Research Article

Evaluating Sustainable Liveable City via Multi-MCDM and Hopfield Neural Network

Zhanbo Chen (ORCID)

School of Information and Statistics, Guangxi University of Finance and Economics, Nanning, China

Correspondence should be addressed to Zhanbo Chen; fin@pku.edu.cn

Research on liveable cities has received increased attention in recent years because of the complexity and diversity of liveability standards. Evaluating the liveable environment is a multiple criteria decision-making (MCDM) problem, and the results can be used to control environmental pollution and protect human health. However, different evaluation methods can lead to different results; hence, determining how to effectively to obtain the consistent results is a main consideration of this study. The objective of this work is to design an optimal method based on the difference ratio concept. A hopfield neural network is selected to validate the experimental results. Referring to the liveable city rankings established by the Economist Intelligence Unit, thirteen large cities in China are used to illustrate the application of the model, evaluate the liveable urban environment, and demonstrate the effectiveness and feasibility of the proposed model. The results show that Hangzhou is the most liveable city and Beijing has the worst liveable urban environment. Therefore, a common policy should be strengthening environmental governance, with a special focus on the development of low-carbon cities, for which both the local and global environmental impacts could be mitigated.

1. Introduction

In recent years, due to the complexity and diversity of liveable city standards, the development of liveable cities has gained increased attention [1]. Urban development seeks to increase or to maintain the quality of life in urban areas by mapping urban structures and building liveable cities with a sustainable development system [2, 3]. The concept of liveability was first introduced at the United Nation's Habitat Conference in 1996, and it stated that every city should be habitable. One key characteristic of liveable cities is their ability to attract a disproportionate amount of the globally mobile resources (such as talents, high net worth individuals, investors, innovators, entrepreneurs, and capital), which are recognised to make positive contributions to economic growth, economic resilience, global political influence, world agenda-setting power, socio-cultural innovation, and international lifestyle [4]. Moreover, it was shown in [5] that the quality of living survey can be used to help governments and major corporations place personnel on international assignments. The survey is used to rank cities based on an evaluation of 39 factors, including political, economic, environmental, personal safety, health, education, transportation, and other public service factors. It has been acknowledged that the environmental pollution has become a major issue and urban populations are expanding and increasing [6]. In practice, these conditions of the liveable environment cannot meet people's living requirements. Therefore, the purpose of this paper is to establish a system to analyse the liveable classes in different cities.

To effectively address the liveable city concept at several spatial scales, liveable urban environment modelling is of the utmost relevance for evaluation. The relevant literature has mainly focused on the urban development status [7], liveability of cities [8], urban quality of life [9], and sustainable development and optimization of the liveable environment of cities [10, 11]. The definitions of a livability system can be used to assess the livability of cities. The conceptual model includes social and economic factors, as well as the principles of environmental sustainability [12]. Giap et al. proposed a new liveability system measure called "the Global Liveable Cities Index" to rank 64 major global cities. The system

advances the measurement of the liveability construct by considering the multidimensional sensibility of diverse groups [4]. In addition, many studies, including a study by the Economist Intelligence Unit [13] and analyses in Europe [12], the UK [14], and the USA [15], have only evaluated the livability of a system by ranking and comparison livability metrics.

As an active research area, many MCDM methods have been proposed. For example, a novel hybrid fuzzy MCDM model combined with the technique for order preference by similarity to an ideal solution (TOPSIS) model and the analytical network process (ANP) was used to evaluate green suppliers [16]; this approach defines green supplier evaluation criteria and formulates a new evaluation model. Some research has suggested that the integration of the TOPSIS model can solve the truck selection problem encountered by land transportation companies [17]. Similarly, a novel conjunctive MCDM approach is combined the analytical hierarchy process (AHP) and TOPSIS to develop an innovation support system that considers the interdependence of higher education institutions to comprehensively evaluate their innovation performance [18].

MCDM is widely used in many evaluation problems and is used to evaluate liveable cities in our research. There are many MCDM methods applied to assess liveable cities; for example, an AHP method was used to develop a liveable city index and determine the long-term trend of city livability [19]. A fuzzy AHP method was applied to determine the relative weights of the evaluation criteria in a sustainable city liveable problem [20]. TOPSIS was used to evaluate sustainable development in livable city [21], and the results suggested that the social, economic, and environmental factors have important influences on liveable cities. Reference [22] presented a multicriteria evaluation for the selection of the optimal configuration of an air quality model. Additionally, some scholars developed support methods to explore the strengths and weaknesses of various alternatives and identified the preferred result based on the integration of Bayesian networks and fuzzy logic to rank and evaluate suppliers [23].

Generally, most of the criteria required in MCDM cannot be accurately evaluated because it is not feasible to obtain precise data for decision-making assessments. Moreover, the use of certain subjective criteria can lead to incorrect results. In these cases, the difference ratio can be used to select the most suitable multiple evaluation method for a liveable city MCDM problem. This approach is not only suitable for the evaluation of liveable urban environments but also solves problems related to city pollution and environmental management. Moreover, economic development will potentially drive pollutant emissions in the future [24]. To address the aforementioned concerns, the different ratio is used to select the most suitable model among the TOPSIS [25], Gini [26], fuzzy Borda [27], principle component analysis (PCA) [28], and TS fuzzy neural network [29, 30] models.

