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Water Ecotourism Route Recommendation Model Based on an Improved Cockroach Optimization Algorithm

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Abstract: Aiming to address the problems of the current research on water ecotourism routes, a water ecotourism route recommendation model based on an improved cockroach optimization algorithm is proposed. The aim is to recommend the tour routes with the lowest exhaust emissions. Firstly, depending on tourists' once-visited water scenic spots, a scenic spot recommendation model based on the improved item-based collaborative filtering algorithm is set up. Then, by combining the recommended scenic spots and integrating the random transportation modes selected by tourists, a tour route recommendation model based on an improved cockroach optimization algorithm is constructed, which can output the tour route that produces the lowest exhaust emissions. Finally, The sample experiment shows that, on the basis of combining with the multivariate random transportation modes, the proposed algorithm has greater advantages than the tour routes planned by the traditional electronic maps, as it can output the tour routes with the lowest exhaust emissions, reduce the damage exhaust emissions cause in the urban water environments and to water resources, and effectively protect the urban water ecological environments.

Keywords: improved cockroach optimization algorithm; multivariate random transportation modes; water ecotourism route; item-based collaborative filtering recommendation

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1. Introduction

Tourism activities have a great impact on urban ecological environments and water resources. As for urban ecotourism, the damage caused by human activities in urban ecological environments and to water resources has a great scale and range, especially in the peak tourism season when tens of thousands of local residents as well as foreign visitors flock into the city, bringing much more damage to the urban ecological environments [1,2]. The whole process of urban tourism includes three aspects: the pre-tour planning, the urban visiting activities, and the post-tour evaluations, in which the urban visiting activities directly cause the damage to the urban ecological environments, and the traveling process is an essential part of the visiting activities. Tourists' behaviors such as arriving at the tourism city, traveling between two scenic spots, visiting the scenic spots, and leaving the tourism city all involve tourism transportation. In urban tourism activities, the traveling behaviors of the tourists are the source of the greenhouse gases and other harmful gases. For individual tourists, the choices regarding tourism transportation modes are random. How to reduce the exhaust emissions in tourism activities is the key issue of ecotourism research [3–5]. The majority of scholars have completed much work on ecotourism route research.

Chen [6] studied the tourism traffic route optimization model from Beijing to Tianjin. This model focuses its analysis on the factors that affect the tourism traffic routes and their design principles. Liu [7] used the shortest time and the minimum spanning tree algorithm to design the tourism traffic node model based on the highways. It designed five tour routes and put forward some suggestions to optimize the tour routes. Zhang [8] studied the optimization designing methods of tourism traffic nodes and tour routes in Hebei province. Feng [9] studied the bus routes in a tourism city, and proposed the optimization model of bus routes based on the particle swarm optimization algorithm. The experiment showed that the method can reasonably optimize tourism bus lines and improve urban traffic capacity. Bai [10] studied the influencing factors of tourists' choices on the green transportation modes. Zhang [11] studied island tourism traffic routes and put forward the related plans for the road network, public transportation, slow traffic, and maritime transportation as the guiding scheme for the engineering design.

Analysis of the former scholars' research on tourism transportation routes shows that there are some deficiencies that should be further studied. First, from the background of urban water ecological protection and water ecotourism, the research on water scenic spots, tourism traffic modes, and tour route optimization methods is insufficient. Second, the research on tourism transportation mainly focuses on the topic of route design, but there is a lack of research on how to accurately integrate water scenic spots into tourism traffic routes, and also, recommendations for water scenic spots are very scarce in tourism traffic research. Lots of existing research is not practical, but rather too theoretical. It is necessary to design tourism traffic routes in line with the actual situation of tourists, namely, for water ecotourism; therefore, recommending water scenic spots should combine with tourists' interests and travel schedules. Then, the constructed tourism route algorithm should depend on the recommended scenic spots. In addition, few methods to realize ways for low-carbon traveling and reduce exhaust emissions from the perspective of tourism traffic route design are studied. In view of the randomness of tourists' traveling modes, it is necessary to design targeted water ecotourism transportation lines to meet tourists' interests and provide low-carbon environmental protection.

To solve these problems, this paper sets up a water ecotourism route recommendation model. The model takes water ecotourism as the research topic, and sets water ecological protection and water ecotourism route optimization as the research objectives. The key findings of the proposed research are as follows:

(1) The water scenic spots output by the proposed algorithm and then used to design the tour routes can fully meet the tourists' interests and follow the once-visited scenic spots' attributes.

(2) When tourists are totally unfamiliar with the urban water scenic spots, especially for tourists who visit the tourism city for the first time, the proposed algorithm will recommend the most suitable ones for the tourists.

(3) Under the condition of meeting the tourists' traveling demands, the exhaust emissions of the tourism traffic routes are controlled to the minimum volume by the proposed algorithm, which could effectively reduce the damage caused by exhaust emissions in water ecological environments.

2. Water Scenic Spot Recommendation Model Based on the Improved Item-Based Collaborative Filtering Algorithm

Tourists need to plan the tour route before arriving at a tourism city, and the selection of water scenic spots is the most important. In the limited tour time, recommending the water scenic spots that best meet tourists' interests is a key function of a recommendation system. For those tourists who visit a tourism city for the first time, they are not familiar with the urban water scenic spots and their functional attributes, or know nothing about it. Blindly choosing water scenic spots may not satisfy their interests. Thus, obtaining tourists' interests is the precondition for the recommendation system to select accurate scenic spots for tourists, relying on the scenic spots' functional attributes. When the specific interests change, the recommended water scenic spots will be completely different, resulting in different tour routes.

For each water scenic spot, the functional attributes are diverse. Taking the commonly visited water scenic spots as the research object, the functional attributes can be precisely divided into the following categories: viewing the water natural scenery, appreciating water history and culture, water sports, leisure and health, sampling the aquatic food products, watching water birds, water scenery photography, taking a sightseeing boat, water-themed festival activities, and water research travel. For tourists, their interest tendencies regarding the functional attributes of water scenic spots are uncertain and random. In order to find out the water scenic spots that best meet the tourists' interests, the recommendation system needs to collect the tourist's once-visited scenic spots and confirm the tourist's interest tendencies through quantitative modeling of the functional attributes of the once-visited scenic spots. As to the above analysis, an improved item-based collaborative filtering algorithm is firstly set up to search for the most suitable recommended scenic spots.

2.1. Tourist-Needs Matrix Model and Water Scenic Spot Functional Attribute Matrix Model

According to the modeling principle, it is firstly necessary to collect the tourist's once-visited scenic spot data, and then quantify the functional attributes of water scenic spots in the tourism city. Based on the collected data, the tourist-needs matrix model and water scenic spot functional attribute matrix model are constructed. Here is the first set of concept and parameter definitions.

Def 1.1 Once-visited scenic spot element $t1(i1)$ and water scenic spot element $t2(i2)$ in the tourism city. The finite scenic spots that were visited by tourists before are used by the front-end of the recommendation system to collect tourist's interest data and are defined as the once-visited scenic spot elements $t1(i1)$, in which $0 < i1 \leq n$, $i1, n \in \mathbf{N}$, where n is the maximum number of elements $t1(i1)$. The water scenic spots in tourism cities that have functional attributes and can meet tourists' interests are defined as the water scenic spot element $t2(i2)$ in the tourism city, in which $0 < i2 \leq m$, $i2, m \in \mathbf{N}$, where m is the maximum number of the water scenic spots in the city. In the definition, $i1$ is the footnote number of the once-visited scenic spot elements and $i2$ is the footnote number of the urban water scenic spot elements.

Def 1.2 Water scenic spot functional attribute factor $pi(j)$. The attributes of the water scenic spots that could meet tourists' interests are defined as the water scenic spot functional attribute factors $pi(j)$, in which $0 < i \leq 2$, $0 < j \leq 10$, $i, j \in \mathbf{N}$. According to the foresaid analysis, the functional attributes could be divided into 10 classifications. Noting the arbitrary one factor as $pi(j)$, they are: $pi(1)$: viewing the water natural scenery, $pi(2)$: appreciating water history and culture, $pi(3)$: water sports, $pi(4)$: leisure and health, $pi(5)$: sampling the aquatic food products, $pi(6)$: watching water birds, $pi(7)$: water scenery photography, $pi(8)$: taking a sightseeing boat, $pi(9)$: water-themed festival activities, and $pi(10)$: water research travel. When $i = 1$, $p1(j)$ stands for the functional attribute factor of the once-visited scenic spots $t1(i1)$. When $i = 2$, $p2(j)$ stands for the functional attribute factor of the water scenic spots $t2(i2)$ in the tourism city.

Def 1.3 Water scenic spot functional attribute factor base vector $\mathbf{p}i(j)$. The max$j$ number of functional attribute factors $pi(j)$ of the water scenic spots $t1(i1)$ or $t2(i2)$ are stored in a $1 \times \max j$ dimension vector in the sequence of footnote j from smallest to largest value, and this vector is defined as water scenic spot functional attribute factor base vector $\mathbf{p}i(j)$. When $i = 1$, $p1(j)$ stands for the functional attribute factor of the once-visited scenic spots $t1(i1)$. When $i = 2$, $p2(j)$ stands for the functional attribute factor of the water scenic spots $t2(i2)$ in the tourism city. In order to distinguish the water scenic spots $t1(i1)$ from $t2(i2)$, note the vector $\mathbf{p}i(j)$ for $t1(i1)$ as $\mathbf{p}1(i1, j)$, and note the vector $\mathbf{p}i(j)$ for $t2(i2)$ as $\mathbf{p}2(i2, j)$, in which $0 < i1 \leq n$, $0 < i2 \leq m$, $i1, i2, n, m \in \mathbf{N}$. The element of $\mathbf{p}i(j)$ is noted as the scenic spot functional attribute factor $pi(j)$, where the element value is 1 or 0.

Def 1.4 Once-visited scenic spot evaluation parameter $\varepsilon1(i1)$. Since tourists have different interest tendencies regarding different once-visited scenic spots, the collection of scenic spots' functional attributes should consider interest tendencies. As to the once-visited scenic spot $t1(i1)$, when the recommendation system collects a tourist's interest data, it quantitatively scores the scenic spots according to interest tendencies, and then converts the scores into the percentage-system parameters. These parameters are defined as the once-visited scenic spot evaluation parameter $\varepsilon 1(i1)$. The function of the parameter $\varepsilon 1(i1)$ is to constrain the n number of the once-visited scenic spots, which makes each scenic spot $t1(i1)$ have different restraint abilities when confirming tourists' interest tendencies. The larger the parameter $\varepsilon 1(i1)$ is, the stronger the restraint ability of the scenic spot $t1(i1)$ and its functional attributes is at laying on the tourist's interest tendencies; on the contrary, the smaller the parameter, the weaker the restraint ability.

Def 1.5 Tourist-needs mining matrix **P**1 and tourist-needs mining-weighted matrix **P**1∗. The matrix that is formed by the once-visited scenic spots $t1(i1)$, as well as their functional attribute factors $pi(j)$ with the row vectors $\mathbf{p}1(i1,j)$, is defined as the tourist-needs mining matrix **P**1. It is used to collect tourists' interest tendencies. By introducing the parameter $\varepsilon 1(i1)$ to constrain the scenic spots' functional attributes in matrix **P**1, it is possible to confirm the abilities of each vector $\mathbf{p}1(j)$ in collecting tourists' interest tendencies. The matrix **P**1 that is merged with the parameter $\varepsilon 1(i1)$ is defined as the tourist-needs mining-weighted matrix **P**1∗, in which $0 < i1 \le n$, $i1, n \in \mathbf{N}$. That is, each row $\mathbf{p}1(i1,j)$ of the matrix **P**1 relates to one $\varepsilon 1(i1)$. The matrix **P**1 is the basic data for collecting tourists' interests, whereas the matrix **P**1∗ is the weighted matrix to precisely confirm tourist's interest tendencies. The matrix's No. $i1$ row relates to $\mathbf{p}1(i1,j)$.

