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Research Article

Location Selection of Digital Cultural Tourism Town Based on Improved Genetic Algorithm and BP Neural Network

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Due to the short development time of cultural and tourism towns in China, local governments and investors lack experience in building cultural and tourism towns and do not pay enough attention to the positioning of towns. Alternatively, this issue results in chaos in domestic cultural and tourism towns and even a large number of empty towns in some provinces. Therefore, how to accurately locate cultural tourism towns is a problem that must be studied in depth at present. This paper uses the regional economic theory to collect the influencing factors of cultural tourism town positioning. Based on the BP neural network and the improved genetic algorithm, a genetic neural network model is constructed to train and predict the samples of cultural tourism towns. Taking a small town in the East as a case, the data were collected and analyzed. Established on the prediction outcomes of the genetic neural network, the best location of a small town was selected according to the actual situation of the region. In terms of accuracy and training time, our experimental evaluation confirmed that the neural network enhanced by genetic algorithms outperforms the conventional BP neural network. Furthermore, we observed that besides the classification capabilities of the BP neural network-based model, the classical BP neural network improved by the genetic algorithm also exhibits great macrosearch capabilities and good global optimization performance.

1. Introduction

With China's economic development stepping into the new normal, the national consumption capacity is growing progressively, the spiritual and cultural demand is growing, and the proportion of the total tourism economy in GDP is also rising rapidly. The tourism industry has gradually become the pillar industry of the national economy. In March 2018, the State Council performed an innovative round of institutional reform, abolished the Ministry of Culture and the National Tourism Administration, integrated their original responsibilities, and established the Ministry of Culture and Tourism as an element Department of the State Council; by the end of 2019, the cultural and tourism departments of 31 provinces (cities and autonomous regions) have completed listing. This historic reform aims to encourage the assimilated growth of cultural endeavors, cultural engineering, and tourism. Similarly, it also aims to bring together the growth of cultural industries, engineering, and tourism resources. It is an important measure to fully affirm the necessity of cultural and tourism industry integration. It can be seen that the integration of culture and tourism is a strategic direction for the innovative growth of national tourism and the improvement of national cultural soft power and the influence of Chinese culture in the future. Since the country initiated "culture + tourism," the development and construction of cultural and tourism towns across the country have entered a hot situation [1, 2].

When things reach extremes, they will turn against each other. In the process of development, cultural and tourism towns across the country are seriously homogenized and the "one town for one" phenomenon occurs, resulting in most cultural and tourism towns having no characteristics. Luo Shugang, Minister of Culture and Tourism of the People's Republic of China, clearly proposed to adhere to the principle of "integration when appropriate, integration when possible, promoting tourism with culture, and highlighting culture with tourism" [3]. This should be noted that compared with other industries, the tourism industry has stronger linkage and more prominent comprehensive driving ability. Especially under the promotion of the "tourism +" strategy, the tourism industry and the primary, secondary, and tertiary industries have had different degrees of linkage. In the context of supply-side structural reform, "tourism +" has been recognized by the public, which not only promotes the in-depth integration of tourism with the internet, industry, agriculture, aviation, science and technology, education, and other fields, but also promotes the emergence of "tourism + culture," that is, the integration of cultural and tourism industries [4, 5].

In 2016, the notice on developing characteristic towns jointly issued by relevant national departments called for the cultivation of 1000 characteristic towns, and characteristic towns have officially risen to the national level. In the past three years, cultural tourism featured towns have been the main force of featured towns. The first and second batches of national characteristic towns announced by the Ministry of Housing and Urban-Rural Development totaled 403, including 253 characteristic towns of cultural tourism type, accounting for 62.8% [6, 7]. By 2019, 31 provinces and cities in China have actively responded to the national call and established cultural and tourism departments; 25 provinces have formulated plans and relevant policies for the integrated development of cultural and tourism industries. With the strong advancement of national policies, the combination of cultural and tourism industries has been continuously and rapidly deepened; therefore, subsequently attracting a large amount of capital injection, and cultural and tourism featured town projects that have become a hot spot for investment have sprung up. Some research institutions predict that there will be more than 1200 cultural and tourism featured towns in China in 2020 [8–10].

In the past two years, in terms of the number and amount of investment and financing events, cultural and tourism featured towns and cultural and tourism complexes have steadily occupied the dominant position in the investment of cultural and tourism projects. It is shown that in 2018, there were 295 investment and financing events in the cultural tourism industry, with a total investment scale of 1.37 trillion yuan [11]. There were 129 Chinese tourism featured towns and cultural tourism complex projects, accounting for 43.7% of the total number of investment and financing events. The total investment scale reached 1.27 trillion yuan, accounting for 92.53% of the total amount. In the first half of 2019, there were 148 investment and financing events in the cultural tourism industry, and the total amount of proposed investment disclosed was 553.176 billion yuan, accounting for 61.5% of the total number of events and 96.3% of the total amount of investment and financing. Cultural and tourism featured towns account for the largest proportion in the whole investment process, which is significantly higher than the cultural and tourism complex, and much higher than the investment in scenic spots, theme parks, and other cultural and tourism projects. However, it should be noted that in the first half of 2019, compared with the same period in 2018, the number of cultural tourism featured town projects increased by 188%, but the total investment decreased by 20.61% [12, 13].