MCDM and integrated machine learning algorithms have been developed in recent years, and some hybrid techniques have been effectively applied in multiattribute inventory analysis. For instance, Naïve Bayes, Bayesian network, artificial neural network (ANN), and support vector machine (SVM) algorithms [31] have successfully been used in inventory classification problems. Similarly, some machine learning approaches have been used in supplier selection problems, and they displayed better predictive performance than individual algorithms [32]. In some research, a score, such as the financial risk prediction score, which is used by MCDM methods (e.g., TOPSIS), has been used to measure the performance of algorithms and develop a two-step approach for evaluating classification algorithms [33]. Their results show that MCDM methods integrated with machine learning (e.g., linear logistic and neural network) can improve the accuracy of this model. The Hopfield neural network model based on the factor analysis method is used in water quality evaluation, and the corresponding results indicate that the factor analysis technique can effectively identify important water quality parameters [34].

The main motivation of this study is the selection of a suitable MCDM model for evaluating the liveable environment of cities. Section 2 presents the methodology of study and introduces characteristics of each MCDM method. The results and discussion are given in Section 3, and the potential improvements of the proposed methodology are discussed. Some conclusions of this study are summarized in Section 4.

2. Methods

In order to address the aforementioned concerns, the difference ratio is used to select the most suitable evaluation method among the Gini, TS fuzzy neural network, TOPSIS, fuzzy Borda, and PCA methods, as shown in Figure 1. Figure 1 indicates that the framework consists of other key phases, including indicator preprocessing, evaluation model training, and simulation and verification of the results [35]. The main contribution of this work is the selection of the most suitable result from multiple model evaluations based on the difference ratio. It is observed from Figure 1 that to create a liveable city evaluation platform, first, some relative factors of liveable city are selected. Then, the max-minimum method is applied to normalized data to avoid negative effects via different sizes of indicators. Data preprocessing is followed by descriptions, and then model training and validation are followed. The most suitable model is selected according to the difference ratio. After that, the Hopfield neural network is used to verify the ranking results. Then, the results are obtained.

2.1. Difference Ratio. The traditional difference ratio (DR) is a measure of the quality of test questions [36, 37], and the DR can be used to measure the relative differences among evaluation strategies in this paper. Obviously, the greater the relative difference is, the less impactful the evaluation method. For m evaluation objects, various evaluation methods are ranked in the descending order according to the evaluation result V. Then, each score is numbered N, where
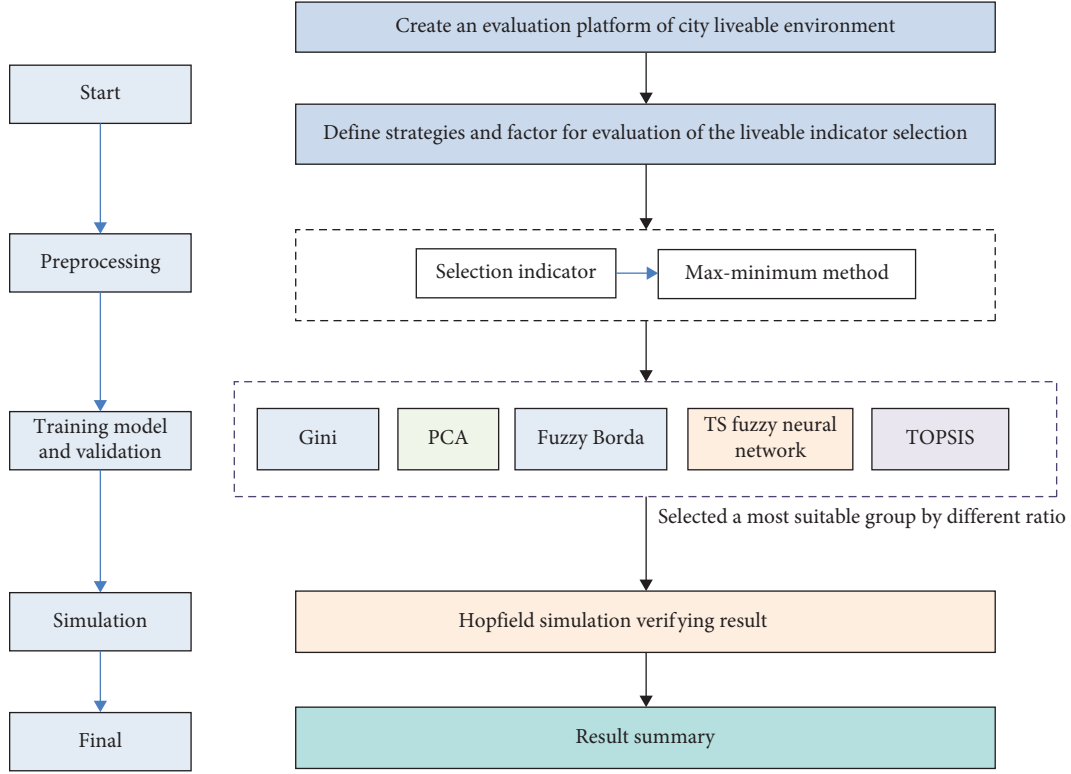
FIGURE 1: Our proposed learning framework.

function $V = f(N)$ is a monotonous decreasing function. The coordinates of the best evaluation result are $(V_1, 1)$, and the coordinates of the worst results are (V_m, m). The DR equation is given as follows:

$$D = \frac{\sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_1)^2 + (N_{i+1} - N_i)^2}}{(V_m - V_1)^2 + (N_m - N_1)^2}. \tag{1}$$

