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Research Article

Analysis and Study on Intelligent Tourism Route Planning Scheme Based on Weighted Mining Algorithm

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In order to study the intelligent tourism route planning scheme based on a weighted mining algorithm, firstly, a traveling salesman problem based on an improved weighted mining algorithm is proposed. Then, based on the traveling salesman problem, the constraints of travel time and driving time are added, and the mathematical model aiming at the minimum number of travel days is established. The improved weighted mining algorithm is used to solve the model: firstly, the scenic spots are divided into regions according to provinces and solved; then, the regions of some scenic spots are modified and solved again according to the solution results, and the specific itinerary is given; finally, based on the route planning problem and considering a variety of transportation modes, a double objective mathematical model with the optimal tourism cost and the best tourism experience is established. When solving, the double objective is reasonably transformed into a single objective, the model is solved by comprehensively considering the tourism cost and tourism experience, and the specific schedule is given according to the solution results.

1. Introduction

With the development of the national economy and the continuous improvement of people's livelihoods, tourism is gradually becoming an integral part of people's lives and entertainment, and tourism is becoming a national industry. With the development of tourism, the diet of tourists has changed significantly, and the demand for quality work has increased. As a new heavy-duty, pollution-free industry, the trip is known as the "smokeless industry" and "eternal industry," and in 1990, it became the world's largest economy. With economic growth, people's incomes and lives have improved, and the economy has developed rapidly. With government support, it has become a new pillar. Tourism has become the first choice for many people to have fun and relax. In addition to promoting and enforcing tourism laws, the popularity of the Internet and the ease of access to information have gradually reduced the role of travel agencies, and more and more people are choosing to travel for free. Many travel websites, forums, and applications provide users with a wealth of information and an interactive platform that allows users to view, select, and plan [1, 2]. At the same time, people can easily share photos, thoughts, and behaviors while walking and share apps with others.

This contradicts the fundamentals that must convey the concept of smart marketing (Figure 1). Knowledge tourism refers to the use of new technologies such as weather, big data, and intelligence to provide a wide range of services to tourists via the Internet/mobile Internet and smartphones, tablets, and other devices [3]. The concept of intellectual tourism has been recognized and supported by the government. As for the topic of tourism, there is always food, accommodation, travel, trade, and entertainment. As an important part of tourism, tourism influences people to travel for their well-being. This line includes items such as travel equipment selection and travel package design. Traveler travels most of the time, and travel costs make up the bulk of the trip. Therefore, a good travel plan can save a lot of time and money on travel [4].

The services provided by these existing tourism plans also have some shortcomings. There are two big problems. First of all, the growth of the tourism sector has supported the development of self-guided tours, self-guided tours, and other self-help services, and the tourism sector has become a