It is clear that the investment volume of tourism featured town projects is significantly declining, and the project development mode of seeking perfection has changed. From the perception of the business form of cultural and tourism featured towns, featured towns of natural resources, culture, health care, sports, and commerce are the mainstream development form. In the past two years, the development trend of cultural tourism industry investment has been consistent. Cultural tourism featured towns and cultural tourism complexes have overwhelming advantages in the number and amount of investment in cultural tourism projects [14]. The facts, as demonstrated in various research outcomes, show that the investment and development of the resource end of the destination have been upgraded from the main development mode of scenic spots to the main development mode of complexes, which is consistent with the trend that the consumption demand of tourists has been developed from sightseeing to leisure and vacation, which demonstrates that supply-side reform and innovative development are now a part of the cultural tourism industry's development.

It is evident that the market size and development trend of the cultural tourism town cannot be understated, particularly in light of the promotion of national policies and the fact that the cultural tourism sector is entering a high-quality development stage of transformation and upgrading to meet consumer needs. From the aspects of reception scale, tourist evaluation, and operating efficiency, the consumption market of tourism featured towns is hot, but at the same time, the competition is fierce, and the supply side needs to be transformed and upgraded. Under the macro background of economic transformation, consumption upgrading, and industrial structure adjustment, people's demand motivation, content, intention, and value demands for tourism are undergoing new changes. This should be noted that with the speedy and fast improvement of cultural tourism real estate, there are also some developers' crazy enclosures under the guise of "culture" and "tourism," resulting in low-level and homogeneous projects blooming everywhere [15].

Nowadays, most real estate enterprises have realized that the "low-level play" of selling houses and tickets is difficult to sustain. At present, the lack of supporting facilities is the main reason for the further development of small town products in the market. High-quality supporting facilities are becoming a hard indicator of whether small town products are qualified or not. The development logic of the cultural tourism town is different from that of the traditional real estate. It first needs a rich "core" before it can leverage the surrounding markets. It is becoming a general trend of cultural tourism to turn from scenic spots to characteristic communities, from prosperous cities to ancient towns, and from shopping places to cultural and expo venues. In the next decade, operation oriented, resource integration, and fine management will become a new model of cultural tourism real estate. Therefore, from the future positioning, it can be seen that the cultural tourism town urgently needs to clarify its own positioning, so as to lay a good foundation for better tourism integration in the future [16]. The fundamental contributions of this research are as follows:

(i) We discuss how to accurately locate cultural tourism towns is a problem that must be studied in depth at present. This paper refines the influencing factors of cultural tourism town positioning, and considers selecting the policy support index to represent the national and local government-oriented factors;

(ii) We use the regional economic theory to collect the influencing factors of cultural tourism town positioning, and based on the traditional BP neural network and the improved genetic algorithm, a genetic neural network model is created to train and predict the samples of cultural tourism towns; and

(iii) Taking a small town in the East as a case, the data were collected and analyzed, and grounded on the prediction outcomes of the genetic neural network, the best location of a small town was selected according to the actual situation of the region.

The remaining part of this paper is structured as follows. We discuss the state-of-the-art related works in Section 2. In Section 3, the selection of evaluation model for cultural tourism town positioning is elaborated. In Section 4, test and result analysis are deliberated in detail. As a final point, Section 5 completes this paper and deliberates some future research guidelines.

2. Related Work

The case study is presented as an illustration of effective tourist growth within a region that is already undergoing economic and social diversification [1]. The primary goal of [3] is to investigate how Bishoftu town residents view the negative effects of urban tourism. The topic of locating the tourist sites in Karo Regency's shortest route is covered by Sembiring et al. [4]. The goal of [6] is to determine how to manage the Instagram account material in order to promote the Banyumas Regency's potential tourism promotion system. On the basis of the five tourist towns in northern Taiwan, [2] adopt the integrated MCDM approach to assess the SDI (sustainable development index) for urban and rural/town tourism. Reference [5] uses logical analysis and literature research to analyze the connotation creation and development path of sports tourism cities. Reference [9] offers a solution to the problem of cultural overtourism, which has serious adverse repercussions. Reference [8] aims to collect information from cultural managers to maintain in time the intangible culture of the oral traditions of the city of Otavalo in a digital magazine. The main idea put forth is how a business owner of tourism-related items in Tanah Karo can use and develop local wisdom as a strategy for the sustainability and steady growth of a particular enterprise in the tourism zone through utilizing scientific cleverness, specifically through the idea of encouraging the marketing of tourism goods founded on local understanding through the online media [10]. Other influential work includes [9].

Foreign cultural tourism towns are generally the product of local cultural and economic development to a certain extent after a long period of historical accumulation. Therefore, most foreign scholars take the successful towns as cases to analyze the influencing factors of project positioning. For example, when (Campeau and Claudia Nicoletta) studied the transformation of the small town of Sigishwara in Transylvania, they found that the successful positioning of the small town was due to the recognition of its unique resource advantage of rich historical and material cultural heritage. Furthermore, Hotten et al. found that the combination of the local characteristic mining material landscape and the unique mining cultural landscape had a qualitative improvement on the urban tourism economy when analyzing the mining towns in the western United States, and believed that the organic combination of the characteristic industry and the characteristic culture played a complementary role. In other research as demonstrated by (Zlatanovi ć, Sanja), the authors believe that the regional cultural heritage, the national and local administrative authorities, and the interests of investors will all affect the positioning and planning of regional cultural tourism [10, 12].