In general, $D \leq 1$ indicates that the larger the distance between adjacent two points is in each method, the better the evaluation result. Therefore, an excellent DR is robust in the interpretation of different evaluation results. Because the value ranges of various types of evaluation methods result are different, the results must be standardized to compare different model results; for example, the TOPSIS values range between 0 and 1, those of the factor analysis method range between −1 and 1, and those of the Delphi method range from 0 to 100. After standardization, the value range is 0-1. However, this value range can lead to ineffective DRs because the D value is too small; therefore, the range of all values after normalization is set between 0 and m, where the coordinates of the maximum point are $(m, 1)$ and those of the minimum point are $(0, m)$. The other points are processed as shown in equation (2) according to the difference between the original value and the maximum value:

$$V_i = m \times \left[1 - \frac{|V_i' - V_1'|}{V_1' - V_m'} \right], \tag{2}$$

where V' is the original value and V_i is the standardized value. The distribution of the evaluation result does not

change because simple linear transformation is applied. Then, a simplified DR can be obtained, as shown in the following equation:

$$D = \frac{\sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_1)^2 + 1^2}}{(m - 0)^2 + (m - 0)^2} = \frac{\sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_1)^2 + 1}}{2m^2 - 2m - 1}. \tag{3}$$

2.2. Evaluation Model.
Five MCDM models are chosen to evaluate liveable cities in this study since they are common and representative. Based on the surveys of overviews on MCDM methods [38, 39], TOPSIS and PCA are widely used in MCDM problems. The Gini coefficient has been widely used in MCDM problem in recent years. Fuzzy Borda and fuzzy TS neural network are evaluated in MCDM problems with the development of other fields, such as fuzzy and machine learning.

2.2.1. Evaluation Based on Gini Coefficient.
The Gini coefficient was first proposed by Gini [40] in 1912, which is a quantitative limit that objectively reflects the heterogenous distribution of income [41]. It has been developed much in MCDM fields. Also, it is widely used in the selection site of surface water [42], coherency identification of generators [43], and water resource evaluation [44]. This paper evaluates liveable cities based on the Gini coefficient. This coefficient considers the fairness of indicators and efficiency, which is conducive to evaluating liveable environmental cities. The Gini coefficient evaluation steps are as follows:

Step 1: calculate the Gini coefficient of a single indicator. First, the economic comprehensive competitiveness index (ECCI) is compared with each indicator; then, the resulting values are sorted in the ascending order. Next, the cumulative value and cumulative percentage of each indicator are calculated. Finally, a Lorentz curve is drawn according to the coordinates $(0, 0), \ldots, (1, 1)$, and so on.

Step 2: regression fitting is performed according to the formula $G = 1 - \sum_{j=1}^{J} (X_j - X_{j-1})(Y_j + Y_{j-1})$, where X is an indicator and Y is the cumulative percentage of comprehensive economic competitiveness; for example, when $i = 1$, (X_{j-1}, Y_{j-1}) are the origin coordinates $(0, 0)$.

Step 3: calculate the Gini coefficient of a single indicator for a city. First, we calculate the cumulative Gini coefficient $AG_{ij} = G_j \times AP_i$, where G_j is the overall Gini coefficient of a single indicator and AP_i is the cumulative percentage associated with a single indicator for the ith city in the ascending order. Then, we calculated the single Gini coefficient $G_{ij} = AG_{i+1,j} - AG_{i,j}$, where j is an indicator and i is a sample of city.

Step 4: calculate the comprehensive Gini coefficient $CG = \sum_j^J W_j G_j$, where W_j is the weight of jth and G_j is the Gini coefficient of jth.

Step 5: conduct a comprehensive evaluation based on the final values, and analyse the results. The evaluation is divided into two parts. One part involves using the overall Gini coefficient in a high-level evaluation, and the other part involves using the product of the Gini coefficient and the weights of all indicators in a certain city to perform between-city evaluation.

2.2.2. Evaluation Based on PCA.
Principal component analysis (PCA) is an objective evaluation method that can reduce redundancy [45]. The original information is reflected in the variance contribution of each indicator. These contributions represent the weights for comprehensive evaluation and reduce the subjectivity of analyses. The PCA evaluation steps are as follows:

Step 1: standardize the initial data

Step 2: calculate the correlation coefficient matrix R

Step 3: calculate the feature value and the feature vector, i.e., the eigenvalue (λ_j, $j = 1, 2, \ldots, J$) of R and the corresponding eigenvector

Step 4: calculate the variance contribution ($\lambda_j / \sum_{j=1}^{J} \lambda_j$), of the principal components and the cumulative variance contribution ($\sum_{j=1}^{k} (\lambda_j / \sum_{j=1}^{J} \lambda_j), k \in [1, J]$)

Step 5: calculate the principal component coefficients

2.2.3. Evaluation Based on the Fuzzy Borda Method.
The Borda method is used to compare the relative positional relationships of m objects to be evaluated by comparing n types of single evaluation method [46]. Then, the Borda value of each object is determined, and values are sorted from high to low. Because the Borda method only uses the ordered relationship of each evaluated object and does not consider the qualitative results associated with the ordered relationships, it is possible to obtain inaccurate results. Therefore, Yang Jimei and Shi Benshan made some improvements to the Borda method and developed the fuzzy Borda method [27]. The evaluation steps of the fuzzy Borda method are as follows:

Step 1: calculate the membership degree according to $u_{ij}^* = (y_{ij}/y_{opt})$

Step 2: find the modulus of the ith object in the hth position and frequency f_{ih}^* based on $\mu_i = \text{diag}(\mu_{i1}, \mu_{i2}, \ldots, \mu_{im})$ and $f_i^* = \delta_i \mu_i E = (f_{i1}^*, f_{i2}^*, \ldots, f_{im}^*)_{1 \times m.}^T$

Step 3: determine the corresponding value $Q_h^* = m + h + 1$, where $h \in [1, m]$

Step 4: calculate the improved fuzzy Borda value $F_i^* = \sum_{h=1}^{m} f_{ih}^* Q_h^*$ for the ith evaluated object

Step 5: sort the results from high to low according to F_i^*.