Def 1.6 Water scenic spot functional attribute matrix **P**2. The matrix that is formed by the water scenic spots $t2(i2)$, as well as the functional attribute factors $pi(j)$ with the row vectors $\mathbf{p}2(i2,j)$, is defined as the water scenic spot functional attribute matrix **P**2. This matrix **P**2 is used to search for the water scenic spots. The matrix's No. $i2$ row relates to $\mathbf{p}2(i2,j)$.

Formulas (1) and (2) are the constructed matrix models **P**1 and **P**1∗. Formula (3) is the constructed matrix model **P**2.

$$\mathbf{P}1 = \begin{bmatrix} \mathbf{p}1(1,j) \\ \cdots \\ \mathbf{p}1(i1,j) \\ \cdots \\ \mathbf{p}1(n,j) \end{bmatrix} = \begin{bmatrix} p1(1,1) & \ldots & p1(1,j) & \ldots & p1(1,\max j) \\ \cdots & & \cdots & & \cdots \\ p1(i1,1) & \ldots & p1(i1,j) & \ldots & p1(i1,\max j) \\ \cdots & & \cdots & & \cdots \\ p1(n,1) & \ldots & p1(n,j) & \ldots & p1(n,\max j) \end{bmatrix} \tag{1}$$

$$\mathbf{P}1* = \begin{bmatrix} \varepsilon 1(1)\cdot \mathbf{p}1(1,j) \\ \cdots \\ \varepsilon 1(i1)\cdot \mathbf{p}1(i1,j) \\ \cdots \\ \varepsilon 1(n)\cdot \mathbf{p}1(n,j) \end{bmatrix} = \begin{bmatrix} \varepsilon 1(1)\cdot p1(1,1) & \ldots & \varepsilon 1(1)\cdot p1(1,j) & \ldots & \varepsilon 1(1)\cdot p1(1,\max j) \\ \cdots & & \cdots & & \cdots \\ \varepsilon 1(i1)\cdot p1(i1,1) & \ldots & \varepsilon 1(i1)\cdot p1(i1,j) & \ldots & \varepsilon 1(i1)\cdot p1(i1,\max j) \\ \cdots & & \cdots & & \cdots \\ \varepsilon 1(n)\cdot p1(n,1) & \ldots & \varepsilon 1(n)\cdot p1(n,j) & \ldots & \varepsilon 1(n)\cdot p1(n,\max j) \end{bmatrix} \tag{2}$$

$$\mathbf{P}2 = \begin{bmatrix} \mathbf{p}2(1,j) \\ \cdots \\ \mathbf{p}2(i2,j) \\ \cdots \\ \mathbf{p}2(m,j) \end{bmatrix} = \begin{bmatrix} p2(1,1) & \ldots & p2(1,j) & \ldots & p2(1,\max j) \\ \cdots & & \cdots & & \cdots \\ p2(i2,1) & \ldots & p2(i2,j) & \ldots & p2(i2,\max j) \\ \cdots & & \cdots & & \cdots \\ p2(m,1) & \ldots & p2(m,j) & \ldots & p2(m,\max j) \end{bmatrix} \tag{3}$$

Based on the above definitions and constructed models, the water scenic spot recommendation model based on the improved item-based collaborative filtering algorithm is set up.

2.2. Water Scenic Spot Recommendation Model Based on the Improved Item-Based Collaborative Filtering Algorithm

A collaborative filtering algorithm based on item attributes or user needs is a commonly used method. The essence of the algorithm is to find out which items are close to the user's preferences or adjacent users' preferences, and then recommend them to the users. A traditional item-based collaborative filtering algorithm is constructed on a huge number of historical users' browsing data, in which users' preferred items are collected and scored and then recommendations are made to the users. This recommendation mode has some drawbacks; for instance, the user interest mining is based on massive internet data and the scores of the items, thus the extracted data reflects public interest tendencies but not an individual user's interests [12–16]. This may cause the recommended items to not match the user's interests. Tourists' concerned items are scenic spots and tour routes. Whether their interests can be satisfied or not determines the high or low scores of evaluated tourism products, which directly influences tourists' evaluations of the tourism city's service. Therefore, confirming each tourist's interests and searching for the matching scenic spots and tour routes is the core function of the recommendation system. Here the second set of parameter definitions is listed, and then the water scenic spot recommendation model based on the improved item-based collaborative filtering algorithm is set up.

Def 2.1 Tourist-needs absolute weight function $f(i1, j)$ and tourist-needs relative weight function $\nabla f(i1, j)$. Tourist-needs matrix $\mathbf{P}1$ contains potential interests of a tourist of different water scenic spots. The weighted matrix $\mathbf{P}1*$ contains the evaluation parameter $\varepsilon 1(i1)$, scoring on the once-visited scenic spots. As to each functional attribute $pi(j)$ of each scenic spot, the impact on the tourist's interests varies, which is determined by the parameter $\varepsilon 1(i1)$. The tourist-needs absolute weight function $f(i1, j)$ relating to the functional attribute $pi(j)$ is introduced. The tourist-needs weight value is a kind of tendency degree on each functional attribute $pi(j)$, which is iterated and calculated by the weighted matrix $\mathbf{P}1*$. The number $i1$ is the current iterating number of the once-visited scenic spot, and j is the number of the functional attribute $pi(j)$. According to the definition, the function $f(i1, j)$ represents the accumulated iteration value of interest tendency; the higher the function $f(i1, j)$ value is, the stronger the ability to reflect the tourist's interest tendencies the related functional attribute $pi(j)$ will have, and the system will be more likely to recommend a scenic spot with the functional attribute $pi(j)$. The recursion formula and the general formula for $f(i1, j)$ are shown as Formulas (4) and (5), where $0 < i1 \leq n$, $0 < j \leq \max j, i1, j, n \in \mathbf{N}$.

$$f(i1, j) = f(i1 - 1, j) + \varepsilon 1(i1) \cdot p1(i1, j) \tag{4}$$

$$f(i1, j) = \sum_{i1=1}^{n} \varepsilon 1(i1) \cdot p1(i1, j) \tag{5}$$

In order to construct the recommendation algorithm, the tourist-needs relative weight function $\nabla f(i1, j)$ is set up. Tourist-needs absolute weight $f(i1, j)$ represents the interest tendency of a tourist to a certain functional attribute $pi(j)$. The absolute weight $f(i1, j)$ is normalized and outputs the tourist-needs relative weight $\nabla f(i1, j)$. Formula (6) is the general formula for the tourist-needs relative weight function $\nabla f(i1, j)$. Function $\nabla f(i1, j)$ reflects the weight of a certain factor $pi(j)$ in the $\max j$ number of factors $pi(j)$. From the perspective of normalization, the tourist's interest tendencies of each attribute $pi(j)$ can be seen easily, in which $0 < i1 \leq n$, $0 < j \leq \max j, i1, j, n \in \mathbf{N}$.

$$\nabla f(i1, j) = \frac{\sum\limits_{i1=1}^{n} \varepsilon 1(i1) \cdot p1(i1, j)}{\sum\limits_{j=1}^{\max j} \sum\limits_{i1=1}^{n} \varepsilon 1(i1) \cdot p1(i1, j)} \tag{6}$$

Def 2.2 Tourist-needs absolute weight vector $\mathbf{f}(j)$ and tourist-needs relative weight vector $\nabla \mathbf{f}(j)$. The iterated values of tourist-needs absolute weight $f(i1, j)$ or tourist-needs relative weight $\nabla f(i1, j)$ are stored into a $1 \times \max j$ dimension vector in the sequence of the footnote of the scenic spot functional attribute $pi(j)$. This vector is defined as the tourist-needs absolute weight vector $\mathbf{f}(j)$ or tourist-needs relative weight vector $\nabla \mathbf{f}(j)$.The vector $\mathbf{f}(j)$ or $\nabla \mathbf{f}(j)$ is used to store values $f(i1, j)$ or $\nabla f(i1, j)$ and calculate the water scenic spot matching degree for the recommendation system.

Def 2.3 Water scenic spot recommendation function $ri2(\nabla \mathbf{f}(j), \mathbf{p}2(i2, j))$. The core of the water scenic spot recommendation algorithm is the constructed recommendation function. Based on the collected tourist's interest tendencies, the water scenic spot recommendation function $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$, that is used to match the interest data and water scenic spot $t2(i2)$, is set up. In the function, $\nabla\mathbf{f}(j)$ is the tourist-needs relative weight vector, and $\mathbf{p}2(i2,j)$ is the water scenic spot functional attribute vector of the tourism city, where $0 < i2 \le m$, $0 < j \le \max j$, $i2, j \in \mathbf{N}$. The correlation of the two vectors is determined by the matching degree of $\nabla\mathbf{f}(j)$ and $\mathbf{p}2(i2,j)$. The second-order Minkowski distance is introduced as the basic function structure to set up the water scenic spot recommendation function, shown in the Formula (7).

$$r(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j)) = \left[\sum_{j=1}^{\max j} |\nabla f(i1,j) - p2(i2,j)|^c\right]^{1/c} \tag{7}$$

Def 2.4 Water scenic spot recommendation function transition matrix **R** and water scenic spot recommendation function matrix $\mathbf{R}*$. the m number of water scenic spots' $t2(i2)$ recommendation function values $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$ are stored in a matrix in a certain sequence. The matrix that is used to dynamically store recommendation function values $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$ is defined as the water scenic spot recommendation function transition matrix **R**, and its element is $R(u,v)$, $u, v \in \mathbf{N}$.

When all the recommendation function values $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$ are stored in the matrix **R**, the matrix **R** with steady values is defined as the water scenic spot recommendation function matrix $\mathbf{R}*$.

Def 2.5 Recommended water scenic spot vector **T**. Tourists choose the w number of water scenic spots that will be visited according to interests, travel schedule, and cost budget, $0 < w \le m$, $w, m \in \mathbf{N}$. In the recommendation algorithm, the optimal w number of water scenic spots in the matrix $\mathbf{R}*$ is searched and stored into a $1 \times w$ dimension vector. This vector is defined as the recommended water scenic spot vector **T**. Its element is noted as $\mathbf{T}(h)$, $0 < h \le w$, $h, w \in \mathbf{N}$.

According to the second set of definitions and the modeling method, the water scenic spot recommendation model based on the improved item-based collaborative filtering algorithm is set up, shown as the following pseudo-code (Algorithm 1). Using the constructed water scenic spot recommendation algorithm, when the once-visited scenic spot set $\mathbf{t}1(i1)$ is input, the system will automatically output the best matched water scenic spot set $\mathbf{t}2(i2)$.

Algorithm 1 The water scenic spot recommendation algorithm based on the improved item-based collaborative filtering

Input	n. number of $t1(i1)$, m number of $t2(i2)$, evaluation value $st1(i1)$, parameter $\varepsilon1(i1)$.
Output	Vector **T**.
Step 1	Confirm $\mathbf{p}1(i1,j)$ and $\mathbf{p}2(i2,j)$. Set up **P1**, $\mathbf{P1}*$ and **P2**.
Step 2	Calculate $f(i1,j)$ and form $\mathbf{f}(j)$. Iterate j, store $f(i1,j)$ into $\mathbf{f}(j)$, $j = j+1$.
Step 3	Calculate $\nabla f(i1,j)$ and form $\nabla\mathbf{f}(j)$. Calculate $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$, form $\mathbf{R}*$.
Sub-step 1	Traverse $0 < j \le \max j$, $0 < i2 < m$. Calculate $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$.
Sub-step 2	Descend to order $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2,j))$.
Sub-step 3	Store descending values into $\mathbf{R}*$.
Step 4	Choose w number of former elements of $\mathbf{R}*$. Store into **T**.

The output **T** is the key for the recommendation system to plan a tour route. Figure 1 shows the modeling process of the proposed water scenic spot recommendation model based on the improved item-based collaborative filtering algorithm. Figure 1a shows the process to output the tourist-needs matrix. Figure 1b shows the process to output the water scenic spot functional attribute-weighted matrix. Figure 1c shows the process to output the tourist-needs relative weight vector. Figure 1d shows the process to finally output the water scenic spot recommendation vector.