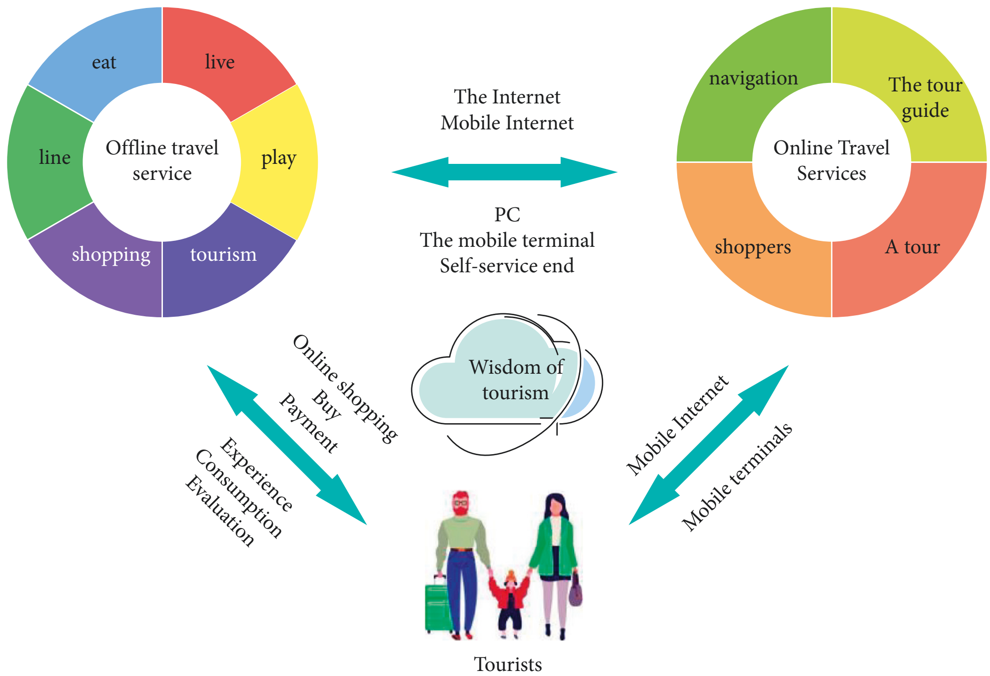

Figure 1: Intelligent tourism.

new tourist destination. However, all of the planned benefits of the existing process are provided by facilities such as commercial companies and dormitories, travel tools. The details of the tourism product are all planned and made for the return trip to the place, the scenic places to travel along the road, and the nearby hotels. It is done by a travel agency, and most consumers are not able to do it and participate in the planning and creation of this topic. Even on the Internet, netizens have begun to help with their own travel. The current situation of independent tourism planning is the gap between digitalization and the introduction of the tourism industry, and new research is needed to fill the gap [5].

The purpose of this topic is to study the smart tourism route through the method of weighted algorithm. First, it further enriches the research content of data mining and intelligent tourism route management. Through theoretical analysis, route management planning, and data mining analysis scheme design, it explores the application of data mining in route management in real tourism service platform and software, further expands the research scope of data mining, and enriches the research content of route data management in the tourism service software. Second, it further promotes the application and development of data mining technology of route management in tourism service software [6]. Specifically, using the weighted algorithm, combined with an example, it analyzes the practicability of the data weighted algorithm for smart tourism route management, verifies the importance of data mining, and provides a theoretical basis and reference measures for the application and development of route information data mining technology in other types of tourism service software, so as to promote the development of smart tourism service software route management.

2. Literature Review

Huang et al. point out that, in the current intelligent tourism, by mining the photo set with Geotag information, we can get information such as urban scenic spot area and user interest preference and use this information to provide users with personalized scenic spot recommendation services. For geophotos (photos with geographical labels), the scenic spot area is extracted by using DBSCAN (density-based spatial clustering of applications with noise) clustering algorithm, and the user's scenic spot interest matrix and scenic spot area heat vector are established. A BIPM (based on interest popularity and month) personalized scenic spot recommendation algorithm based on user preference, photo time context, and scenic spot area heat is proposed to build a personalized scenic spot recommendation model [7]. Peng et al. point out that there are information construction problems in the application of big data mining in smart tourism. From the perspective of smart tourism development, the current information construction still needs to be strengthened. There are problems with big data mining methods. At present, in the development of smart tourism in China, what is actually lacking is big data mining methods. In addition, data identification and correlation data analysis methods are difficult [8]. Liang et al. point out that intelligent systems perceive the surrounding environment, and intelligent systems are increasingly applied to the search, decision-making, and workflow of tourism information, resulting in intelligent tourism. In order to model the tourism field, intelligent system needs to have a deep understanding of its nature. Through the study of the existing tourism literature, this paper discusses the key gap of knowledge in the tourism field so as to understand the impact of intelligent system design. Specifically, it discusses the application of conceptualization technology in tourism research [9]. Liu and Zhang believe that, at the level of Internet development and tourism development, smart tourism is actually the intelligent development of tourism services, that is, using Internet technology to carry out tourism services and providing more convenient tourism services for people with the convenience of the Internet [10]. Qi C. believes that smart tourism is a new tourism management system combining the tourism industry and Internet technology. She points out that the four core contents of smart tourism are the Internet, mobile terminal, cloud computing, and artificial intelligence. On the basis of information technology, the application model of smart tourism is proposed, and its core is the data management system of the Internet [11]. Zhang believes that smart tourism cannot be equated with smart tourism in fact. He believes that smart tourism is only a product of a new era produced by the combination of tourism services and Internet information technology. Smart tourism should refer more to mobile tourism service apps, tourism products, or tourism service software. Smart tourism cannot even cover other current online tourism platforms or large tourism websites. Smart tourism is a practical tourism product relying on Internet mobile devices [12]. Zhang discusses the parameter setting of the weighting algorithm in solving the traveling salesman problem, and the results have a certain reference value [13]. Ying et al. proposes an improved ant colony algorithm by combining the ant colony algorithm and simulated annealing algorithm. The algorithm selects and repeats the paths of the ant colony algorithm through the simulated annealing algorithm to obtain the global optimal solution, which is applied to the route planning of tourist attractions.