2.2.4. Evaluation Based on a TS Fuzzy Neural Network.
Lotfi Aliasker Zadeh, an American cybernetics expert at the University of California, pioneered the concept of fuzzy sets in 1965 [47]. Fuzzy theory has captured the characteristics of the ambiguity of human thinking and can thus be used to solve conventional problems. Conventional fuzzy pattern recognition problems and complex measurement problems are often difficult to solve. The fuzzy comprehensive evaluation method considers the fuzzy transformation and maximum subordination degree principles to evaluate the relevant factors. The corresponding formula is as follows:

$$A \cdot R = B, \tag{4}$$

where A represents the evaluation weights in a $1 \times m$ normalized matrix, R represents each evaluation indicator in an $m \times n$ fuzzy relation matrix, and B is the result of comprehensive evaluation.

TS fuzzy systems have very strong self-adaptive abilities, and they can automatically update and modify the membership function of fuzzy subsets. Therefore, the error of a model is slowly reduced in the running process, and the result correspondingly improves. A TS fuzzy system has set of "if-then" rules that must be defined. Concerning the rules for R, the fuzzy reasoning strategy is as follows:

$$R^i: \text{If } x_1 \text{ is } A_1^i, x_2 \text{ is } A_2^i, \ldots, x_n \text{ is } A_n^i, \text{ then}$$
$$y_i = p_0^i + p_1^i x_1 + \cdots + p_n^i x_n, \tag{5}$$

where $i = 1, 2, 3, \ldots, m$; $j = 1, 2, 3, \ldots, n$; and so on. Hereinafter, A_j^i represents the fuzzy sets for fuzzy systems, p_j^i represents the parameters of the fuzzy system, and y_i is the output according to the fuzzy rules. If the input part

(i.e., If) is fuzzy, the output part (i.e., THEN) is determined.

For an input value $x = [x_1, x_2, \ldots, x_n]$, the membership of each input variable is x_j according to the fuzzy rules as follows:

$$\mu A_j^i = e^{-\left((x_j - c_j^i)^2 / b_j^i\right)}, \tag{6}$$

where c_j^i and b_j^i represent membership function center and width, respectively; n is the input parameters; and m is the number of fuzzy subsets.

The calculation of the fuzzy degree of membership with a fuzzy operator for the multiplication operator is as follows:

$$w^i = \mu A_j^i(x_1) \times \mu A_j^i(x_2) \times \cdots \times \mu A_j^i(x_n). \tag{7}$$

According to the fuzzy results, the following equation is used to compute the model output value $\hat{y}$:

$$\hat{y} = \frac{\sum_{i=1}^m w^i y_i}{\sum_{i=1}^m w^i}. \tag{8}$$

The TS fuzzy neural network method is an iterative process, and the total error function of each iteration changes with the relevant parameters. The network parameters are constantly modified until the value of the total error function is minimized [35].

The TS fuzzy neural network is divided into an input layer, a fuzzy classification layer based on fuzzy programming, and an output layer. The input layer is connected to the input vector x_i, which has the same number of nodes and dimension as the input vector. The fuzzy classification layer uses the fuzzy degree values of the membership functions of input values to obtain the fuzzy membership values. The layers of fuzzy rules are based on the fuzzy multiplication formula. The output layer uses the formula to calculate the output of the fuzzy neural network. The learning algorithm of the fuzzy neural network is as follows:

(1) The error is computed as follows:

$$e = \frac{1}{2}(y_d - y_c)^2, \tag{9}$$

where y_d is the expected network output, y_c is the actual output of the network, and e is the actual error of the output.

(2) The modification coefficient is expressed as follows:

$$p_j^i(k) = p_j^i(k-1) - \alpha \frac{\partial e}{\partial c_j^i},$$

$$\frac{\partial e}{\partial p_j^i} = \frac{(y_d - y_e)^2 w^i}{\sum_{i=1}^m w^i} x_j, \tag{10}$$

where $p_j^i(k)$ is a coefficient of the neural network, α is the network learning rate, x_y is the network input parameter,

and w^i is the product of the degree of membership of the input parameters.

(3) The modification parameter is expressed as follows:

$$c_j^i(k) = c_j^i(k-1) - \beta \frac{\partial e}{\partial c_j^i},$$

$$b_j^i(k) = b_j^i(k-1) - \beta \frac{\partial e}{\partial b_j^i}, \tag{11}$$

where c_j^i and b_j^i represent the membership function center and width, respectively.