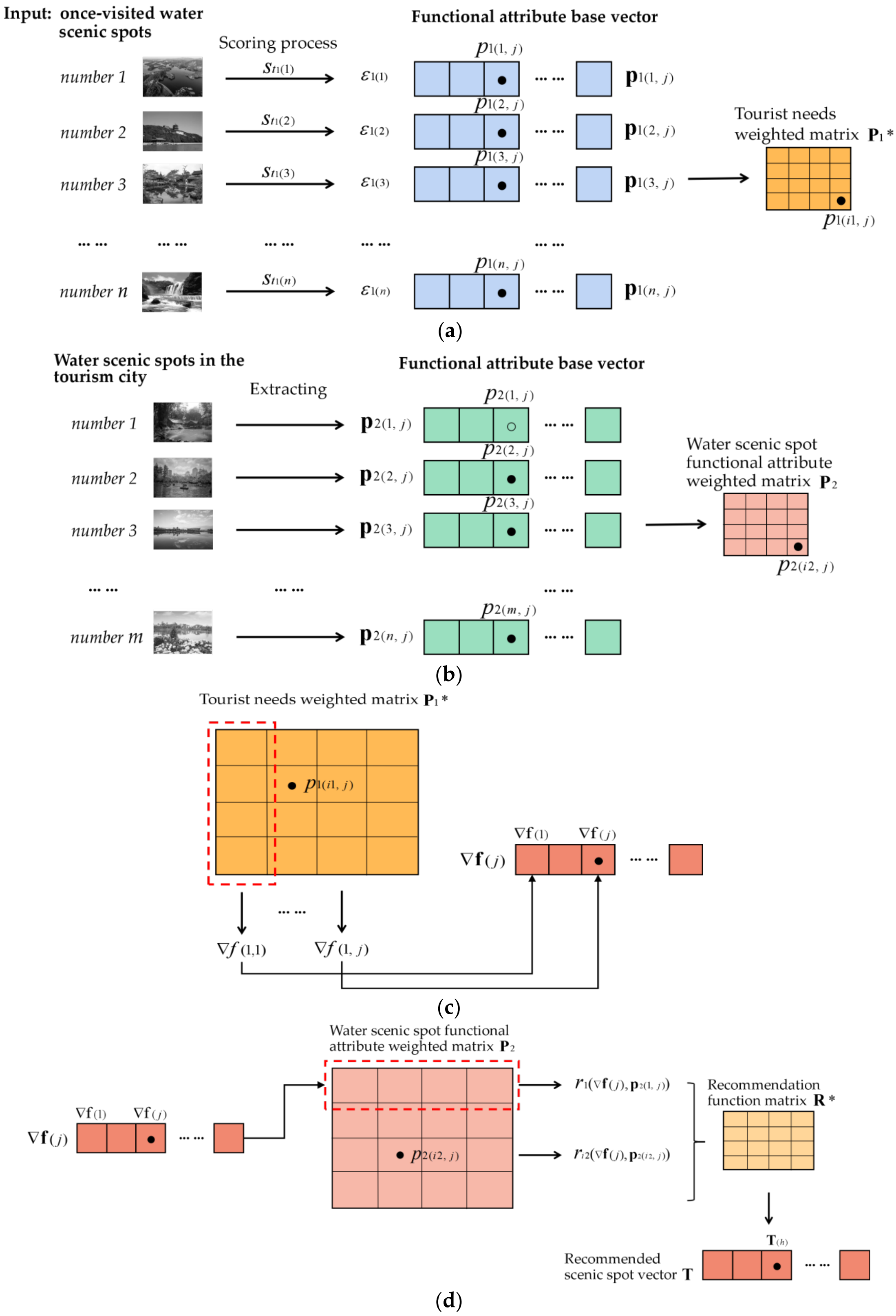


Figure 1. The process of water scenic spot recommendation. (**a**) shows the process to output the tourist-needs matrix. (**b**) shows the process to output the water scenic spot functional attribute-weighted matrix. (**c**) shows the process to output the tourist-needs relative weight vector and (**d**) shows the process to finally output the water scenic spot recommendation vector.

3. Water Tour Route Recommendation Model Based on an Improved Cockroach Optimization Algorithm

Tourists will visit the water scenic spots along a certain tour route within the scheduled time; thus, the tour route is also the key to influence tourists' activities, since moving and ferrying among scenic spots is an important part of an itinerary. Therefore, tour route planning plays a very important role in tourism activities [17–19].

In ecotourism, several key issues should be considered in planning the tour routes. First, the time cost. Since the ferrying process between two scenic spots is not for sightseeing, having the time occupied on the way is not expected by tourists. Second, the transportation mode. Tourists usually choose transportation modes randomly. The commonly used transportation modes include public bus, taxi, online ride-hailing, rail transit, shared bike, walking, etc. When tourists choose different transportation modes, the ferrying time and cost will be different. Third, green and low-carbon traveling, as well as water ecological protection. Under the condition of the fixed urban traffic system, tourists are encouraged to freely choose transportation modes. How to plan the optimal route based on the transportation modes selected by tourists on the premise of meeting their interests, minimizing exhaust emissions, and decreasing the pollution of urban ecology and water resources is the key issue of ecotourism route planning [20–23].

According to the key issues, a good tour route should not only meet the tourists' interests, but should also be economical. At the same time, it is necessary to minimize the amount of waste gas generated by transportation tools, realize ways for green and low-carbon traveling, and reduce the damage to the urban ecological environments and water resources.

3.1. The Spatial Structure Model of Water Ecotourism Routes

To set up the tour route algorithm, it is necessary to construct the spatial structure. Here is the third set of definitions and parameters.

Def 3.1 The spatial structure of water ecotourism route $\mathbf{S}$ and its element group $\mathbf{S}(i)$. Tourists are influenced by the urban geographical environments when traveling in a tourism city. The tourism traffic environment, as well as its elements constructed by the urban geographic information data, is defined as the spatial structure of water ecotourism route $\mathbf{S}$. In the spatial structure $\mathbf{S}$, the visible fundamental facilities include the water scenic spots, urban road networks, urban road intersections, transportation tools, etc. The invisible fundamental facilities include the geographical positions of water scenic spots, the geographical positions of urban road networks and urban road intersections, the public bus lines, the traveling cost, etc. The visible and invisible fundamental facilities in the spatial structure $\mathbf{S}$ are the basic conditions from which to build water ecotourism routes; these facilities are defined as spatial structure $\mathbf{S}$ elements, where each element is noted as element group $\mathbf{S}(i)$, $0 < i \leq \max i$, $i \in \mathbf{N}$. According to the definitions, the spatial structure $\mathbf{S}$ and element group $\mathbf{S}(i)$, as well as the quantization units, are constructed.

Def 3.1.1 Water scenic spot element group $\mathbf{S}(1)$ and its spatial distribution matrix $\mathbf{S}M(1)$. The water scenic spots $t2(i2)$ are stored in a one-dimensional array $\mathbf{S}(1)$ in the sequence of note $i2$. The array is defined as the water scenic spot element group $\mathbf{S}(1)$, $0 < i2 \leq m$, $i2, m \in \mathbf{N}$. The water scenic spots as elements $t2(i2)$ are noted and stores in the square matrix $\mathbf{S}M(1)$, where the matrix is defined as the spatial distribution matrix $\mathbf{S}M(1)$.

Def 3.1.2 Water scenic spot road element group $\mathbf{S}(2)$ and its spatial distribution vector $\mathbf{S}M(2)$, water scenic spot intersection element group $\mathbf{S}(3)$ and its spatial distribution matrix $\mathbf{S}M(3)$. The path formed in the ferrying process is based on urban roads. The ferrying section between the scenic spots $t2(i2)$ and $t2(\neg i2)$ is taken as the research object to set up the water scenic spot road element group and distribution vector. The roads $l(o1)$ that directly or indirectly connect the scenic spots $t2(i2)$ and $t2(\neg i2)$ are stored in a one-dimensional array $\mathbf{S}(2)$, $0 < o1 \leq \max o1$, $o1 \in \mathbf{N}$, this array is defined as the water scenic spot road element group. The roads $l(o1)$ are stored in the vector $\mathbf{S}M(2)(o1)$ with the same dimension as the array $\mathbf{S}(2)$ in the sequence of road number $o1$. This vector

$\mathbf{S}M(2)(o1)$ is defined as the water scenic spot road spatial distribution vector $\mathbf{S}M(2)$. The road notes that may be passed through by tourists between the two scenic spots are called the road intersections $P(o2)$, $0 < o2 \leq \max o2$, $o2 \in \mathbf{N}$. All of the road intersections $P(o2)$ between the scenic spots $t2(i2)$ and $t2(\neg i2)$ generated by the vector $\mathbf{S}M(2)$ are stored in a one-dimensional array $\mathbf{S}(3)$. This array $\mathbf{S}(3)$ is defined as the water scenic spot road intersection element group. The road intersections $P(o2)$ of $\mathbf{S}(3)$ are stored in the square matrix $\mathbf{S}M(3)$; this square matrix is defined as the water scenic spot road intersection spatial distribution matrix.

Def 3.1.3 Multivariate tourism traffic mode vector $\mathbf{T}m$. One tour route contains several water scenic spot road element groups $\mathbf{S}(2)$. According to the w number of water scenic spots confirmed by the tourist, when he starts from the location St and visits the w number of water scenic spots, he will ferry in w number of sections. In each section, he might randomly choose a kind of transportation mode, which is noted as $Tm(i)$.

The transportation modes could be quantified as: $Tm(1)$, public bus; $Tm(2)$, taxi; $Tm(3)$, online ride-hailing; $Tm(4)$, rail transit; $Tm(5)$, shared bike; and $Tm(6)$, walking. When the tour route is confirmed, tourists choose one transportation mode $Tm(i)$ for each section according to their interests. The $1 \times w$ dimension vector, which is used to store the w number of transportation modes $Tm(i)$ for the tour route, is defined as the multivariate tourism traffic mode vector $\mathbf{T}m$. Its element is $\mathbf{T}m(i)$, $0 < i \leq w$, $i, w \in \mathbf{N}$.

Def 3.2 Water tour route feasible solution space $\Phi 1$ and space element $\Phi 1(i)$. When the vector $\mathbf{T}$, spatial structure $\mathbf{S}$, and element groups $\mathbf{S}(i)$ are confirmed, the quantity of the water tour routes will be finite. If the total amount of the points is $w + 1$, there must be $A(w, w)$ kinds of tour routes. The vector that is composed by the $A(w, w)$ kinds of tour routes is defined as the water tour route feasible solution space $\Phi 1$, and its element is noted as $\Phi 1(i)$, $0 < i \leq A(w, w)$, $i \in \mathbf{N}$. In the space $\Phi 1$, one feasible water tour route is noted as $\mathbf{T}R(j)$, $0 < j \leq A(w, w)$, $j \in \mathbf{N}$. One $\mathbf{T}R(j)$ relates to an element $\Phi 1(i)$ in the space $\Phi 1$.

Def 3.3 Exhaust emission quantization section $\Phi 2$, tour route exhaust emission volume $V2(j)$, exhaust emission quantization subsection $\Phi 2(i)$, and tour route subsection exhaust emission volume $V2(j, i)$. In the different sections $\mathbf{S}M(2)$ of a water tour route $\mathbf{T}R(j)$, a tourist chooses different transportation modes $Tm(i)$ and then travels along the route. In this process, waste gas is produced. Taking an entire water tour route $\mathbf{T}R(j)$ as a metering unit, the whole section of the water tour route that produces waste gas is defined as the exhaust emission quantization section $\Phi 2$. The total volume of the waste gas produced in the section $\Phi 2$ is defined as the tour route exhaust emission volume $V2(j)$, where j is the tour route number, $0 < j \leq A(w, w)$, $j \in \mathbf{N}$. Based on $\Phi 2(i)$, in the section $\Phi 2(i)$, the section between two scenic spots that produces waste gas is defined as the exhaust emission quantization subsection $\Phi 2(i)$. In the subsection $\Phi 2(i)$, the volume of the produced waste gas is defined as the tour route subsection exhaust emission volume $V2(j, i)$, where j is the tour route number, i is the subsection number, and $0 < j \leq A(w, w)$, $0 < i \leq w$, $j, i, w \in \mathbf{N}$. The section $\Phi 2$ relates to one water tour route $\mathbf{T}R(j)$ and total emission volume $V2(j)$. The subsection $\Phi 2(i)$ relates to the element $\mathbf{T}m(i)$ of the vector $\mathbf{T}m$ and subsection emission volume $V2(j, i)$. As to the section $\Phi 2$ of one tour route $\mathbf{T}R(j)$, when the transportation mode elements $\mathbf{T}m(i)$ of the vector $\mathbf{T}m$ change, the subsection volume $V2(j, i)$ of $\Phi 2(i)$ and the total volume $V2(j)$ of $\Phi 2$ will change simultaneously.

