be paid to the use of hierarchical analysis and the need to minimize subjective influences. In addition to the measures used in this paper, Wu Dianting [50] proposed that the fuzzy comprehensive evaluation method should be reasonably combined with the analytic hierarchy process, and that the appropriate evaluation method should be selected based on the number of evaluation objects. According to Yuan ze [51], in addition to genetic algorithms, other methods of machine learning can also be used to optimize BP neural network methods. Almahameed, B.A. proposed that the use of particle swarm optimization and other machine learning methods for predictive modeling can reduce the cost of architectural design [52]. In the future, more in-depth research can be conducted on the above methods, which will make the evaluation results of green campuses more precise.

4. Example Validation of AHP-BP Neural Network Models

The Jinhua Campus of Xi'an University of Technology is used as an example for the trial evaluation of a green campus in cold areas to confirm the model's viability and practicability, based on China's Thermal Design Code for Civil Buildings GB 50176-2016 building thermal zoning [53]. Most of Shaanxi is a cold region. Located in the Beilin District of Xi'an City, Shaanxi Province, the campus has a long history and deep cultural heritage, with many ancient buildings and facilities. During the development of the campus, it has continuously renovated old buildings, performed energy-saving and emission-reduction renovations, and insisted on practicing the concept of green development to establish a harmonious green campus (Figure 5). The geographical location and transportation facilities of this campus are shown in Figure 6.

Figure 5. Green campus energy-saving and low-carbon measures.

Figure 6. Evaluation of campus location.

4.1. AHP-BP Neural Network Model Calculation

After on-site research and in-depth assessments of the campus' green status, relevant experts were invited to score each factor, and the final scores for each factor were C11 = 4.53, C12 = 3.88, C13 = 3.55, C21 = 3.53, C22 = 3.75, C23 = 3.85, C31 = 3.96, C32 = 4.22, C41 = 3.76, C42 = 3.45, C43 = 4.12, C51 = 4.28, C52 = 3.98, C53 = 3.65, C61 = 3.57, C62 = 3.78, C63 = 3.97, C71 = 3.67, C72 = 4.32, C81 = 4.01 and C91 = 4.35. According to the code results set by the BP neural network above, the score is predicted after an evaluation, and the result is 3.9423, which represents a good grade.

"Missing points" are mainly found in the areas of motorized and nonmotorized parking and the use of underground space. The campus' nonmotorized parking lots are not well delineated. The BP neural network samples were trained and predicted many times. The deviation of the results was within the range of 0.001~0.0001. The evaluation model showed sufficient stability and was in line with the actual scoring situation. This shows that the paper's green campus evaluation model is feasible and reasonable, and can be used to evaluate the green campus in cold areas.

4.2. Assessment Standard for Green Campus GB/T 51356-2019 Calculation

The current green campus evaluation standard divides the evaluation index system into the following two groups: one for primary and secondary schools and one for vocational schools, colleges and universities. The indicator system is the same for both types of campuses, consisting of five categories, C1 (planning and ecology), C2 (energy and resources), C3 (environment and health), C4 (operation and management) and C5 (education and promotion), with corresponding scores of Q_{1C}, Q_{2C}, Q_{3C}, Q_{4C}, and Q_{5C}. The natures of schools are different, and the corresponding weight values for each type of indicator are different; this paper only discusses vocational schools, colleges and universities. The corresponding weight values of each type of indicator in the green campus evaluation index system are $W_{1C} = 0.25$, $W_{2C} = 0.25$, $W_{3C} = 0.20$, $W_{4C} = 0.15$, and $W_{5C} = 0.15$, respectively. Additional bonus points for features and innovations, with a score of $\sum Q_6$. The total score $\sum Q_C$ for the campus evaluation was calculated according to Formula (3), which is divided into three star ratings: when $50 \leq \sum Q_C < 60$, it is one-star; when $60 \leq \sum Q_C < 80$, it is two-star; when $\sum Q_C \geq 80$, it is three-star. Equation (9) is as follows:

$$\sum Q_C = W_{1C}Q_{1C} + W_{2C}Q_{2C} + W_{3C}Q_{3C} + W_{4C}Q_{4C} + W_{5C}Q_{5C} + Q_{6C}, \tag{9}$$

The green campus evaluation scores for the selected college cases are as follows (Table 13).

According to Equation (9), the total score calculated using the Assessment standard for Green Campus GB/T 51356-2019 (Qc = 59.35) makes it a one-star green campus.

Table 13. Green Campus evaluation scores.

Project	C1	C2	C3	C4	C5	C6
Score	60	54	52	50	53	5
W	0.25	0.25	0.2	0.15	0.15	/
Final score	15	13.5	10.4	7.5	7.95	5

4.3. Comparative Analysis of Green Campus Evaluation Results

The green campus evaluation of the AHP-BP neural network model studied in this paper yielded better scores, while the calculation using the Assessment Standard for Green Campus GB/T 51356-2019 resulted in a one-star rating, which is a lower rating. This paper establishes a green campus evaluation system for cold regions that takes into account regional differences. It carefully selects and defines evaluation indexes based on the actual climatic conditions of cold regions, providing detailed quantitative ranges for the objective and accurate scoring of green campuses. The current Assessment Standard for Green Campus GB/T 51356-2019 does not associate the evaluation indicators with the climatic environment. Here, energy consumption is scored by the capacity for reducing energy consumption year by year. Most of the indicators do not have clear scoring instructions, which makes the scoring results inaccurate, and the final green campus evaluation scores do not match the actual situation, meaning the rating is not accurate enough. This shows that the AHP-BP neural network model for green campus evaluation in cold regions that this paper establishes has scientific accuracy, making it suitable for cold-climate green campus evaluation.

5. Conclusions

This paper uses domestic and international literature, relevant standards, and the idea of green development to extract the evaluation indexes of green schools in cold area. It also determines the weights of evaluation indexes using hierarchical analysis, takes the data derived from the AHP evaluation results for use as the neural network's input, and uses sufficient samples to train the model. Finally, it establishes the AHP-BP neural network model. One can come to the following conclusions:

(1) An evaluation strategy that combines neural network algorithms and hierarchical analysis algorithms is proposed in this paper. Evaluation indicators are extracted based on existing standards, AHP is used to reasonably allocate weights, and a large number of qualitative indicators are quantified, so that subjective judgments are changed into objective descriptions, and the scientificity and operability of evaluation results are enhanced;

(2) A BP neural network model containing an input layer of 21 neurons, a hidden layer of 8 neurons, and an output layer of 1 neuron was developed with errors between 0.0001 and 0.001. The model absorbs the knowledge and experience of experts, realizes highly nonlinear mapping from input to output, has the advantages of being quick, fast, and accurate, and avoids a lot of complicated calculations, reducing the interference due to subjectivity in the evaluation process;

(3) In this paper, a university in Xi'an City, located in a cold area, was chosen as the subject of the study, and the evaluation score using the AHP-BP model was 3.9423, with an evaluation grade of good, which verifies that the model was able to carry out an accurate green evaluation of campuses in cold regions.

This paper offers a system for evaluating green campuses in cold regions that can effectively assess the construction and design of new and existing campuses, but it does not involve the publicity and promotion of green campuses. Future research could take this into account to make the assessment of green campuses in cold regions more comprehensive.

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