2.2.5. Evaluation Based on TOPSIS.

TOPSIS was first proposed by Hwang and Yoon in 1981, and developments were expanded by Chen and Hwang in 1992 [48]. The TOPSIS model was used to evaluate the characteristics of the comprehensive evaluation index systems of liveable cities in this paper. The basic concept of the TOPSIS method is to calculate the distance between the best scheme and the worst scheme based on continuous time series of samples and use the relative degree of the ideal solution as the standard for comprehensive evaluation. The TOPSIS method determines the distance between the evaluation object and the optimal solution, and these values are sorted to identify the worst solution. If the evaluation object is close to the optimal solution and far from the worst solution, it may be an optimal solution.

First, the original data sets were standardized. Then, $Y = (y_1, y_2, y_3, \ldots, y_j) = y_{ij}$ was normalized as a dimensionless data matrix, where $y_{ij} = (x_{ij}/\sqrt{\sum_{i=1}^n x_{ij}^2})$, $i = 1, 2, \ldots m$; $j = 1, 2, \ldots, n$.

Second, the optimal and worst samples for each indicator were determined. The optimal samples were determined using the maximum value of each indicator for all samples. The minimum samples for each index were used to form the worst sample sets; these sets were represented as Y^+ and Y^-:

$$Y^+ = (y_1^+, y_2^+, \ldots, y_i^+),$$

$$Y^- = (y_1^-, y_2^-, \ldots, y_i^-), \tag{12}$$

where $Y^+ = \max_{1 \leq i \leq m} y_{ij}$ and $Y^- = \min_{1 \leq i \leq m} y_{ij}$, $j = 1, 2, \ldots n$.

Third, we determined the relative proximity of each sample point to the optimal sampling point:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \tag{13}$$

where D_i^+ and D_i^- are the distances from each sample point to the optimum and the worst sample points, respectively. Specifically, $D_i^+ = \sqrt{\sum_{j=1}^n (y_{ij} - y_i^+)^2}$ and $D_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_i^-)^2}$, where $i = 1, 2, \ldots m$. The larger C_i is, the closer the sample is to the optimal sample point.

Finally, in this paper, the improved entropy method was used to determine the weights of the indicators; more details are shown in Reference [49].

2.3. Evaluation Based on Hopfield Neural Network Simulation.

The Hopfield neural network was proposed by J. J. Hopfield in 1982 and has a symmetric connected structure in which any two neurons are connected. This network has been successfully used to solve real-world problems, including assignment, scheduling, shortest-path, travelling salesman, and vehicle routing problems [50]. Based on the form of the output function, Hopfield networks can be classified into one of two popular forms: discrete and continuous-time models. In this work, a discrete Hopfield neural network was chosen to classify the liveable environment of cities. The discrete Hopfield neural network is a single-layer and binary-type feedback neural network. All the nodes are connected to each other, and the connection weights of nodes accept information feedback from the other nodes. Therefore, the output of any neuron is controlled by the other neurons, meaning that the output of each neuron can restrict that of other neurons. As a result, each neuron has a threshold value that controls the input of noise [51]. The network is shown in Figure 2.

For a binary neuron, $u_{ij} = \sum_i w_{ij} y_j + x_j$, where x_j is the outside input. If $u_j \geq \theta$, then $y_j = 1$; otherwise, $y_j = -1$. The output of the discrete neural network is a set of neuron information, and the state at time t is a n-dimensional vector $Y(t) = [y_1(t), y_2(t), \ldots, y_n(t)]^T$. Considering the general node state of a discrete Hopfield neural network, $y_j(t)$ represents the jth neuron, and the state of the next node $(t + 1)$ can be obtained by using the second neuron:

$$y_j(t + 1) = f\left[u_j(t)\right] \begin{cases} 1, & u_j \geq 0, \\ -1, & u_j \leq 0, \end{cases}$$
$$u_{ij} = \sum_i w_{ij} y_j(t) + x_j - \theta_j. \qquad (14)$$

If $w_{ij} = 0$ and $i = j$, then the output of a neuron cannot feedback to its input, which indicates that a discrete Hopfield neural network does not provide self-feedback. In other cases, a discrete Hopfield neural network can be designed as a self-feedback network.

This paper uses a binary Hopfield network to evaluate the liveable environmental competitiveness of cities, and the rationality of previous learning evaluation methods is verified. According to the data size and comprehensive indicator, the liveable competitiveness of a city is divided into four levels: excellent (I), good (II), general (III), and poor (IV). With the associative memory ability of discrete Hopfield neural networks, this paper establishes an evaluation model of city liveable environment competitiveness based on a discrete Hopfield network. First, the Hopfield neural network equilibrium point based on traditional classification levels is established. Then, the learning result is
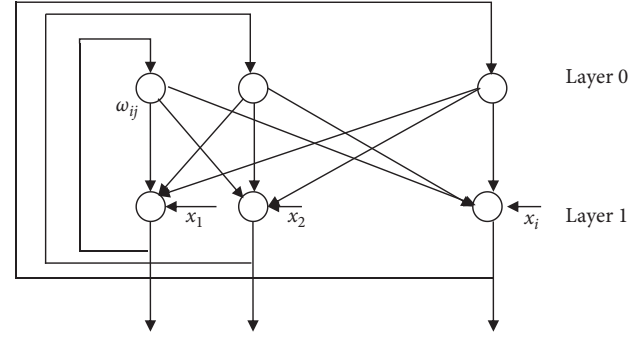

Figure 2: Structure of Hopfield neural network.

treated as an evaluation index corresponding to each classification level and stored in memory. A Hopfield neural network classifies the index values according to the stored equilibrium points.