The authors (Heydari Chianeh *R* et al.) believe that for regions with a long history and cultural heritage, it is advisable to take cultural tourism as the leading industry [21]. Deng D. et al. established the regional tourism product framework of small towns on the basis of summarizing the tourism literature of small towns [22]. Taking Morden as an example, they believe that the positioning of small towns needs to consider a variety of factors, such as regional advantages, mature characteristic industries and cultural and creative industries, and local policy guidance. The authors (Vukovi ć Predrag, Č Avlin Gordana, and Č Avlin Miroslav) in various works proposed that the success of both rural tourism town in the UK benefits from natural hot spring resources, location conditions, and convenient transportation [16–19]. When studying the STP theory, (Daan Francois Toerien) found that the cultural and tourism towns have achieved good benefits in the innovative use of local characteristic resources [23, 24]. When (Tosun C) studied the towns of Urgup in Turkey, the authors found that political and economic policies and linear national planning methods had a great impact on the development direction of regional tourism [25].

3. Selection of Evaluation Model for Cultural Tourism Town Positioning

3.1. Basics of the BP Neural Network and the Improved Genetic Algorithm. This research suggests a genetic algorithm grounded on adaptive mutation probability to enhance the classical BP neural network as an alternative to the conventional genetic algorithm. An EM-AGA-BP positioning evaluation model, which is established on the entropy technique, the BP neural network (BPNN), and adaptive mutation genetic algorithm (GA), is constructed, according to the improved cultural tourism town positioning evaluation system, to give a method for the positioning evaluation of cultural tourism towns.

An adaptive mutation genetic algorithm (AGA) is suggested in this study. The algorithm's goal is to make the genetic algorithm's mutation process better. The genetic algorithm population's variety is increased by the mutation operation. The mutation probability is currently determined by ongoing experiments. Every living thing in nature is dynamically adaptable. The adaptive mutation probability should be used when using a genetic algorithm to identify the overall best solution. To upsurge the multiplicity of the population and the proportion of exceptional individuals, the mutation probability should be raised when the population fitness value is low. The mutation probability should be decreased when the fitness value is higher, or when it is close to the global optimal solution [20]. Formula (1) illustrates how the adaptive mutation probability P was calculated in this study as follows:

$$P = \frac{(P_1 + P_2)}{2} = \frac{\left(P_0 - (P_0 - P_{\min}) * m/M + P_0 * \max\limits_{X_K \in \Omega} F(X_K)/\overline{F}\right)}{2}, \tag{1}$$

where K is the supposed as the initial mutation probability, and $P_{\min}$ is the smallest value of the variation probability value range. Furthermore, F is the average or statistical mean fitness value of the present population, and $\max_{X_K \in \Omega} F(X_K)$ is the maximum fitness value of the current population. Furthermore, M characterizes the supreme evolutionary algebra, and, in fact, on the other hand, M is the contemporary evolutionary algebra. This should be noted that P1 is the wrong way round proportionate to the evolutionary algebra (M), while P2 is the wrong way round proportional to the statistical mean or average fitness value [21].

The initial weight and threshold are determined at random, although they have a momentous influence on the performance of the BP neural network. This should be noted that researchers frequently combine the neural network with various contemporary optimization strategies to improve it. For instance, the weight and threshold of neural networks are frequently optimized using evolutionary algorithms. Genetic algorithms are used in this technique, which is not dependent on the BP neural networks, to find the best answer throughout the entire domain. As a result, it can address some of the drawbacks of gradient descent-based neural networks, including their propensity to easily slip into local minima and their slow convergence rates. In this research, the BP neural network is enhanced using the adaptive mutation genetic method, which optimizes the BP neural network model. The BP neural network and the adaptive mutation genetic algorithm make up the bulk of the model [22]. Figure 1 depicts the BP neural network's flowchart:

The normalized data are calculated, and the initial evaluation findings are obtained, using the entropy approach [23]. The following are the steps involved in the entropy method's calculation:

(1) The first step is the process of standardization of the original evaluation data, using the equation as shown in formula (2) as follows:

$$\dot{x}_{ij}' = \frac{\left(x_{ij} - \overline{x}\right)}{s_j}, \tag{2}$$

where $\dot{x}_{ij}'$ is the normalized value, and x_{ij} is the score of the i-th sample in the j-th index. Furthermore, $\overline{x}$ and s_j are the average value and standard deviation of index j, correspondingly. In order to encounter the requirements of logarithm in the entropy technique, the standardized value shall be shifted, using the mathematical equation as shown in formula (3):

$$Z_{ij} = \dot{x}_{ij}' + A, \tag{3}$$

where A is the length of the translation, and Z_{ij} is the value, which is attained after the translation.

(2) The second step is to quantify the small town positioning evaluation indicators at the same level and subsequently estimate the percentage of the i^{th} sample under the j^{th} indicator in this indicator p_{ij}.

$$p_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}} \, (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n), \tag{4}$$

where Z_{ij} indicates the amount and town positioning evaluation data after the translation stage.

(3) The third step is to determine the entropy, symbolized by e, of the j^{th} index E_j. This computation is shown in formula (5) as follows:

$$E_j = -k \sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right). \tag{5}$$

(4) In the fourth step, we calculate the difference in the coefficient G_j of index j. This calculation is mathematically given as shown in formula (6) as follows:

$$G_j = 1 - E_j, \tag{6}$$

where E_j is the entropy of the index j.