The produced waste gas volume when the transportation tool of mode $Tm(i)$ travels one kilometer is set as $Vm(i)$, and in the subsection, the traveling distance is $d2(i)$ (km). Then, the waste gas volume $V2(j, i)$, produced in subsection $\Phi 2(i)$ in the mode $Tm(i)$, is shown as Formula (8). The total waste gas volume $V2(j)$ produced in the section $\Phi 2$ is shown as Formula (9). Different $Tm(i)$ relate to different $Vm(i)$.

$$V2(j, i) = Vm(i) \cdot d2(i) \tag{8}$$

$$V2(j) = \sum_{i=1}^{w} Vm(i) \cdot d2(i) \tag{9}$$

3.2. Water Ecotourism Route Recommendation Model

After the water scenic spot recommendation vector **T**, of which the water ecotourism route spatial structure **S** and its spatial elements $\mathbf{S}(i)$ are confirmed under the constraint of the feasible solution space Φ1, the core aim of planning a water ecotourism route is to decrease the ferrying time, the waste gas emissions, and the damage to the urban ecological environments and water resources. Usually, the optimization algorithm is used to solve the problem; the frequently used optimization algorithms include the ant colony algorithm, genetic algorithm, particle swarm optimization, simulated annealing algorithm, etc. [24–27]. The optimization algorithms are used to plan tour routes in the literature. As for the ant colony algorithm, it has the benefit that it can calculate the results by means of distributed and parallel computing, which enhances the algorithm's operating efficiency. However, it has the drawback that the parameters for the algorithm are complicated, and if the parameters are not properly set, the global optimal solution may not be found out. As for the genetic algorithm, it has the benefit that it has a flexible searching process and good scalability, and it also has good capacity to search for the optimal solution. However, it has the drawback that it is difficult to find out the global optimal solution. As for the particle swarm optimization, it has the benefit that it runs rapidly, and the parameters can be easily set. However, it has the drawback that it easily falls into the local optimal solution.

Of all the optimization algorithms, the cockroach optimization algorithm has advantages. It simulates the food-seeking process of a cockroach swarm through group collaboration; thus, the global optimal solution can be found out. Each cockroach follows the current optimal cockroach's behavior, in which food redistribution, equal search, and homing strategy are used to set up the optimal searching model. The advantages of the cockroach optimization algorithm are: It has very excellent capacity to search for the global optimal solution and not fall into the local optimal solution. The formulas used to set up the algorithm are simple; thus, it also has moderate computational complexity. Considering the good performance of the cockroach optimization algorithm, the research work used it as the basic algorithm to set up the water ecotourism route recommendation model. In the study, the constructed spatial structure **S** has the characteristics of massive elements, massive points, and complicated data sources. Therefore, this study chose the cockroach optimization algorithm as the basic model. Here is the fourth set of definitions and parameters.

Def 4.1 Subsection tour route feasible solution vector $\mathbf{Z}(i)$ based on the road intersection element group $\mathbf{S}(3)$. According to Definition 3.1.2, when the matrix $\mathbf{S}M(3)$ between scenic spots $t2(i2)$ and $t2(\neg i2)$ is confirmed, there is a certain amount of feasible path solutions. The sequence vector that is composed by all the road intersections $P(o2)$ in a feasible path is defined as the subsection tour route feasible solution vector $\mathbf{Z}(i)$, $0 < i \leq A(\max o2, \max o2)$, $i \in \mathbf{N}$. The vector $\mathbf{Z}(i)$ is determined by the locations of the road intersections $P(o2)$. When the location of the arbitrary $P(o2)$ changes, the feasible solution and path will change, too.

Def 4.2 Cockroach moving unit $\text{Step}(x, y)$. When an individual cockroach $C(\sigma)$ crawls in the solution vector space $\mathbf{Z}$, $0 < \sigma \leq \max\sigma$, $\sigma \in \mathbf{N}$, the action of crawling from the solution $\mathbf{Z}(i1)$ to $\mathbf{Z}(i2)$ is the process in which the q number of replacements of the element $Z(i, j)$ in $\mathbf{Z}(i)$ take place. The one-time replacement of the element x and element y in a vector $\mathbf{Z}(i)$ is noted as $\text{Step}(j1, j2)$. According to the definition, the cockroach will crawl through q number of units, as shown in Formulas (10) and (11), in which the *Path* represents the cockroach crawling distance from $\mathbf{Z}(i1)$ to $\mathbf{Z}(i2)$.

$$Path = \text{Step}(jx1, jy1) + \text{Step}(jx2, jy2) + \ldots + \text{Step}(jxq, jyq) \quad (10)$$

$$Path = \sum_{i=1}^{q} \text{Step}(jxi, jyi) \quad (11)$$

Def 4.3 Current solution $FC(\sigma)$ of individual cockroach and current optimal solution $FO(\sigma)$. In the process of the cockroach $C(\sigma)$ crawling in the space $\mathbf{Z}$, the function determined by the current destination solution vector $\mathbf{Z}(i)$ of the cockroach $C(\sigma)$ in the time t is defined as the current solution $FC(\sigma)$ of the individual cockroach. In the space $\mathbf{Z}$, in the process of crawling from the time 0 to the time t, the optimal solution of all the feasible solution vectors $\mathbf{Z}(i)$ is defined as the current optimal solution $FO(\sigma)$ of the individual cockroach.

Def 4.4 Food redistribution regulating parameter $\Delta\text{Step}(x, y)$. In the iterating process of the cockroach optimization algorithm, if all cockroaches $C(\sigma)$ reach the same optimal solution $FO(\sigma)$ in a certain time t, namely, $FO(1) = FO(2) = \ldots = FO(\max\sigma)$, in order to make the algorithm perform normally, the food redistribution regulating parameter $\Delta\text{Step}(x, y)$ should be introduced to the optimal solution $FO(\sigma)$. The impact of parameter $\Delta\text{Step}(x, y)$ on the current optimal solution is shown as Formula (12).

$$FO(\sigma) + Path(\cdot)\Delta\text{Step}(x, y) = FC(\sigma)new \tag{12}$$

The algorithm principle is as follows. The tourist chooses the transportation modes $Tm(i)$ according to the water scenic spot recommendation vector $\mathbf{T}$, and then the transportation mode vector $\mathbf{T}m$ is confirmed. The water ecotourism route spatial structure $\mathbf{S}$ and spatial element groups $\mathbf{S}(i)$ are initialized, then the water tour route feasible solution space $\Phi1$ and space elements $\Phi1(i)$ are confirmed. One cockroach is set as $C(\sigma)$, $0 < j, \sigma \leq A(w, w)$, $j, \sigma \in \mathbf{N}$. One tour route relates to one exhaust emission quantization section $\Phi2$. Then, the exhaust emission quantization subsection $\Phi2(i)$, road intersection element groups $\mathbf{S}(3)$, and spatial distribution matrix $\mathbf{S}M(3)$ are confirmed. The subsection path feasible solution vector $\mathbf{Z}(i)$ based on the road intersection element groups $\mathbf{S}(3)$ is set up. The road nodes $P(o2)$ are used to set up the path between two water scenic spots, namely, the space $\mathbf{Z}$, in which each path $\mathbf{Z}(i)$ is a cockroach $C(\sigma)$ in this section, $0 < \sigma \leq \max\sigma$, $0 < i \leq A(\max o2, \max o2)$, $\sigma, i, o2 \in \mathbf{N}$. Based on the transportation modes chosen by the tourist, through the proposed route algorithm, the optimal tour route is searched and recommended to the tourist. The water tour route algorithm based on the improved cockroach optimization model is set up, shown as the following pseudocode (Algorithm 2).

Algorithm 2 The water tour route algorithm based on the improved cockroach optimization model

Input:	Vector $\mathbf{T}$, $\mathbf{T}m$.
Output:	Tour route vector $\mathbf{T}R(j)$.
Step 1	Confirm $\mathbf{S}M(1)$, $\mathbf{S}M(2)$, $\mathbf{S}M(3)$, $\Phi1$, and $\mathbf{Z}(i)$.
Step 2	Calculate $V2(j, i)$ in $\Phi2(i)$.
Sub-step 1	Initialize $\Phi2(i)$, $\mathbf{S}M(3)$, $\mathbf{Z}(i)$, and$C(\sigma)$, $0 < i, \sigma \leq A(\max o2, \max o2)$.
Sub-step 2	Confirm $FC(\sigma) \sim V2(j, \sigma)$ for each $C(\sigma)$.
Sub-step 3	All $C(\sigma)$ crawl to $FC(\sigma)$ along $Path(\sigma)$, find the new optimal $FC(\sigma)$.
Sub-step 4	All $C(\sigma)$ go homing. Turn back to the initial state.
Step 3	Repeat Step 2 and find the optimal $C(\sigma)$. As to arbitrary time t, judge whether $FO(1) = FO(2) = \ldots = FO(\max\sigma)$.
Sub-step 1	If it exists, perform $\Delta\text{Step}(x, y)$, output new optimal $FC(\sigma)$.
Sub-step 2	If it does not exist, judge whether current $FC(\sigma)$ is the global optimal one. Yes, output $FC(\sigma)$; no, turn back to Step 2 and continue searching.
Step 4	Find all global optimal $C(\sigma)$ for each $\Phi2(i)$.
Step 5	Initialize $\Phi1(i)$ as $C(\sigma)$. Calculate $V2(j)$ in $\Phi1$.
Sub-step 1	Set each route $\mathbf{T}R(j)$ as $C(\sigma)$. Confirm $FC(\sigma) \sim V2(j)$ for each $C(\sigma)$.
Sub-step 2	All $C(\sigma)$ crawl to $FC(\sigma)$ along $Path(\sigma)$, find the new optimal $FC(\sigma)$.
Sub-step 3	All $C(\sigma)$ go homing. Turn back to the initial state.
Step 6	Repeat Step 5 and find the optimal $C(\sigma)$. As to arbitrary time t, judge whether $FO(1) = FO(2) = \ldots = FO(\max\sigma)$.
Sub-step 1	If it exists, perform $\Delta\text{Step}(x, y)$, output new optimal $FC(\sigma)$.
Sub-step 2	If it does not exist, judge whether current $FC(\sigma)$ is the global optimal one. Yes, output $FC(\sigma) \sim \mathbf{T}R(j)$; no, turn back to Step 5 and continue searching.
Step 7	Ascend to order $\mathbf{T}R(j) \sim V2(j)$.

Figure 2 is the modeling process of the water tour route recommendation model. Figure 2a shows the generation of each cockroach for the feasible path solution in the water scenic spot subsection. Figure 2b shows the process to search the optimal path in one subsection. Figure 2c shows the generation of each cockroach for the feasible tour route solution in the water scenic spot section. Figure 2d shows the process to search the optimal tour route.