This paper identifies and analyzes smart business planning. On the basis of the mathematical model of the self-driving travel route planning problem, it comprehensively considers factors such as the choice of transportation mode, travel time, and travel cost and establishes a mathematical model for the problem of smart tourism route planning. Combined with specific examples, it discusses how to solve the mathematical model of self-driving tour route planning problem and convert the solution results into specific itinerary.

3. Intelligent Tourism Planning Model

The goal of tourism is to spend less money and get the largest and most comfortable tourism experience, which is the main purpose of this function [14].

According to the current survey of transportation means, aircraft, high-speed rail, and self-driving tour are generally selected for interprovincial transportation means. It is assumed that f_{ij} is set as whether the transportation means from the provincial capital i to j is aircraft. f_{ij} is set as 1 if it is an aircraft; otherwise, it is set as 0. The ticket price of the aircraft is p_{ij}. Whether the adopted means of transport is a high-speed rail is set as h_{ij}. h_{ij} is 1 if it is high-speed rail and 0 if it is not high-speed rail [15], and the ticket price of high-speed rail is q_{ij}. Whether the adopted vehicle is a self-driving vehicle is set as c_{ij}. c_{ij} is set as 1 if it is a self-driving vehicle and 0 if it is not a self-driving vehicle, and the cost of a self-driving vehicle is r_{ij}. Suppose there is a tourist group with a total of m people, $m \leq 5$. Considering the number of people, the vehicle used is self-driving, so the sum of the costs from the provincial capital to the provincial capital is as follows:

$$2 \times \left(f_{ij} \times p_{ij} \times m + h_{ij} \times q_{ij} m + c_{ij} \times r_{ij} \right). \tag{1}$$

The dynamic between the scenic spots i and j is expressed by S_{ijk}. If it changes between the scenic spots on the k-th day, it is 1. If it does not change, it is 0. There are two options for the road between the two scenic spots, one is an expressway, with a total length of v_{ij} [16], and the other is an ordinary highway, with a total length of $w_{ij} w_{ij}$; then, the cost from the scenic spot i to j is as follows:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{K} s_{ijk} \times \left(v_{ij} + w_{ij} \times 0.5 \right). \tag{2}$$

It is assumed that the sum of accommodation expenses on the k-th day is z_k, the sum of accommodation expenses on the trip is $\sum_{k=1}^{K} z_k$, the cost of vehicle rental is $(1 - c_{ij}) \times 300 \times k$, and the minimum value of the sum of expenses on the trip M is as shown in equation (3).

$$\begin{aligned} &2 \times \left(f_{ij} \times p_{ij} \times m + h_{ij} \times q_{ij} \times m + c_{ij} \times r_{ij} \right) \\ &\quad + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{K} s_{ijk} \times \left(v_{ij} + w_{ij} \times 0.6 \right) + \sum_{k=1}^{K} z_k. \end{aligned} \tag{3}$$

According to the investigation on the influencing factors of tourists' tourism experience, the results show that the longer the tourism time in each scenic spot, the higher the tourists' experience evaluation of this tourism [17]. The more certain the sum of travel time of each scenic spot, the less the time spent on the whole tour; that is, the less time spent on nonscenic spots, the higher the tourists' experience evaluation of this tourism. It can be concluded that the experience of tourists is related to time. Assume that F is a tourism experience function:

$$\% F = \frac{\text{Total time spent visiting the site}}{\text{Total time spent traveling + total time spent visiting scenic spots}}. \tag{4}$$