(5) In the fifth step, we normalize the difference coefficient and estimate the weight w_j of the j^{th} index. This estimation is carried out using equation as shown in formula (7) as follows:

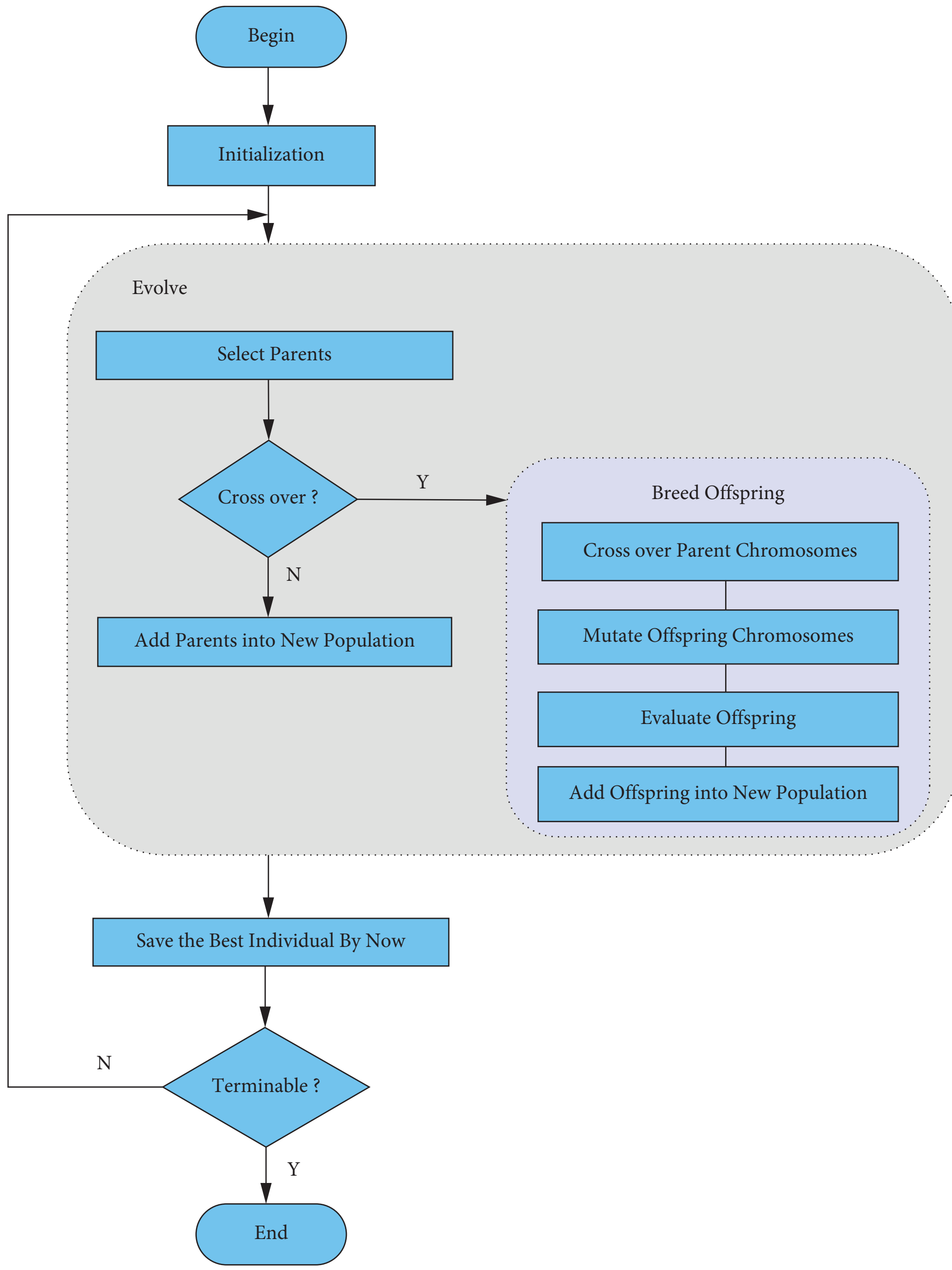

Figure 1: The BP neural network flowchart.

$$w_j = \frac{G_j}{\sum_{j=1}^{n} G_j}, \tag{7}$$

where G_j is the difference coefficient of index j.

(6) In the sixth step, we determine the town positioning evaluation F_i of the i^{th} sample, and the process of this step is mathematically given as shown in formula (8) as follows:

$$F_i = \sum_{j=1}^{n} w_j p_{ij}, \tag{8}$$

where p_{ij} is the proportion of the i^{th} sample in the j^{th} index, and w_j is the weight of index j. The main modeling steps of the cultural tourism town positioning evaluation model are given as follows:

(1) we may make improvements and create a more accurate and useful index system by carefully examining the issues that currently exist in the positioning and evaluation of cultural tourism cities [24];

(2) bring together the sample data for the assessment of the positioning of a cultural tourism town, choose the evaluation indicators in accordance with the

positioning features of the cultural tourism towns, and distribute the sample data using some sort of percentages into the following: (i) training samples and (ii) test samples;

(3) we identify the BP neural network algorithm's parameters, such as the learning rate, the quantity of hidden layer neuron nodes, the extreme amount of iterations, the minimum error correctness, the transfer function, and the training duration;

(4) iterative training is accomplished while waiting for the trigger algorithm ends by feeding data into the assessment model;

(5) subsequently, we enter the test samples for the positioning evaluation of cultural tourism towns to see whether the improved genetic algorithm's training effect on the BP neural network model is sufficient. We continue to the next step if the forecast result satisfies the stop criteria; otherwise, reoccurrence to the preceding step, i.e., step (3), and reeducate the network model; and

(6) we enter the samples into the model used to evaluate the location of cultural tourism cities to get the evaluation results. The next two points primarily illustrate how the model uses the benefits of the entropy approach and the AGA-BP algorithm to make up for the drawbacks of the other methods.