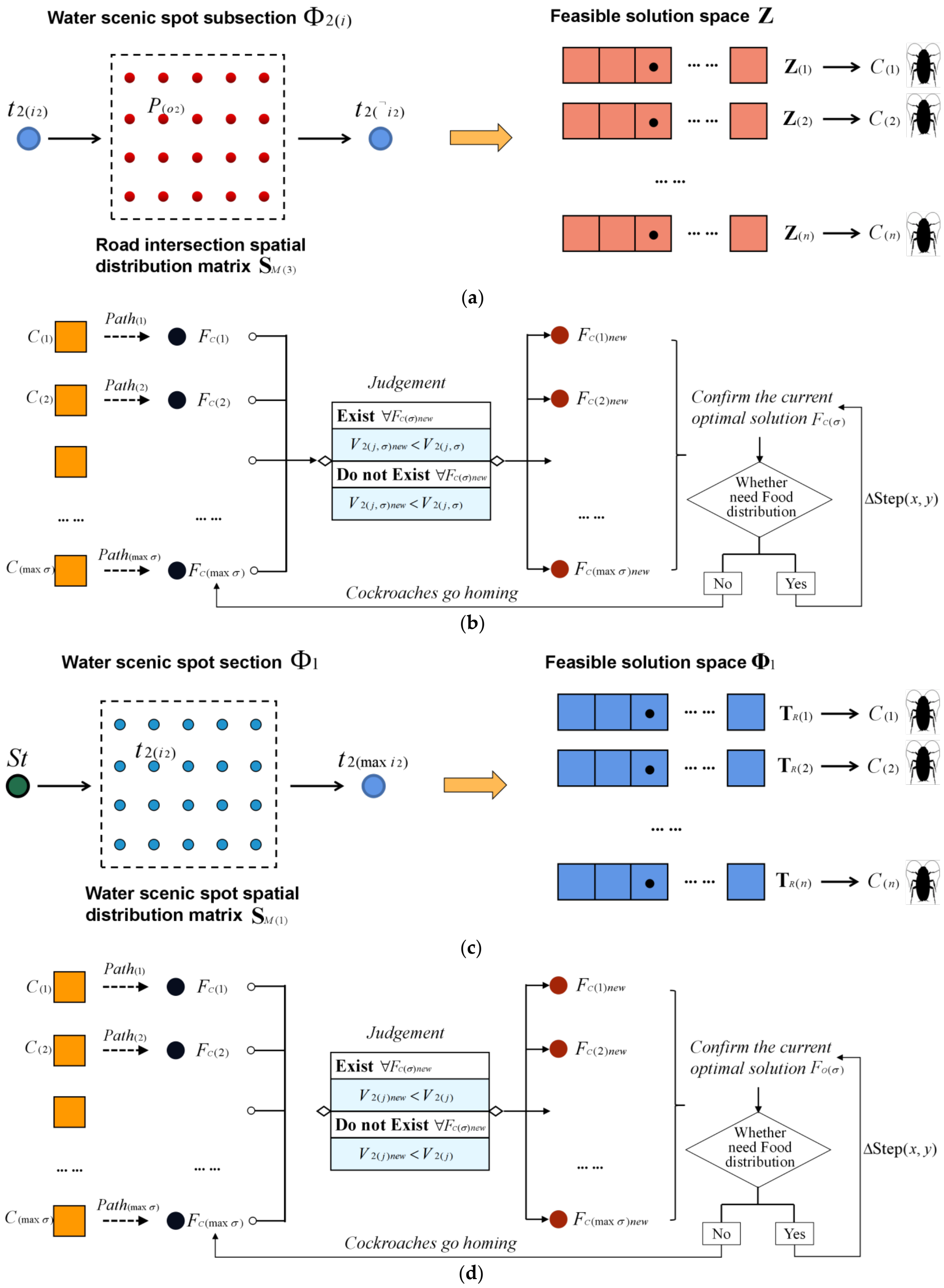


Figure 2. The modeling process of the water ecotourism recommendation model. (**a**) shows the generation of each cockroach for the feasible path solution in the water scenic spot subsection. (**b**) shows the process to search the optimal path in one subsection. (**c**) shows the generation of each cockroach for the feasible tour route solution in the water scenic spot section. (**d**) shows the process to search the optimal tour route.

4. Sample Experiment and Results Analysis

The experiment used the tourism city of Chengdu as the research object, and selected 20 representative water scenic spots in the downtown area of the city. The scenic spots have different functional attributes and can meet the interest needs of different tourists. The experimental principle is as follows: A tourist chooses his favorite once-visited scenic spots, and scores these scenic spots using the percentage system. Then, the evaluation parameters are confirmed. Based on the scenic spot functional attributes, the tourist-demands matrix and the tourist-demands weighted matrix are outputted. By calculating the tourist-needs relative weights, the needs relative weight matrix is obtained. Then, the recommended scenic spot vector is outputted. Based on the vector, the tourist chooses the traffic modes, then the system outputs the water ecotourism route with minimum exhaust emissions through the tour route algorithm. The experiment compares the proposed method with the commonly used route planning methods on maps, and verifies that the proposed method has obvious advantages.

4.1. Experimental Data Sampling and Preprocessing

The sampled urban water scenic spots in Chengdu downtown area were: $t2(1)$: Huanhua Brook; $t2(2)$: East Lake; $t2(3)$: Jincheng Lake; $t2(4)$: Shengxian Lake; $t2(5)$: People's Park: $t2(6)$: Wangjianglou/Funan Lake; $t2(7)$: Sansheng Flower Town; $t2(8)$: Happy Valley; $t2(9)$: Xinzhendi Golf Club; $t2(10)$: Boya Sports Club; $t2(11)$: Fenghuangshan Park; $t2(12)$: Giant Panda Base; $t2(13)$: Qinglong Lake; $t2(14)$: North Lake; $t2(15)$: Chenghua Park; $t2(16)$: International Intangible Cultural Heritage Expo Park; $t2(17)$: Funan River Running Water Park; $t2(18)$: Tazishan Park; $t2(19)$: Shahe Park; and $t2(20)$: Shahe City Park. The input once-visited water scenic spots were: $t1(1)$: Heilongtan Reservoir; $t1(2)$: Hangzhou West Lake; $t1(3)$: Nanjing Xuanwu Lake; $t1(4)$: the Summer Palace; $t1(5)$: Swan Lake in Sanmenxia; $t1(6)$: Guilin scenery; $t1(7)$: Qinghai Lake; and $t1(8)$: Suzhou gardens. Figure 3 shows the distribution of the sampled water scenic spots and the extracted scattered dots. Figure 3a is the sampled water scenic spots distribution. Figure 3b is the extracted scattered dots. Table 1 shows the evaluation parameters $\varepsilon1(i1)$ obtained from the scores of the once-visited water scenic spots. Based on the scenic spot functional attribute base vector $\mathbf{p}i(j)$, Tables 2 and 3 are outputs, in which Table 2 is the tourist-needs weighted matrix and Table 3 is the water scenic spot functional attribute matrix, where the number in its first row represents the serial number j of $p2(j)$.

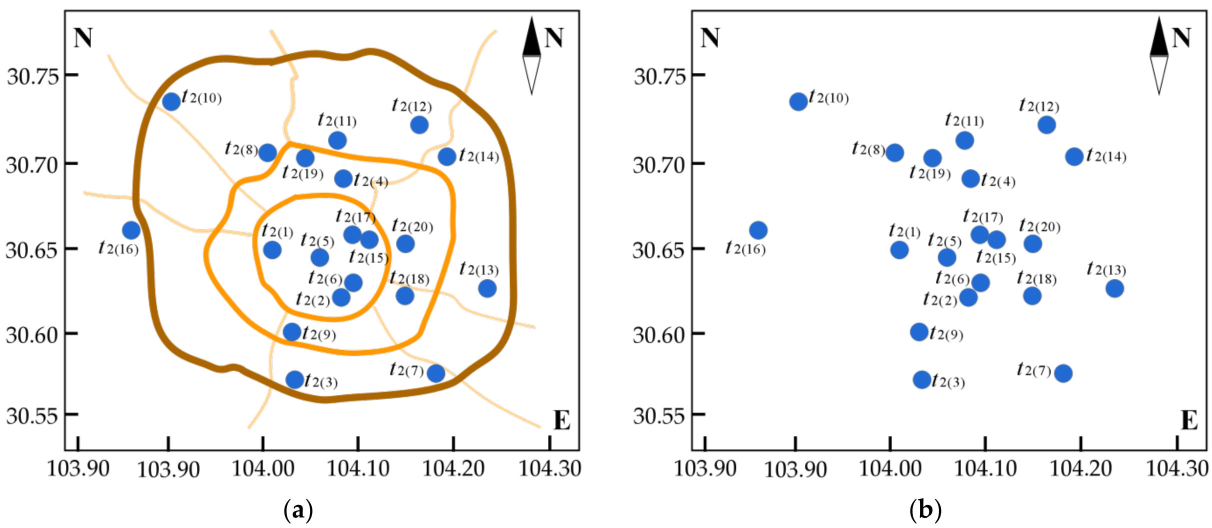


Figure 3. The distribution of the sampled water scenic spots and the extracted scattered dots. (**a**) is the sampled water scenic spots distribution. (**b**) is the extracted scattered dots.

Table 1. Water scenic spot evaluation parameter.

Evaluation parameter	$\varepsilon 1(1)$	$\varepsilon 1(2)$	$\varepsilon 1(3)$	$\varepsilon 1(4)$
Parameter value	0.86	0.66	0.46	0.98
Evaluation parameter	$\varepsilon 1(5)$	$\varepsilon 1(6)$	$\varepsilon 1(7)$	$\varepsilon 1(8)$
Parameter value	0.76	0.92	0.88	0.96

Table 2. Tourist-needs weighted matrix and the once-visited scenic spots functional attribute-weighted evaluation data.

	$\boldsymbol{p}1(1)$	$\boldsymbol{p}1(2)$	$\boldsymbol{p}1(3)$	$\boldsymbol{p}1(4)$	$\boldsymbol{p}1(5)$	$\boldsymbol{p}1(6)$	$\boldsymbol{p}1(7)$	$\boldsymbol{p}1(8)$	$\boldsymbol{p}1(9)$	$\boldsymbol{p}1(10)$
$t1(1)$	0.86	0.00	0.86	0.86	0.86	0.00	0.86	0.86	0.86	0.00
$t1(2)$	0.66	0.66	0.66	0.66	0.66	0.00	0.66	0.66	0.66	0.66
$t1(3)$	0.46	0.46	0.46	0.46	0.46	0.00	0.46	0.46	0.46	0.46
$t1(4)$	0.98	0.98	0.98	0.98	0.00	0.00	0.98	0.98	0.00	0.98
$t1(5)$	0.76	0.00	0.76	0.00	0.00	0.76	0.76	0.00	0.76	0.76
$t1(6)$	0.92	0.92	0.92	0.92	0.92	0.00	0.92	0.92	0.92	0.92
$t1(7)$	0.88	0.00	0.88	0.88	0.00	0.00	0.88	0.88	0.00	0.00
$t1(8)$	0.96	0.96	0.96	0.96	0.00	0.00	0.96	0.00	0.96	0.96

Table 3. Water scenic spot functional attribute matrix.

$\boldsymbol{p}2(j)$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	$\boldsymbol{p}2(j)$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
$t2(1)$	1.0	1.0	0.0	1.0	0.0	1.0	1.0	0.0	1.0	1.0	$t2(11)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0
$t2(2)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	$t2(12)$	1.0	0.0	0	0	0.0	1.0	1.0	0.0	1.0	1.0
$t2(3)$	1.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	$t2(13)$	1.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0
$t2(4)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	$t2(14)$	1.0	0.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	0.0
$t2(5)$	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	$t2(15)$	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0
$t2(6)$	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	$t2(16)$	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0
$t2(7)$	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	$t2(17)$	1.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0
$t2(8)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	$t2(18)$	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	0.0
$t2(9)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	$t2(19)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0
$t2(10)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	$t2(20)$	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0

4.2. The Calculation Data of the Water Scenic Spot Recommendation and the Recommendation Results

According to the tourist's once-visited water scenic spots and interest tendencies, the system calculates and outputs the absolute weight vector $\mathbf{f}(j)$ and relative weight vector $\nabla\mathbf{f}(j)$. By calculating the water scenic spot recommendation function values $ri2(\nabla\mathbf{f}(j), \mathbf{p}2(i2, j))$, the recommendation function matrix $\mathbf{R}*$ is obtained. The top w number of elements in $\mathbf{R}*$ are extracted and stored in vector $\mathbf{T}$. Then, the recommended w number of scenic spots are obtained.