3. Case Study

Numerical experiments have been performed to assess liveable environments. MCDM is a comprehensive method that can be applied to build and analyse structural models involving the causal relationships among liveable city factors. The liveable city indicators and the corresponding relationships are given in Section 3.1. The common evaluation model results are shown in Section 3.2, and difference ratio results are given in Section 3.3. We analyse the key findings from the multiple evaluation results in Section 3.4. Finally, the Hopfield neural network is used to verify the result of the difference ratio evaluation in Section 3.5.

3.1. Selected Indicators of the Liveable Environment of a City.

The environmental system is a complex system; therefore, evaluations of city liveable environments must be the result of multifactor interactions. This process involves collecting data for different action factors, analysing the data, and introducing a quantification index to evaluate the degree of influence of each factor. According to this quantitative index, we can determine the indicator value of the liveable environment.

The evaluation indices were determined according to environment protection standards of the European Environment Agency [52] and the Technical Criterion for Ecosystem Status Evaluation of PRC [53] and included the average temperature, urban greening coverage, population density, sewage treatment rate, equivalent sound level, days of good air quality, per capita urban road area, and per capita GDP.

The study area included four cities with municipalities directly under the central government and nine cities with representative provincial capitals, including Jinan (JN), Tianjin (TJ), Guizhou (GZ), Wuhan (WH), Nanjing (NJ), Changsha (CS), Shenyang (SY), Chengdu (CD), Hangzhou

(HZ), Shanghai (SH), Beijing (BJ), Zhengzhou (ZZ), and Chongqing (CQ). The 13 large cities from China and eight indicators were selected to measure city liveability.

The IBM SPSS 22 software and Matlab R2013a software are used in this platform. For example, PCA is computed by using SPSS, and TS fuzzy neural network is computed by using Matlab.

3.2. Evaluation Results of Every Model.

Combined with the actual and related research on the liveable cities, the TOPSIS method ranks city liveability based on the difference between the evaluation object and the idealized target. The Gini coefficient method is not limited by the data range and can maximize or minimize the difference between indicators; thus, the results can be compared with those of other data standardization evaluation methods. The PCA is based on the proportion of each indicator to determine the corresponding weights; then, the results are ranked to select the best evaluation result. In addition, the TS fuzzy neural network uses the training sample dimension to determine the number of fuzzy neural network inputs and output nodes for a specific evaluation scenario. This paper introduces the TS fuzzy neural network to evaluate the liveable environment of cities. The final rankings and values for the five models are shown in Table 1. Notably, the rankings and results are inconsistent among the five MCDM models.

3.3. Difference Ratio Comparison.

Similarly, the rankings and results of the five methods considering the difference ratio are shown in Table 2 after equation (2) is standardized. The difference ratio values are shown in Table 3 according to equation (3).

The TS fuzzy neural network displays the best evaluation effect in the comprehensive evaluation of city liveable environment competitiveness. The identification and discrimination results indicate that the TS fuzzy neural network has a notable advantage over the traditional evaluation methods, and that the evaluation results are better than those of other methods. Therefore, the paper uses the evaluation results of the TS fuzzy neural network to rank the liveable environment competitiveness in the 13 studied cities. The specific evaluation results are shown in Table 4.

3.4. Comparison of Multiple Evaluation Results.

The TS fuzzy neural network yields the highest discrimination score among those of the five evaluation methods, which indicates that the TS fuzzy neural network method has a large degree of discrimination in the city liveable environment rankings. Moreover, the misjudgements in the evaluation rankings may be relatively small, and the ranking results are stable and reliable. The range of the Gini coefficient method is $[0, 1]$, and few extreme values occur; thus, the degree of discrimination is not obvious. However, after the weighting of indicators, the numerical gap is gradually widened, which makes the differentiation advantage more prominent. The TOPSIS method has the lowest difference

ratio because it is mainly used to assess the relative closeness among evaluation objects and does not reflect the relative proximity to the ideal optimal solution. PCA uses standardized data, but the calculations and evaluation are based entirely on indicator data and do not consider the status or effect of each indicator in real life (i.e., practical considerations based on the situation are not included in the analysis, and only the cumulative contribution variance of each indicator is considered). Therefore, the evaluation results deviate from the actual situation, which leads to a low difference ratio.

It should be noted that a variety of evaluation methods can be used to evaluate and analyse specific problems. The advantages and disadvantages of each evaluation method in this study are compared, and the most reasonable evaluation results are obtained. Through tests bases on the Gini coefficient, fuzzy Borda, TOPSIS, PCA, and TS fuzzy neural network methods, the TS fuzzy neural network evaluation method is found to be the most suitable for liveable city evaluation in this work. Note that in specific analyses of various problems, because different indicators, data, and evaluation indexes are used, the final advantages and disadvantages of the above evaluation methods will be different.

3.5. Verifying the Difference Ratio Evaluation Results with Hopfield Neural Network.

The city liveable environment simulations were classified into four levels. The normalized data, as training samples, were trained by the Hopfield neural network to evaluate the liveable environment of cities, and the results and rankings are shown in Table 5. Cities are classified into four levels according to Table 6. After Hopfield neural network training, the results of the simulation are shown in Figure 3.