3.1. Solution Process of Weighting Algorithm. In the weighting algorithm, the path selection probability $P_{ij}^{k}(t)$ of time t weighted k transfer from city i to j is

$$P_{ij}^{k}(t)=\left[\frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s\in\text{allowed}}\left[\tau_{is}(t)\right]^{\alpha}\left[\eta_{is}(t)\right]^{\beta}}\right]. \tag{5}$$

As can be seen from equation (5), there are mainly 4 parameters that determine the probability of path selection: pheromone value $\tau_{ij}(t)$ of the edge (i, j) at time t , heuristic function $\eta_{ij}(t)$, information heuristic factor α, and expectation heuristic factor β. The heuristic function is $\eta_{ij}(t) = 1/d_{ij}$, where d_{ij} represents the length of the edge (i, j).

During initialization, the weighting algorithm makes the initialization pheromone $\tau_{ij}(0) = \tau_0$ of each edge (i, j), where τ_0 is a constant. This means that, in the initial stage, there will be a greater probability of selecting the next city with a larger heuristic function (shorter edge distance). In this way, after obtaining the initial solution, the global pheromone update will make the probability of the algorithm moving in the fixed direction exceed the probability of moving in other directions so as to form a local optimum.

A sign Y is set to judge whether the optimal solution is updated in this cycle. If it is not updated, it is not necessary to repeatedly calculate the optimal solution that has been locally searched, which also reduces the solution time of the algorithm to a certain extent. The termination condition of the weighted algorithm is $N_c \geq N_{\max} N_c \geq N_{\max}$; actually, the value of $N_{\max}$ is difficult to determine. When its setting is too small, the algorithm has not completed the search. If the setting is too large, an invalid cycle will be carried out after the search is completed, which increases the solution time of the algorithm. This paper sets the cycle sign C. If the current optimal solution L_{best} for 10 consecutive times remains unchanged, it is considered that the current cycle has been completed and the cycle is ended.

3.1.1. Parameter Selection. The setting of parameters has a great impact on the ant colony algorithm to solve the traveling salesman problem, so it is necessary to determine reasonable parameters for the weighting algorithm. By consulting the literature [18], heuristic factor α, expected heuristic factor, and pheromone volatilization coefficient P have a great impact, while weighted quantity m and pheromone intensity Q have a small impact.

In order to select the appropriate heuristic factor α and expected heuristic factor β, we use Oliver 30 in TSPLIB as test data. The default values of parameters are as follows: pheromone intensity $Q = 100$, pheromone volatilization coefficient $P = 0.3$, maximum number of iterations of the algorithm $N_{c-\max} = 100$, weighted quantity $m = 30$, and the combination of heuristic factor α and expected heuristic factor β is $(\alpha, \beta) \in \{(1,3), (1,4), (1,5), (2,3), (3,4), (2,5)\}$. Each group of combinations is solved 10 times, and the mean value is obtained. The solution results are shown in Table 1 [19].

As can be seen from Table 1 and Figure 2, when the pairing of heuristic factor α and expected heuristic factor β is

Table 1: Relationship between heuristic factor α, expected heuristic factor β, and average path length.

(α, β)	(1,3)	(1,4)	(1,5)	(2,3)	(2,4)	(2,5)
Average path length	423.27	424.05	424.21	424.31	414.26	423.42

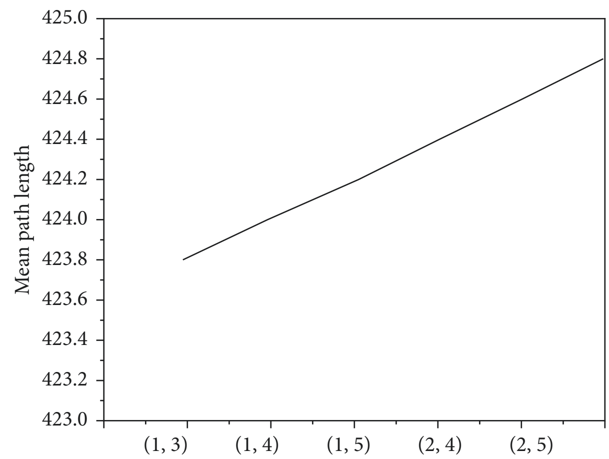

Figure 2: Relationship between heuristic factor α, expected heuristic factor β, and average path length.