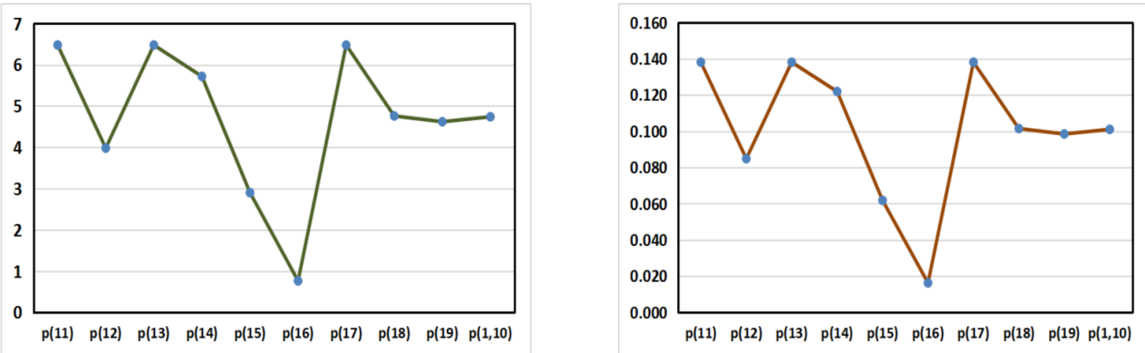
Table 4 shows the needs absolute weight $f(i1, j)$ and relative weight $\nabla f(i1, j)$ obtained from the once-visited water scenic spots. Table 5 shows the calculated recommendation function values of the water scenic spots in Chengdu city. Figure 4 shows the fluctuating histograms for the needs absolute weight $f(i1, j)$ and relative weight $\nabla f(i1, j)$. Figure 4a shows the tourist-needs absolute weight $f(i1, j)$. Figure 4b shows the tourist-needs relative weight $\nabla f(i1, j)$. Figure 5 shows the recommendation function value for each water scenic spot. Figure 5a shows the function values for the water scenic spots $t2(1)$~$t2(10)$. Figure 5b shows the function values for the water scenic spots $t2(11)$~$t2(20)$. According to the algorithm principle, the experiment set the quantity of the scenic spots that will be visited as $w = 4$. The recommendation vector provided by the system was: $\mathbf{T}$: {$t2(4)$, Shengxian Lake; $t2(9)$, Xinzhendi Golf Club; $t2(11)$, Fenghuangshan Park; $t2(20)$, Shahe City Park}.

Table 4. The needs absolute weight $f(i1, j)$ and relative weight $\Delta f(i1, j)$ obtained from the once-visited water scenic spots.

	$p1(1)$	$p1(2)$	$p1(3)$	$p1(4)$	$p1(5)$	$p1(6)$	$p1(7)$	$p1(8)$	$p1(9)$	$p1(10)$
$f(i1, j)$	6.480	3.980	6.480	5.720	2.900	0.760	6.480	4.760	4.620	4.740
$\nabla f(i1, j)$	0.138	0.085	0.138	0.122	0.062	0.016	0.138	0.101	0.098	0.101

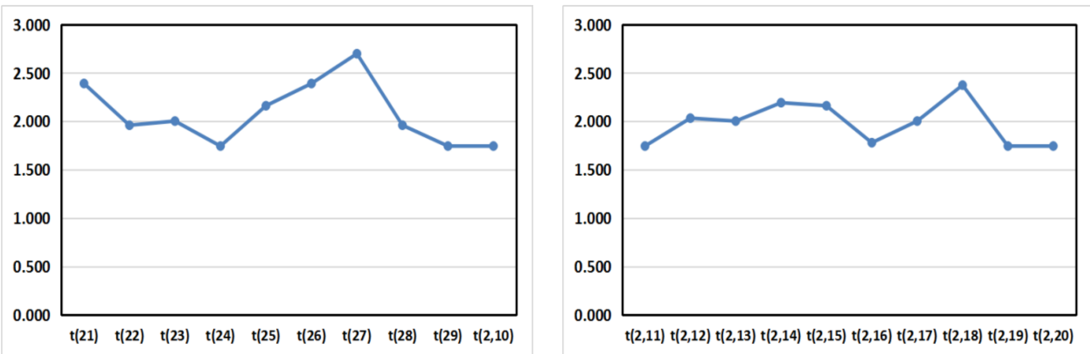
Table 5. Recommendation function value *ri*2 of each water scenic spot.

	$t2(1)$	$t2(2)$	$t2(3)$	$t2(4)$	$t2(5)$
$ri2$	2.391	1.959	2.002	1.744	2.161
	$t2(6)$	$t2(7)$	$t2(8)$	$t2(9)$	$t2(10)$
$ri2$	2.391	2.699	1.959	1.744	1.744
	$t2(11)$	$t2(12)$	$t2(13)$	$t2(14)$	$t2(15)$
$ri2$	1.744	2.033	2.002	2.193	2.161
	$t2(16)$	$t2(17)$	$t2(18)$	$t2(19)$	$t2(20)$
$ri2$	1.779	2.002	2.374	1.744	1.744



(**a**) (**b**)

Figure 4. The fluctuating histograms for the needs absolute weight $f(i1, j)$ and relative weight $\nabla f(i1, j)$. (**a**) shows the tourist-needs absolute weight $f(i1, j)$. (**b**) shows the tourist-needs relative weight $\nabla f(i1, j)$.



(**a**) (**b**)

Figure 5. The recommendation function value for each water scenic spot. (**a**) shows the function values for the water scenic spots $t2(1)$~$t2(10)$. (**b**) shows the function values for the water scenic spots $t2(11)$~$t2(20)$.

4.3. The Recommendation Results and the Comparison Results of the Water Tour Routes

According to the vector **T**: {$t2(4)$: Shengxian Lake; $t2(9)$: Xinzhendi Golf Club; $t2(11)$: Fenghuangshan Park; $t2(20)$: Shahe City Park}, the tourist chooses the transportation modes $Tm(i)$ for each subsection and the system confirms the traffic mode vector $\mathbf{T}m$. Then, the system confirms the specific transportation tool for each subsection according to the vector $\mathbf{T}m$, and the unit of waste gas emission volume $Vm(i)$ for each transportation mode $Tm(i)$ is confirmed. The proposed improved cockroach algorithm is used to search the optimal path among the scenic spots, calculate the subsection's minimum exhaust emission volume, and search the optimal tour route in the space Φ1.

In order to verify the advantages of the proposed algorithm, the experiment set the proposed algorithm as the experimental group. Then, two electronic maps that are commonly used as tools to plan tour routes were set as the control group; they awe 360 map and Baidu map. The three methods are noted as PRA(Proposed Algorithm), 360A(360 map Algorithm), and BDA(BaiDu map Algorithm), in which PRA stands for the proposed tour route planning algorithm used in the research, 360A stands for the tour route planning method that used the 360 electronic map of China, and BDA stands for the tour route planning method that used the Baidu electronic map of China. Under the same experimental conditions and the same transportation mode vector $\mathbf{T}m$, the minimum exhaust emission tour routes were searched and found by the three methods. Then, the gas volumes of the tour routes were calculated. Table 6 shows the transportation modes chosen by the tourist in accordance with the recommended scenic spots. In the table, the transportation modes were: $Tm(1)$: public bus, $Tm(2)$: taxi, $Tm(5)$: shared bike. The unit of exhaust emission volume was valued by the commonly used type of fuel bus, five seater taxi, and shared motorcycle, where $Tm(1) \sim Vm(1)$: 1.05 kg; $Tm(2) \sim Vm(2)$: 0.190 kg; and $Tm(5) \sim Vm(5)$: 0.00 kg. The starting point St for the three methods was Tianfu Square in Chengdu city. Table 7 shows the exhaust emission volumes for each scenic spot subsection and for the entire tour routes for the three methods under the same experimental conditions (unit: kg). Figure 6 shows the comparisons of the exhaust emission volumes for each scenic spot subsection and for the entire tour routes for the three methods (unit: kg). The blue column stands for PRA, red column stands for 360 A, and green column stands for BDA. Figure 6a–c are the comparison results for water tour route 1, route 2, and route 3, respectively. Figure 7 shows the differences of the exhaust emission volumes of the three tour routes in each subsection and the entire tour route between 360A and PRA, and between BDA and PRA. The blue column stands for the difference between 360A and PRA, whereas the red column stands for the difference between BDA and PRA. Figure 7a–c are the comparison results for water tour route 1, route 2, and route 3, respectively.

Table 6. The transportation modes chosen by the tourist in accordance with the recommended scenic spots.

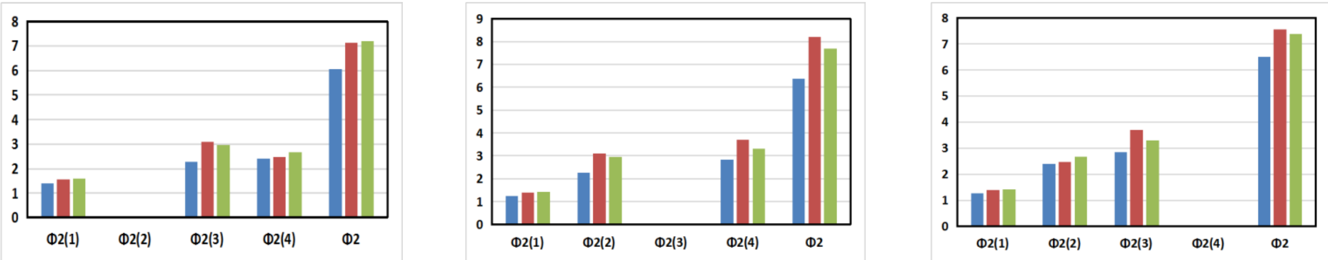
	St	$t2(4)$	$t2(9)$	$t2(11)$	$t2(20)$
St	–	$Tm(2)$	$Tm(1)$	$Tm(2)$	$Tm(2)$
$t2(4)$	$Tm(2)$	–	$Tm(2)$	$Tm(5)$	$Tm(1)$
$t2(9)$	$Tm(1)$	$Tm(2)$	–	$Tm(2)$	$Tm(2)$
$t2(11)$	$Tm(2)$	$Tm(5)$	$Tm(2)$	–	$Tm(2)$
$t2(20)$	$Tm(2)$	$Tm(1)$	$Tm(2)$	$Tm(2)$	–

Table 7. The waste gas emission volumes for each scenic spot subsection and for the entire tour routes for the three methods under the same experimental conditions (unit: kg).