Based on a comparison of the simulation results in Figure 3, the accuracy of the model is 80%, which indicates reasonable performance. The first layer is the default layer, which is classified according to the ideal indicator. When a city belongs to a specific level, the column in which it is located is given as a solid point (black). The second and third layers are the actual layer and the training layer, respectively. The actual layer is the result of the TS fuzzy neural network, and the training layer is the result of the Hopfield training. The training layer is compared with the actual level, and the Hopfield training results are basically consistent with the actual distribution of the actual layer; that is, the two results are highly consistent. After comparison, the evaluation results of the Hopfield network and TS fuzzy neural network are similar, suggesting that the evaluation results of the TS fuzzy neural network are reasonable.

3.6. Discussion.

In summary, many aspects of human lives are embraced by the concept of the liveable urban environment. Exploring different aspects of the liveable urban environment can broaden our understanding of the patterns and major driving factors of liveability. The best liveable urban environment is Hangzhou, and the worst liveable

Table 1: Ranking value based on different models.

City	Gini		Fuzzy Borda		TOPSIS		PCA		TS fuzzy neural network	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
BJ	0.0251	11	6.2158	3	0.3360	11	0.4715	2	0.4208	13
TJ	0.0280	2	5.3277	5	0.4196	7	0.1297	5	1.6089	2
SY	0.0262	6	3.7102	6	0.4516	3	0.2895	4	1.6011	7
SH	0.0255	9	1.9391	11	0.3913	10	0.1224	6	0.8072	12
NJ	0.0267	5	5.3422	4	0.3914	8	−0.2305	11	1.5273	10
HZ	0.0255	9	1.9959	10	0.4271	5	−0.0023	7	1.6090	1
JN	0.0293	1	2.3179	8	0.5194	1	−0.0626	9	1.5992	8
ZZ	0.0248	12	1.0047	12	0.3360	13	−1.313	13	1.6024	6
WH	0.0275	4	3.1492	7	0.4197	6	−0.088	10	1.6087	5
CS	0.0262	6	10.8861	2	0.4468	4	0.4072	3	1.5981	9
GZ	0.0279	3	18.8123	1	0.4626	2	0.6470	1	1.6088	3
CQ	0.0208	13	0.6597	13	0.3586	12	−0.3259	12	1.6088	3
CD	0.0256	8	2.2143	9	0.3921	9	−0.0440	8	1.3059	11

Table 2: Difference ratio value for five methods.

Gini	City	JN	TJ	GZ	WH	NJ	CS	SY	CD	HZ	SH	BJ	ZZ	CQ
	Value	13.0000	11.0118	10.8588	10.2471	9.0235	8.2588	8.2588	7.3412	7.1882	7.1882	6.5765	6.1176	1
	Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13
Fuzzy Borda	City	GZ	CS	BJ	NJ	TJ	SY	WH	JN	CD	HZ	SH	ZZ	CQ
	Value	13	7.3236	3.979	3.3534	3.343	2.1846	1.7829	1.1875	1.1133	0.9569	0.9162	0.2471	1
	Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13
TOPSIS	City	JN	GZ	SY	CS	HZ	WH	TJ	NJ	CD	SH	BJ	CC	ZZ
	Value	13	8.9715	8.1901	7.8504	6.4556	5.9299	5.9229	3.9969	3.9752	3.9202	2.0146	1.6018	1
	Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13
PCA	City	GZ	BJ	CS	SY	TJ	SH	HZ	CD	JN	WH	NJ	CQ	ZZ
	Value	13	11.8372	11.4103	10.6307	9.5713	9.5229	8.695	8.4192	8.2952	8.1262	7.1828	6.5504	1
	Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13
TS fuzzy neural network	City	HZ	TJ	GZ	CQ	WH	ZZ	SY	JN	CS	NJ	CD	SH	BJ
	Value	13	8.7721	3.3156	1.894	1.1184	1.1066	1.0863	1.0715	1.0027	1.0013	1.0012	1.0002	1
	Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13

Table 3: Difference ratio values.

	Gini	Borda	TOPSIS	PCA	TS fuzzy neural network
Difference ratio	1.1355	1.1562	1.1087	1.1242	1.2876

Table 4: Rankings based on the TS fuzzy neural network.

City	Value	Ranking
HZ	1.6091	1
TJ	1.6090	2
GZ	1.6089	3
CQ	1.6089	4
WH	1.6087	5
ZZ	1.6024	6
SY	1.6011	7
JN	1.5992	8
CS	1.5982	9
NJ	1.5273	10
CD	1.3060	11
SH	0.8073	12
BJ	0.4209	13

urban environment is Beijing according to the final ranking results of the TS fuzzy neural network. Notably, Hangzhou is a "paradise on Earth" city with beautiful West Lake, which attracts many people. Additionally, this city has thousands of years in its history, and it is also famous for the classical elegance of the Jiangnan Waterfront and the cutting-edge international fashion industry. Beijing has an unsuitable living environment in many areas, such as, high housing prices and serious environmental pollutions.

Moreover, it is shown that equivalent sound level, per capita urban road area, urban greening coverage, and days of good air quality are important and top-four indicators from ranking results, which means that to develop them firstly is beneficial for building liveable city. For example, the protection and renewal of vegetation to increase vegetation coverage can improve air quality on ecological

environment construction. Moreover, air quality has been greatly improved by limiting the number of vehicles and issuing license plates.

There no approach can achieve the best performance on all measurements for any data set, and it is necessary to utilize more than one single performance measure to evaluate algorithms. The experimental study indicates that the most

TABLE 5: Liveable city level ranking.