  (i) The AGA-BP algorithm model may overcome the drawback of the entropy technique, which lacks a horizontal comparison of indicators, by having the advantage of nonlinear mapping in any accuracy.

  (ii) A way of weighting that is objective is the entropy method. The primary idea behind it is to calculate each index value's degree of volatility in order to estimate the index weight. This approach can lessen deviation brought on by human variables and offer a solid foundation for the neural network architecture. This method's initial evaluation result is used as a prior guidance sample for the AGA-BP algorithm model.

3.2. Source and Processing of Sample Data in Cultural Tourism Towns. By collecting the cases of cultural tourism towns that have been put into operation in China, and through careful screening, 50 town samples were selected as the training samples of the neural network for network training, and then, 5 samples were selected as the prediction samples to predict and verify the neural network after training. The basic data come from the statistical yearbook of provinces and cities, the network of characteristic towns, the public information of local government websites, etc., and then, the final data are calculated by formulas (8) and (9) and the evaluation system of historical and cultural tourism resources. In the table, $X1$ is the policy support index (P), $X2$ is the traffic accessibility index (g), $X3$ is the cultural and tourism industry influence index (a), $X4$ is the output scale index of characteristic industries (z), $X5$ is the ecological environment quality index (EI), $X6$ is the regional online tourism development index (T), and $X7$ is the human and historical resource index (H).

3.2.1. Policy Support Index (P). Whether the cultural tourism town project complies with the relevant local development policies or whether the local government gives relevant preferential policies: 1 is in conformity, 0 is not in conformity

3.2.2. Traffic Accessibility Index (G). The location conditions of the town are standardized and synthesized from the traffic (railway station, expressway, and airport) and location (distance from the adjacent urban area or scenic spot) to obtain the traffic accessibility index, which reflects the location and traffic convenience of the town.

$$G = \frac{\sum_{\substack{j\neq i \\ j=1}}^{n_{ij}^{n}} \left(t_{ij}+t_i\right)\times P_j}{\sum_{\substack{j\neq i \\ j=1}}^{n} P_j} \times k_i, \tag{9}$$

where G is the traffic accessibility index of the town; t_{ij} is the shortest time distance from small town i to the nearest urban area j; t_i is the resistance within the city; and P_j is the total population of the local area.

3.2.3. Cultural Tourism Industry Influence Index (A). This index is the influence of the cultural tourism industry in the region on all industries. The higher the impact index, the greater the impact of the tourism industry. In particular, it shall be calculated by constructing the Leontief inverse matrix as follows:

$$A = \frac{\sum_{j=1}^{n} \overline{z}_{lj}}{1/n \sum_{i=1}^{n} \sum_{j=1}^{n} \overline{z}_{lj}}, \ (i = 1, 2, \ldots, n). \tag{10}$$

3.2.4. Output Value Scale Index of Characteristic Industries (Z). The output value scale of characteristic industries refers to the proportion of the total output value created by the characteristic industries (except cultural and tourism industries) in a period of time in the comprehensive output value of all industries.

3.2.5. Eco-Environmental Quality Index (EI). The eco-environmental index refers to the index that reflects the quality of the eco-environment in a certain region.

3.2.6. Regional Online Tourism Development Index (T). Regional online tourism development refers to the tourism development level of each region, which can be queried through the big data report of China's online tourism development.

3.2.7. Human History Resource Index (H). The index of cultural and historical resources adopts the evaluation system of historical and cultural tourism resources, evaluates

Table 1: Normalized data of training samples.