	Water Tour Route	Method	Tour Route Subsection $\Phi2(i)$/Transportation Mode				Tour Route Section Φ2
			$Stt2(4)/Tm(2)$	$t2(4)t2(11)/Tm(5)$	$t2(11)t2(20)/Tm(2)$	$t2(20)t2(9)/Tm(2)$	
1	$St - t2(4) - t2(11)$ $-t2(20) - t2(9)$	PRA	1.406	0.000	2.261	2.394	6.061
		360A	1.558	0.000	3.097	2.470	7.125
		BDA	1.596	0.000	2.945	2.660	7.201

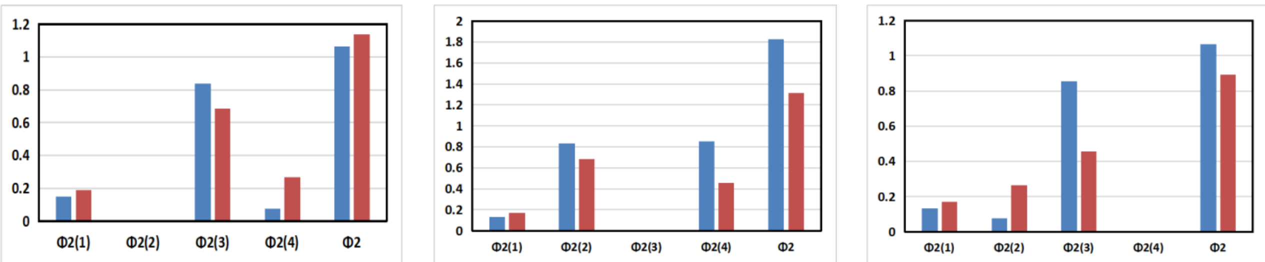
Table 7. *Cont.*

	Water Tour Route	Method	Tour Route Subsection $\Phi2(i)$/Transportation Mode				Tour Route Section $\Phi2$
2	$St-t2(20)-t2(11)$ $-t2(4)-t2(9)$		$Stt2(20)/Tm(2)$	$t2(20)t2(11)/Tm(2)$	$t2(11)t2(4)/Tm(5)$	$t2(4)t2(9)/Tm(2)$	
		PRA	1.254	2.261	0.000	2.850	6.365
		360A	1.387	3.097	0.000	3.705	8.189
		BDA	1.425	2.945	0.000	3.306	7.676
3	$St-t2(20)-t2(9)$ $-t2(4)-t2(11)$		$Stt2(20)/Tm(2)$	$t2(20)t2(9)/Tm(2)$	$t2(4)t2(9)/Tm(2)$	$t2(11)t2(4)/Tm(5)$	
		360A	1.254	2.394	2.850	0.000	6.498
		BDA	1.387	2.470	3.705	0.000	7.562
		PRA	1.425	2.660	3.306	0.000	7.391



(**a**) (**b**) (**c**)

Figure 6. The comparisons of the waste gas emission volumes for each scenic spot subsection and for the entire tour routes for the three methods (unit: kg). Blue column is PRA, red column is 360A, green column is BDA. (**a**–**c**) are the comparison results for water tour route 1, route 2, and route 3, respectively.



(**a**) (**b**) (**c**)

Figure 7. The differences of the waste gas emission volumes of the three tour routes in each subsection and the entire tour route between 360A and PRA, and between BDA and PRA. Blue column is the difference between 360A and PRA, red column is the difference between BDA and PRA. (**a**–**c**) are the comparison results for water tour route 1, route 2, and route 3, respectively.

4.4. Experiment Results Analysis and Findings

Of the three aspects of data sampling and processing, the calculation data and results of the water scenic spot recommendation, water tour route recommendation results and comparison results, and the experimental results were analyzed and related conclusions were obtained.

(1) The analysis and findings of the data sampling and processing.

The sampled water scenic spots were analyzed. The water scenic spots are all representative ones in the Chengdu downtown area, and each scenic spot has all-around functional attributes. They were related to the functional attribute base vectors.

① Finding one: the sampled water scenic spots had strong accessibility.

As seen from Figure 3, the water scenic spots were uniformly distributed, which meets the requirements of tourists on selecting scenic spots. There were no scenic spots that were too far away from the city center and difficult for tourists to travel to. Therefore, the accessibility of the sampled water scenic spots is strong.

② Finding two: the inputted once-visited water scenic spots reflected the tourist's interest tendencies.

Analyzing the data in Table 1, tourists had different preferences in regard to the once-visited scenic spots. They had the greatest preference for $t1(4)$: the Summer Palace, followed by $t1(8)$: Suzhou gardens and $t1(6)$: Guilin landscapes; the lowest preference was for $t1(3)$: Nanjing Xuanwu Lake. It shows that the collected once-visited scenic spots, regarded as the original data for constructing the recommendation algorithm in this paper, can reflect the different interest tendencies of tourists and ensure that the recommendation algorithm can output the matched scenic spots.

③ Finding three: the functional attribute-weighted value influenced the attribute's capacity for regulating the recommendation result.

Analyzing the data in Table 2, it can be seen that based on the evaluation parameters of the once-visited water scenic spots and the scenic spot functional attribute base vector, the tourist-needs weighted matrix was outputted, and the matrix element values were the weighted evaluation parameters of the once-visited water scenic spot functional attributes. The functional attribute values of different scenic spots vary with the changes of the water scenic spot evaluation parameters, indicating that the weighted functional attributes of a scenic spot have different intensity effects on the recommendation results. The larger the weighted value is, the greater the effect will be on the recommendation results of the functional attributes related to the weighted value, and vice versa.

④ Finding four: the sampled water scenic spots have different capacities for satisfying the same tourist's interests.

Analyzing the data in Table 3, the sample water scenic spots had different functional attribute vectors and element values, indicating that the capacities of the scenic spots to meet the needs of the same tourist are quite different, and the samples selected in the experiment were diverse. For a scenic spot, the larger the quantity of the element 1 is, the more comprehensive the scenic spot's functional attributes will be, and more probable that it can meet the tourists' needs.

(2) The analysis and findings of the calculation data and results of the water scenic spot recommendation.

① Finding one: the tourist-needs absolute weights and relative weights directly influenced the recommending results of the functional attributes.

Analyzing the data in Table 4 and the comparison chart in Figure 4, it can be seen that the tourist-needs absolute weights and relative weights are different for the once-visited scenic spots. The three functional attributes of $pi(1)$: viewing the water natural scenery, $pi(3)$: water sports, and $pi(7)$: water scenery photography had the highest weight value, which can be interpreted as the three interests meeting the largest proportion of the tourist's needs, and meaning the tourist is more likely to visit the scenic spots that have the three functional attributes. The functional attribute of $pi(6)$: watching water birds had the lowest weight value, which can be interpreted to mean that the tourist has the lowest need for this attribute. When recommending scenic spots, the absolute weights and relative weights both have important influence, and they directly impact the recommendation results.

② Finding two: the recommendation function values had direct influence on the recommending results of the water scenic spots.

Analyzing the data in Table 5 and the comparison chart in Figure 5, it can be seen that the recommendation function values $ri2$ outputted by the tourist-needs weight and water scenic spots were greatly different. From the water scenic spot $t2(1)$ to $t2(20)$, the function values fluctuated with the scenic spot sequence, in which the scenic spots $t2(4)$, $t2(9)$, $t2(10)$, $t2(11)$, $t2(19)$, and $t2(20)$ had the smallest function value; that is, these scenic spots were close to the tourist's needs. The recommendation system preferentially provided the scenic spots for the tourist.

(3) The analysis and findings of the water tour route recommendation and comparison results.

① Finding one: the choice of transportation mode directly influenced the exhaust emission volume, and the three algorithms produced different exhaust emission volumes.

Analyzing the data in Table 6 and the comparison chart in Figure 6, it can be seen that there were great differences in the transportation modes among scenic spots selected by tourists according to the recommended results. For those distant scenic spots, tourists tend to take taxis, for scenic spots with moderate distance, tourists tend to take buses, and for those nearby scenic spots, tourists tend to use shared motorcycles. Three optimal tour routes with the lowest exhaust emissions were outputted. The route with the lowest exhaust emissions was $Stt2(4)t2(11)t2(20)t2(9)$, followed by $Stt2(20)t2(11)t2(4)t2(9)$ and $Stt2(20)t2(9)t2(4)t2(11)$.

As for the same tour route, the exhaust emissions of the three algorithms varied in different subsections. They fluctuated up and down with the order of the scenic spots' sequence and the process of sightseeing, and were directly affected by the transportation modes. In the same subsection, the exhaust emissions outputted by the three algorithms were quite different, resulting in great differences of total gas emissions for the whole tour route. According to the transportation modes selected by tourists, when choosing the shared bicycle the exhaust emissions of the tour route is 0, which is the most environmentally friendly way of traveling, but the time cost is the highest.

② Finding two: As to the three recommended tour routes, the PRA produced the lowest exhaust emissions for each subsection and for the whole tour route. Thus, the PRA is superior to the control group algorithms BDA and 360A in the aspect of producing exhaust gases.

(I) Tour route 1:$Stt2(4)t2(11)t2(20)t2(9)$

The subsections with the largest and smallest waste gas generated by PRA were $t2(20)t2(9)/Tm(2)$ and $t2(4)t2(11)/Tm(5)$, respectively. The subsections with the largest and smallest waste gas generated by 360A were $t2(11)t2(20)/Tm(2)$ and $t2(4)t2(11)/Tm(5)$, respectively, and the subsections with the largest and smallest waste gas generated by BDA were $t2(11)t2(20)/Tm(2)$ and $t2(4)t2(11)/Tm(5)$, respectively. In the same subsection, PRA produced the smallest amount of exhaust gas, with both 360A and BDA producing more exhaust gas than PRA. BDA produced the largest amount of exhaust gas in the subsections $Stt2(4)/Tm(2)$ and $t2(20)t2(9)/Tm(2)$, and 360A produced the largest amount of exhaust gas in the subsection $t2(11)t2(20)/Tm(2)$. For the whole tour route, PRA produced the smallest amount of waste gas, whereas BDA produced the largest amount of waste gas.

(II) Tour route 2: $Stt2(20)t2(11)t2(4)t2(9)$

The subsections with the largest and smallest waste gas generated by PRA were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively. The subsections with the largest and smallest waste gas generated by 360A were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively, and the subsections with the largest and smallest waste gas generated by BDA were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively. In the same subsection, PRA produced the smallest amount of exhaust gas, with both 360A and BDA producing more exhaust gas than PRA. BDA produced the largest amount of exhaust gas in the subsection $Stt2(20)/Tm(2)$, and 360A produced the largest amount of exhaust gas in the subsections $t2(20)t2(11)/Tm(2)$ and $t2(4)t2(9)/Tm(2)$. For the whole tour route, PRA produced the smallest amount of waste gas, whereas 360A produced the largest amount of waste gas.

(III) Tour route 3: $Stt2(20)t2(9)t2(4)t2(11)$

The subsections with the largest and smallest waste gas generated by PRA were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively. The subsections with the largest and smallest waste gas generated by 360A were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively, and the subsections with the largest and smallest waste gas generated by BDA were $t2(4)t2(9)/Tm(2)$ and $t2(11)t2(4)/Tm(5)$, respectively. In the same subsection, PRA produced the smallest amount of exhaust gas, with both 360A and BDA producing more exhaust gas than PRA. BDA produced the largest amount of exhaust gas in the subsections $Stt2(20)/Tm(2)$ and $t2(20)t2(9)/Tm(2)$, and 360A produced the largest amount of exhaust gas in the subsection $t2(4)t2(9)/Tm(2)$. For the whole tour route, PRA produced the smallest amount of waste gas, whereas 360A produced the largest amount of waste gas.

③ Finding three: the control group algorithms BDA and 360A produced more exhaust gases than PRA, and the different volume values between the control group algorithms and PRA were different in each subsection, reaching the maximum for the whole tour route.

Analyzing the comparison diagram in Figure 7, it can be seen that the exhaust emission volumes of 360A and BDA in each subsection of the three tour routes were larger than PRA, and the difference values between PRA and 360A and between PRA and BDA fluctuated with the subsection's sequence. In each scenic spot subsection, for the first tour route, the maximum difference value between PRA and 360A appeared at $t2(11)t2(20)/Tm(2)$, and the maximum difference value between PRA and BDA appeared at $t2(11)t2(20)/Tm(2)$. For the second tour route, the maximum difference value between PRA and 360A appeared at $t2(4)t2(9)/Tm(2)$, and the maximum difference value between PRA and BDA appeared at $t2(20)t2(11)/Tm(2)$. For the third tour route, the maximum difference value between PRA and 360A appeared at $t2(4)t2(9)/Tm(2)$, and the maximum difference value between PRA and BDA appeared at $t2(4)t2(9)/Tm(2)$. Each algorithm had the maximum difference value between PRA and 360A and between PRA and BDA for the total tour route.