City	Average temperature	Urban greening coverage	Population density	Sewage treatment rate	Equivalent sound level	Days of good air quality	Per capita urban road area	Per capita GDP	Level
HZ	0.007274	0.002158	0.006426	0.005264	0.015454	0.009776	0.010926	0.010374	1
TJ	0.004020	0.000001	0.004950	0.006397	0.028530	0.006099	0.021465	0.011787	1
GZ	0.011307	0.011162	0.003926	0.006160	0.011888	0.015695	0.019424	0.016895	1
CQ	0.009078	0.011266	0.004497	0.004964	0.039229	0.012466	0.000000	0.000000	1
WH	0.007072	0.008141	0.005068	0.005103	0.008321	0.006278	0.025262	0.009755	2
ZZ	0.005565	0.008885	0.005018	0.005637	0.091535	0.002511	0.000930	0.001186	2
SY	0.000001	0.004792	0.006239	0.005473	0.000001	0.007444	0.021826	0.0063351	2
JN	0.005353	0.008438	0.005796	0.005534	0.002378	0.000001	0.037815	0.006250	3
CS	0.007412	0.011430	0.006258	0.006360	0.001189	0.010493	0.018003	0.010757	3
NJ	0.006498	0.014094	0.005038	0.000001	0.032097	0.007264	0.034431	0.007861	3
CD	0.008532	0.011117	0.005382	0.004589	0.008321	0.009776	0.013586	0.006763	4
SH	0.006984	0.005164	0.000001	0.004511	0.001189	0.015336	0.000594	0.011399	4
BJ	0.003579	0.019154	0.004890	0.003827	0.009510	0.005471	0.001188	0.011163	4

TABLE 6: Four classification levels.

| Level	Average temperature	Urban greening coverage	Population density	Sewage treatment rate	Equivalent sound level	Days of good air quality	Per capita urban road area	Per capita GDP
1	0.007920	0.006147	0.00495	0.005696	0.023775	0.011009	0.012954	0.009764
2	0.004212	0.007273	0.005442	0.005404	0.033285	0.005411	0.016006	0.005759
3	0.006421	0.011321	0.005697	0.003965	0.011888	0.005919	0.030083	0.008289
4	0.006365	0.011812	0.003424	0.004309	0.00634	0.010194	0.005123	0.009775
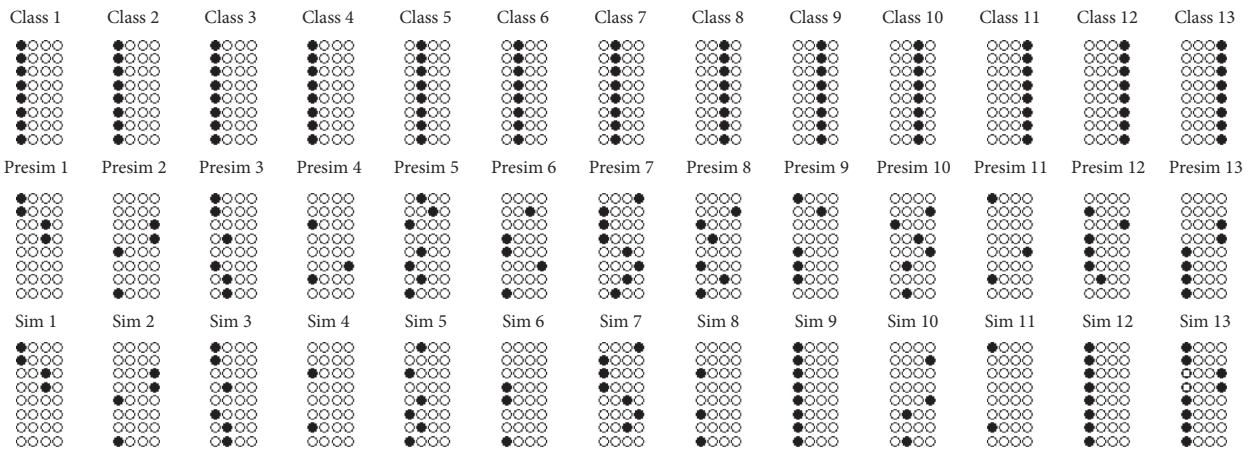
FIGURE 3: Simulation evaluation results for city liveability.

suitable method on the city liveable data sets can be selected using the difference ratio. Therefore, a more accurate method could potentially be employed in future studies.

4. Conclusions

The optimal model configuration in a liveable environment using MCDM was investigated in this paper. By comparing five types of evaluation methods, we found that the results of different evaluation methods varied for the same sample. Therefore, the most suitable method must be selected from various evaluation methods, and the difference ratio can solve this selection problem. This paper

combined the TOPSIS, Gini, PCA, fuzzy Borda, and TS fuzzy neural network methods to evaluate the liveable environment of cities. Meanwhile, the other MCDM methods, such as AHP, will be investigated in our work in the future work. Moreover, the Hopfield neural network method was introduced to assess the TS fuzzy neural network evaluation results for city liveability, and the evaluation results passed the test.

The purpose of this work was to evaluate city liveability and potentially improve environmental quality in the future. According to the evaluation results of liveable environment quality, we hope that the government can establish

countermeasures for the management of environmental quality in the future. Furthermore, based on the compatibility issues identified between the compliance assessments and the practical environmental quality evaluation, a compatible grading evaluation and management scheme should be developed for improved private and public decision-making.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

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