No.	Name	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$
1	Town 1	1.0000	−0.4942	−0.8014	−0.6482	0.0206	0.8872	−0.4206
2	Town 2	1.0000	−0.9244	0.9778	−0.2349	0.6698	−0.5113	0.7658
3	Town 3	1.0000	−0.0717	−0.7387	−0.2391	−0.5797	−0.8496	−0.3975
4	Town 4	1.0000	−0.1796	−0.0780	1.0000	0.0844	−0.3609	0.0992
5	Town 5	1.0000	0.8551	−0.3049	−0.6400	0.0882	−0.3383	0.1575
6	Town 6	1.0000	0.4002	0.1159	0.8047	0.8874	1.0000	0.3011
7	Town 7	1.0000	−0.9630	0.9686	−0.8983	0.5910	−0.6541	0.6771
8	Town 8	1.0000	0.6715	−0.9534	−0.8396	−0.5385	0.2932	−0.9772
9	Town 9	1.0000	−0.0902	0.4665	0.4766	0.4484	−1.0000	0.0992
10	Town 10	1.0000	0.9877	−0.9094	−0.8056	−1.0000	1.0000	−1.0000
11	Town 11	1.0000	−0.6006	−0.8306	−0.7115	−0.2045	−0.8496	−0.1388
12	Town 12	1.0000	−0.7687	−0.3820	−0.8159	−0.8124	−0.6541	−0.9651
13	Town 13	1.0000	0.6808	−0.0405	−0.6529	−0.0131	−0.6541	0.1067
14	Town 14	1.0000	0.7394	−0.0832	−0.8501	0.5272	−0.5113	−0.0721
15	Town 15	1.0000	0.5451	−0.2130	−0.8044	0.2533	−0.3383	0.1307
16	Town 16	1.0000	0.0964	0.0422	−0.5341	−0.1632	−0.7744	0.2647
17	Town 17	1.0000	−0.3524	−0.2722	−0.5812	0.1220	−0.6541	−0.1639
18	Town 18	1.0000	−0.9306	0.9016	−0.6529	0.8274	−0.2857	0.4981
19	Town 19	1.0000	−0.9013	0.8798	−0.1237	0.1520	1.0000	0.4978
20	Town 20	1.0000	−0.9352	0.9386	−0.8409	0.6360	0.8872	0.5350
21	Town 21	1.0000	0.9013	0.6141	0.4753	0.3246	1.0000	0.0328
22	Town 22	1.0000	0.5035	0.3850	0.2289	0.2458	0.0451	0.0209
23	Town 23	1.0000	0.2768	0.1829	0.3709	0.3621	−0.3383	0.0068
24	Town 24	1.0000	−0.6931	−0.0958	0.9233	0.7561	1.0000	0.2014
25	Town 25	1.0000	−0.0625	0.7260	−0.1516	−0.0169	−0.5714	0.4475
26	Town 26	1.0000	−0.7687	0.8280	−0.8757	0.5910	−0.0752	0.7996
27	Town 27	1.0000	−0.8443	0.8885	−0.4925	0.3396	0.8872	0.4747
28	Town 28	1.0000	−0.8628	0.8558	−0.8774	0.6510	−0.0226	1.0000
29	Town 29	1.0000	−0.9291	0.8680	−0.4129	0.7974	0.8872	0.5495
30	Town 30	1.0000	−0.8504	1.0000	−0.2421	−0.0169	0.0827	0.5379
31	Town 31	1.0000	−0.8520	0.8127	−0.9338	−0.0469	−0.4737	0.5581
32	Town 32	1.0000	−0.0625	−0.0231	0.2288	0.3621	−0.3609	0.0752
33	Town 33	1.0000	0.3277	0.2657	0.3873	0.9625	1.0000	0.2061
34	Town 34	1.0000	0.2876	0.2861	0.4520	−0.2570	0.4361	0.1549
35	Town 35	1.0000	−0.9198	0.9199	−0.8819	0.4559	0.0451	0.8440
36	Town 36	1.0000	−0.8766	0.9525	−0.2954	−0.0094	−0.3609	0.5841
37	Town 37	1.0000	−0.9075	0.8558	−0.4235	0.3021	0.2180	0.4966
38	Town 38	1.0000	−0.9938	0.9003	−0.9513	0.6623	−0.0977	0.5073
39	Town 39	1.0000	−1.0000	0.9843	−0.4645	1.0000	−0.5113	0.7149
40	Town 40	1.0000	−0.8381	0.9037	−0.2522	−0.0131	0.0451	0.5396
41	Town 41	1.0000	−0.9861	0.9817	−0.2351	0.9475	−0.5113	0.6791
42	Town 42	1.0000	0.3894	0.1781	0.3685	0.1257	−1.0000	−0.0542
43	Town 43	1.0000	1.0000	−0.3685	−0.7740	0.3021	0.2180	−0.0120
44	Town 44	1.0000	0.8350	−1.0000	−0.2298	−0.3884	−0.2932	−0.3632
45	Town 45	1.0000	−0.5374	0.6485	−0.8856	−0.2120	0.3910	0.1275
46	Town 46	1.0000	−0.8134	0.8754	−0.6399	0.3471	−0.0226	0.8501
47	Town 47	1.0000	−0.5698	0.9159	−0.9996	0.6098	0.7970	0.0129
48	Town 48	1.0000	−0.9722	0.9961	−1.0000	0.3696	0.1278	0.7089
49	Town 49	1.0000	−0.8843	0.4268	−0.8773	0.4934	−1.0000	0.2092
50	Town 50	1.0000	−0.9553	0.9582	−0.8111	0.5985	−0.5113	0.6999

and calculates through AHP, and takes the regional historical and cultural resources as the object for the weighted calculation to obtain the final index.

The output range of the neural network in this research is (0, 1) since the transfer function employed in the output layer is an S-shaped function, and because of this, the output of training data must be normalized to fall within the [0, 1] interval. The preliminary assessment value range of cultural tourism town positioning determined by the entropy method is (0, 1). Therefore, Tables 1 and 2 can be obtained by data standardization again.

4. Test and Analysis

The evaluation outcomes for groups 1 through 50 are anticipated by the simulation experiment of the cultural tourist town placement evaluation based on the BP neural network, which is boosted by the enhanced genetic algorithm, and

Table 2: Predicted sample normalized data.