In conclusion, 360A and BDA are inferior to PRA in the capacity of planning low-carbon tour routes. PRA is relatively more stable. It can find the tour route with the shortest distance and the lowest exhaust emissions, indicating that PRA has better performance and advantages than 360A and BDA in outputting low-carbon tour routes. In each algorithm, the transportation mode had a direct impact on the subsection's exhaust emissions, the entire tour route exhaust emissions, and the process of outputting the optimal tour route. In this experiment, the tourist chose $Tm(1)$: public bus as the transportation mode in the subsections $Stt2(9)$ and $t2(4)t2(20)$; thus, the gas emission volume of the tour routes containing the two subsections was very large, and the optimal tour route did not contain the two subsections $Stt2(9)$ and $t2(4)t2(20)$. If the tourist chooses $Tm(5)$: the shared motorcycle as the transportation mode in the subsection $t2(4)t2(11)$, the gas volume produced by a motorcycle will be 0; thus, the optimal tour route must contain the subsection $t2(4)t2(11)$. Since different transportation modes have different unit emissions $Vm(1)$, PRA integrates the transportation modes $Tm(i)$ selected by tourists in different subsections when searching the tour route. Therefore, the searched tour route is always based on the aim of searching for the lowest exhaust emissions for the entire tour route rather than searching for the shortest distance, which reflects the core idea of the proposed algorithm in the research.

(4) The predicted and long term effects of the proposed algorithm.

Another important finding is the predicted and long-term effects of the proposed algorithm. Since the experiment reflects one sample tourist's example, it could be interpreted that one tourist's traveling activities will produce exhaust emissions, and to some extent cause damage to the urban water ecosystem. Based on the fact that there are about 200 million tourists and local residents visiting the water scenic spots in Chengdu every year, if the tour routes and transportation modes recommended in this research are used, the exhaust emissions would be reduced by hundreds of thousands of tons. On the basis of meeting the tourists' traveling experiences and needs, the proposed method can reduce the damage to the urban water scenic spots and water resources, and protect the urban water ecological environments.

5. Conclusions

Focusing on the aim of protecting the urban water ecological environments and water resources, taking water ecotourism as the research object, and considering the phenomenon that a large number of tourists use different transportation modes in the traveling process, a water ecotourism route recommendation model based on an improved cockroach optimization algorithm was proposed. This research analyzed the impact of tourism activities on the urban ecological environments and water resources, especially the fact that the exhaust emissions from tourism transportation cause damage to the urban ecological environments. In this research, the proposed algorithm took a tourist's once-visited scenic spots and their evaluation parameters as the original data to find out the tourist's interests. Based on the tourist's interests, the to-be-visited urban water scenic spots were recommended. In order to reduce the exhaust emissions generated by the ferrying process in tourism activities and protect the urban water ecological environments, a water ecotourism route recommendation model was proposed. It searches for the path with the lowest exhaust emissions among scenic spots based on the subsection transportation mode, and outputs the tour routes with the globally lowest exhaust emissions. A sample experiment was carried out, based on the tourist's interests, and the low-carbon water tour routes in Chengdu city were outputted. The comparative experiment shows that the proposed algorithm is superior to the control group algorithms in regard to the aspect of producing exhaust emissions. On the basis of meeting tourists' traveling needs, it could effectively reduce the exhaust emissions and protect the urban water ecological environments and water resources.

Compared with the methods in the relevant scientific literature, the proposed algorithm uses novel and original ideas and methods. It is summarized as follows.

(1) Compared with [6], the novelty and originality of the proposed algorithm is that it recommends specific scenic spots according to tourists' interests. In [6], only the optimal traveling traffic routes between two cities were studied, but not the scenic spots in an accessible area involving urban traffic modes. In addition, [6] mainly studied the traffic route, whereas the proposed algorithm tends to find out the optimal tour route with the lowest exhaust emissions. Furthermore, [6] does not consider the route nodes between two cities, whereas the proposed algorithm sets up an improved cockroach optimization to search the optimal tour route along the recommended scenic spot route; between two scenic spots, the proposed algorithm is also able to search along the road nodes. Thus, the proposed algorithm is better suitable for accessible areas involving urban traffic modes.

(2) Compared with [7] and [8], the novelty and originality of the proposed algorithm is the specific recommendations in regard to the scenic spots and tour route. In [7], the tour routes in the range of the whole Qinghai province were studied, and all 35 road nodes that form traffic routes were connected. In [8], the tour routes in the range of the whole Hebei province were studied, and all 63 tour nodes to form the traffic routes were connected. The method used in [6] and [7] is a theoretical and idealized mode. In the proposed algorithm, the tourists' interests are used to find the most matched scenic spots, and then the recommended scenic spots are used as the nodes to find the lowest exhaust emission route. It is more practical and accurate for travel route searching.

(3) Compared with [9], the novelty and originality of the proposed algorithm is the acquisition method of the tourists' requirements and interests. In [9], big data was used to find out the tourists' interests, but big data cannot represent one specific tourist's requirements. The proposed algorithm finds out a tourist's interests by inputting the object tourist's once-visited scenic spots, and through the evaluation parameters, the interest tendency is accurately confirmed. Meanwhile, scenic spots' attributes are set as the factors for the proposed algorithm, which ensure that the recommended scenic spots match the tourist's interests.

(4) Compared with [10], the novelty and originality of the proposed algorithm is the choice motivation regarding the traffic mode. In [10], the study tried to find out the factors that influence tourists' choice motivation when choosing a traveling traffic mode; for instance, behavior, code of conduct, traffic policy, etc. The proposed method aims to find out the optimal tour route with the lowest exhaust emissions using a random choice for traffic mode. The proposed algorithm is better suitable for actual traveling circumstances.

(5) Compared with [11], the novelty and originality of the proposed algorithm is the tour route searching method. In [11], the research set out to find out a proper method to

optimize tourism traffic planning. The proposed algorithm provides a method to search the optimal traveling traffic route with the lowest exhaust emissions. It lays emphasis on the specific algorithm process, whereas [11] tended to interpret the strategies and solutions.

In future research work, the working group will carry out further in-depth research on the following two aspects: First, in regard to the urban water ecotourism research, its spatial scope and research object will be constrained to the water scenic spots within the downtown area. In the next step, the research will further expand the spatial scope and research object, bringing the water scenic spots and tourism resources within the downtown area and the whole administrative area into the research scope, and study the green and low-carbon water tour routes within the whole city and surrounding counties. Second, based on the expanded research scope, tourism transportation modes are not limited to public buses, taxis, and shared bicycles in the downtown area. More transportation modes such as intercity rail transit, intercity buses, railways, and long-distance buses should be considered. In the next step, further in-depth research will be made for the recommendation of cross-region traveling, as well as low-carbon tour routes.

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References

1. Wang, J.; Li, Y.; Zhang, Y. Research on Carbon Emissions of Road Traffic in Chengdu City Based on a LEAP Model. *Sustainability* **2022**, *14*, 5625. [CrossRef]
2. Sun, Y.; Liu, S.; Li, L. Grey Correlation Analysis of Transportation Carbon Emissions under the Background of Carbon Peak and Carbon Neutrality. *Energies* **2022**, *15*, 3064. [CrossRef]
3. Chen, Y.; Xie, C.; Jiang, R.; Che, S. Optimization of Ecosystem Services of Shanghai Urban–Suburban Street Trees Based on Low-Carbon Targets. *Sustainability* **2021**, *13*, 13251. [CrossRef]
4. Jo, H.; Kim, H. Developing a Traffic Model to Estimate Vehicle Emissions: An Application in Seoul, Korea. *Sustainability* **2021**, *13*, 9761. [CrossRef]
5. Moffatt, D.; Dia, H. Development and Evaluation of Simulation-Based Low Carbon Mobility Assessment Models. *Future Transp.* **2021**, *1*, 134–153. [CrossRef]
6. Chen, J. Title Research on the Optimization of Tourist Traffic Routes in Beijing, Tianjin and Hebei Province Starting form Beijing and Tianjin. *Tianjin Soc. Insur.* **2019**, *2*, 71–81.
7. Liu, M.J. Study on the Design of Road Transportation and Tourism in Qinghai Province. Master's Thesis, Qinghai Normal University, Xining, China, April 2017.
8. Zhang, S.L. Evaluation of Accessibility of the Tourism Node and Study on Optimization of Tour-Routes in Hebei Province. Master's Thesis, Hebei Normal University, Shijiazhuang, China, May 2015.
9. Feng, X.Y. Research on Urban Tourism Bus Route Planning Based on Multi Source Data. Master's Thesis, Xi'an University of Architecture and Technology, Xian, China, April 2021.

10. Bai, S.Q. Study on the Impact Mechanism of Green Transportation Mode Choice for Tourists—A Case Study of Beijing. Master's Thesis, Beijing Jiaotong University, Beijing, China, June 2020.
11. Zhang, H.H. Study on sea island tourism traffic planning based on green traffic theory—Take Qingdao Hengtian island as an example. *House* **2020**, *13*, 8.
12. Bobadilla, J.; Dueñas, J.; Gutiérrez, A.; Ortega, F. Deep Variational Embedding Representation on Neural Collaborative Filtering Recommender Systems. *Appl. Sci.* **2022**, *12*, 4168. [CrossRef]
13. Cui, L.; Wang, X. A Cascade Framework for Privacy-Preserving Point-of-Interest Recommender System. *Electronics* **2022**, *11*, 1153. [CrossRef]
14. Sarkar, M.; Roy, A.; Agrebi, M.; AlQaheri, H. Exploring New Vista of Intelligent Recommendation Framework for Tourism Industries: An Itinerary through Big Data Paradigm. *Information* **2022**, *13*, 70. [CrossRef]
15. Wang, X.; Liu, Y.; Zhou, X.; Wang, X.; Leng, Z. A Point-of-Interest Recommendation Method Exploiting Sequential, Category and Geographical Influence. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 80. [CrossRef]
16. Nguyen, L.; Hong, M.; Jung, J.; Sohn, B. Cognitive Similarity-Based Collaborative Filtering Recommendation System. *Appl. Sci.* **2020**, *10*, 4183. [CrossRef]
17. Tsushima, H.; Matsuura, T.; Ikeguchi, T. Searching Strategies with Low Computational Costs for Multiple-Vehicle Bike Sharing System Routing Problem. *Appl. Sci.* **2022**, *12*, 2675. [CrossRef]
18. Sajid, M.; Singh, J.; Haidri, R.; Prasad, M.; Varadarajan, V.; Kotecha, K.; Garg, D. A Novel Algorithm for Capacitated Vehicle Routing Problem for Smart Cities. *Symmetry* **2021**, *13*, 1923. [CrossRef]
19. Khamsing, N.; Chindaprasert, K.; Pitakaso, R.; Sirirak, W.; Theeraviriya, C. Modified ALNS Algorithm for a Processing Application of Family Tourist Route Planning: A Case Study of Buriram in Thailand. *Computation* **2021**, *9*, 23. [CrossRef]
20. Chen, R.; Liu, X.; Miao, L.; Yang, P. Electric Vehicle Tour Planning Considering Range Anxiety. *Sustainability* **2020**, *12*, 3685. [CrossRef]
21. Yu, F.; Lee, P.; Ku, P.; Wang, S. A Theme Park Tourist Service System with a Personalized Recommendation Strategy. *Appl. Sci.* **2018**, *8*, 1745. [CrossRef]
22. Hua, C.; Niu, R.; Yu, B.; Zheng, X.; Bai, R.; Zhang, S. A Global Path Planning Method for Unmanned Ground Vehicles in Off-Road Environments Based on Mobility Prediction. *Machines* **2022**, *10*, 375. [CrossRef]
23. Haider, S.; Nauman, A.; Jamshed, M.; Jiang, A.; Batool, S.; Kim, S. Internet of Drones: Routing Algorithms, Techniques and Challenges. *Mathematics* **2022**, *10*, 1488. [CrossRef]
24. Lao, G. Optimization Method of Tourist Route in Peak Period Based on Ant Colony Algorithm. *Comput. Simul.* **2022**, *37*, 353–357.
25. Damos, M.; Zhu, J.; Li, W.; Hassan, A.; Khalifa, E. A Novel Urban Tourism Path Planning Approach Based on a Multiobjective Genetic Algorithm. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 530. [CrossRef]
26. Duan, L. A Prediction Model of Tourist Attractions Based on Neural Network Optimized by Particle Swarm Algorithm. *Microcomput. Appl.* **2020**, *36*, 154–156.
27. Li, J.; Li, X.; Jiang, J.; Yu, N. Application of Improved Simulated Annealing Algorithm in Tourism Route Customization. *Sci. Technol. Eng.* **2020**, *20*, 10808–10814.