No.	Name	X1	X2	X3	X4	X5	X6	X7
1	Town 1	1.0000	−0.3348	0.8370	−1.0000	1.0000	−0.9762	−0.2947
2	Town 2	1.0000	−0.6319	0.0886	−0.7199	0.7029	−0.9762	−0.9240
3	Town 3	1.0000	−1.0000	0.8961	1.0000	−1.0000	−1.0000	0.1426
4	Town 4	1.0000	−0.0200	1.0000	−0.5814	0.2464	0.2857	1.0000
5	Town 5	1.0000	1.0000	−1.0000	−0.8284	−0.7754	1.0000	−1.0000

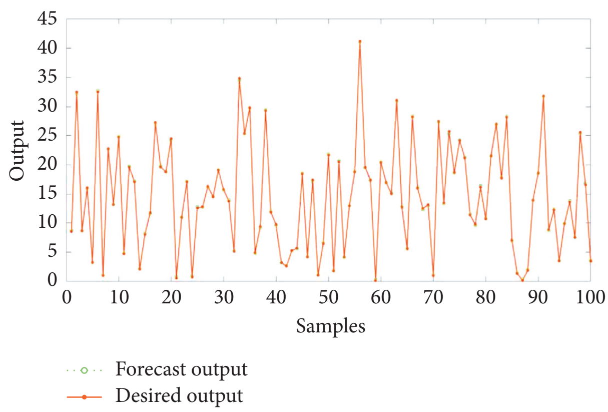

Figure 2: Improved genetic algorithm to boost the prediction results of the BP neural network model.

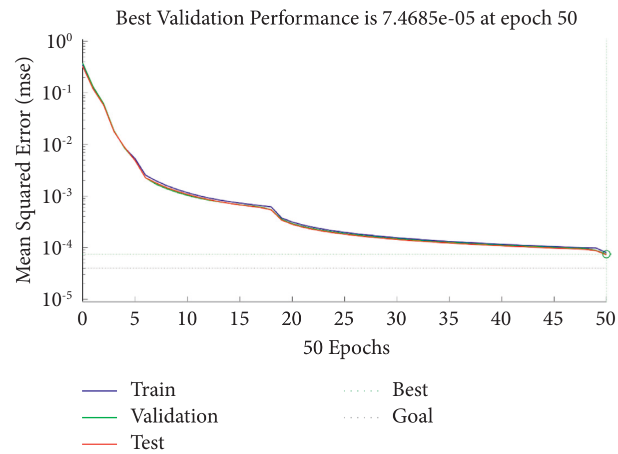

Figure 4: Mean square error convergence.

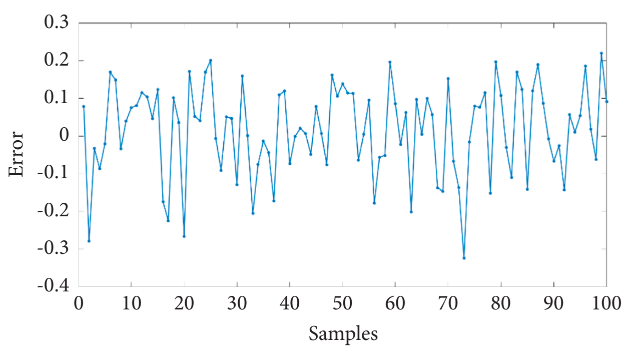

Figure 3: Improved genetic algorithm neural network prediction error percentage.

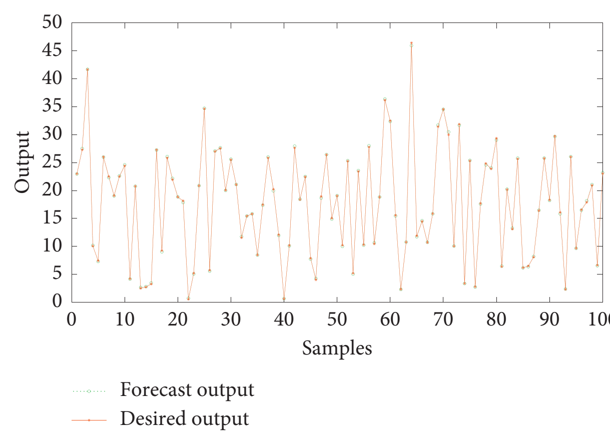

Figure 5: Prediction results of the AGA-BPNN model.

Figures 2–4 are generated. The mean square error (MSE) of the neural network model, which is enriched by the genetic algorithm, significantly drops during the first 10 iterations, nevertheless gradually over the subsequent 21 to 30 iterations, rendering to a comparison of the curve formed by the mean square error. In fact, we observed that the mean square error converges to 8.6066e-08 after 40 iterations. The neural network model is optimized by a genetic technique that practices adaptive mutation. The first generation iterates more quickly, whereas the second through eighth generations iterate more slowly. The ninth iteration is when convergence occurs, and the mean square error converges to 3.3839e-12, which somewhat increases the BP neural network's convergence speed and accuracy. The convergence accuracy is approximately twice as high, and the convergence rate is 82.13% greater than that of the neural network model optimized using the genetic algorithm. It demonstrates that applying adaptive mutation GA to optimize BPNN can increase the model's prediction accuracy while also speeding up the network's convergence rate.

We further compare the change in GA-BPNN error square sum with the AGA-BPNN error square sum of adaptive mutation. It can be seen from Figures 2 and 3 that the GA-BPNN average error square sum and minimum error square sum converge quickly before the 10th generation and slowly from the 10th to the 25th generation. When it finally reaches the 30th iteration, the sum of the squared errors is roughly 0.9. After just six cycles, the adaptive mutation GA-BPNN reaches convergence. The network's total error squares are stable, they converge to 0.19, the pace

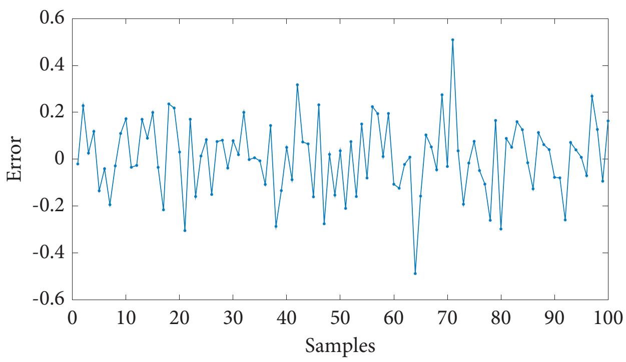

Figure 6: AGA-BPNN prediction error percentage.

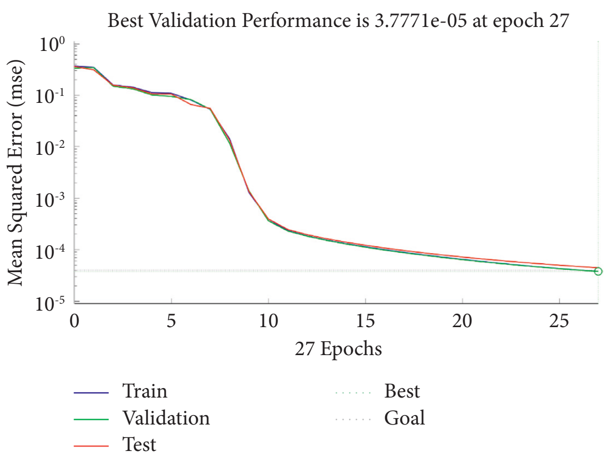

Figure 7: Mean square error convergence.

of convergence is raised by 84%, and the average total error square is decreased by 94%. It is clear from a comparison that the adaptive mutation GA-BPNN can efficiently carry out the entire bureau optimization. Both the BP neural network model and the enhanced model are applied to the latest 50 groups of test sample data in order to forecast the assessment results.

The outcomes of the predictions are displayed in Figures 4–7. It is evident that the evolutionary algorithm-optimized BP neural network model's prediction error is excessive, and the improved model's predictions essentially match the actual outcomes. The comparison of the three models' prediction accuracy is shown in Figure 8. As can be observed, the upgraded model has a much greater evaluation accuracy than both the BP neural network (BPNN) model and the BP neural network model improved by the genetic algorithm. As a result, the revised genetic algorithm-based BP neural network assessment model has better application value. The positioning of cultural tourist towns can be evaluated using the model in a fast, efficient, and scientific manner.

The average assessment correctness of the classical BP neural network model for approximately 50 collections of data is up to 84.23 percent, that of an optimized genetic algorithm is 91.84 percent, and that of an optimized genetic algorithm, which is founded on the adaptive mutation, is

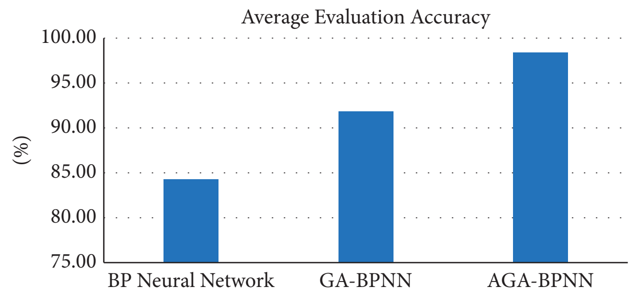

Figure 8: Average evaluation accuracy with different models.

approximately 98.37 percent, which is, respectively, 14.01 percent and 6.39 percent greater than the other two methods. The assessment outcome of the BP neural network approach that was improved by a genetic algorithm grounded on the adaptive mutation is superior, as can be observed.

5. Conclusions and Future Work

Based on the concept of sustainable development and regional economic theory, this paper refines the influencing factors of cultural tourism town positioning, and considers selecting the policy support index to represent the national and local government-oriented factors; using the traffic accessibility index to represent location and traffic factors; ecological environment index, regional online tourism development index, and human and historical resource index are used to represent the ecological environment and historical and cultural factors; the influence index of cultural and tourism industry and the output value scale index of characteristic industries are used to represent the industrial structure factors of the project area. It can be seen that the genetic algorithm can successfully address the drawback that the BP neural network may fall into the local lowest value by training and prediction of samples using the BP neural network and the BP neural network improved by the genetic algorithm. In terms of accuracy and training time, the neural network enhanced by genetic algorithms outperforms the conventional BP neural network. In addition to the classification capabilities of the BP neural network, the BP neural network improved by genetic algorithm also exhibits great macrosearch capabilities and good global optimization performance. The genetic neural network model trained by a sample database can quickly and accurately classify different cultural and tourism towns.

In the future, we will employ other PSO and machine learning method variations with the ability to adaptively modify different parameters in order to enhance algorithm convergence. Additionally, we will take into account the PSO's Markov jumping technique, which can split up the entire population into smaller stages and prevent the convergence of local optima. On the other hand, we will investigate alternative deep learning models in depth and raise prediction accuracy. The network's training and prediction times are directly impacted by the underlying problem of scarce resources. As a result, we will look into how big data analysis and technologies like cloud and edge will assist to shorten the time needed for model training and prediction in the future.

Data Availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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