(1, 4), the average path length is the shortest. Therefore, the pairing of selected heuristic factor α and expected heuristic factor β is (1, 4).

Pheromone volatilization coefficient ρ and pheromone residue coefficient $1-\rho$ mainly affect the change of pheromone size. If the pheromone volatilization coefficient ρ is large, the pheromones on the path will increase or decrease rapidly and pile up when selecting the next path so that the algorithm falls into the local optimal solution. In order to select the appropriate pheromone volatilization coefficient, we use Oliver 30 in TSPLIB as the test data. The default values of the parameters are as follows: information heuristic factor $\alpha = 1$, expected heuristic factor $\beta = 4$, pheromone intensity $Q = 100$, maximum number of iterations of algorithm $N_{c-\max} = 100$, and weighted quantity $m = 30m = 30$. Select the pheromone strength pheromone volatilization coefficient $\rho = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$, solve it 10 times, and calculate the mean value. The solution results are shown in Table 2.

It can be seen from Table 2 and Figure 3 that the average path length is the shortest when the pheromone volatilization coefficient is $\rho = 0.3$. In the process of pheromone updating, the pheromone volatilization coefficient ρ is very important. In most algorithms, pheromone volatilization coefficient ρ is usually set as a constant coefficient [20]. Based on the above considerations, we first link ρ with the number of cycles, and pheromone volatilization coefficient ρ is

$$\rho=\left\{\begin{array}{ll} 0.2 & N_c \in \left[0, 0.35N_{c-\max}\right] \\ 0.3 & N_c \in \left[0, 0.35N_{c-\max}, 0.7N_{c-\max}\right] \\ 0.4 & N_c \in \left[0.7N_{c-\max}, N_{c-\max}\right] \end{array}\right\}. \tag{6}$$

Table 2: Relationship between pheromone volatilization coefficient ρ and average path length.

Pheromone volatilization coefficient ρ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Average path length	424.20	423.18	424.44	424.32	423.46	424.86	424.11	424.54

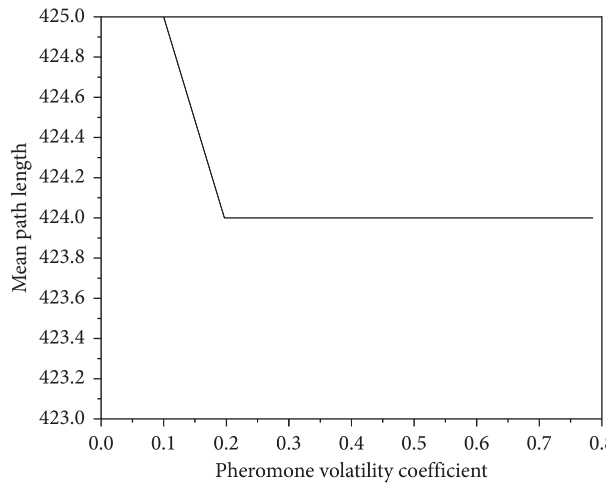

Figure 3: Relationship between pheromone volatilization coefficient ρ and average path length.

Table 3: Relationship between ant colony quantity m and average path length.

Ant colony quantity m	5	10	15	20	25	30	35	40
Average path length	425.49	425.05	424.33	424.43	424.27	424.22	424.28	424.30

In order to select the appropriate weighted quantity m, we use Oliver 30 in TSPLIB as the test data. The default values of the parameters are as follows: information heuristic factor $\alpha = 1$, expected heuristic factor $\beta = 4$, pheromone volatilization coefficient $\rho = 0.3$, maximum iteration times of the algorithm $N_{c-\max} = 100$, and pheromone intensity $Q = 100$. Select $m = \{5, 10, 15, 20, 25, 25, 30, 35, 40\}$, solve 10 times, and calculate the mean value. The solution results are shown in Table 3.

In order to select the appropriate pheromone intensity Q, we use Oliver 30 in TSPLIB as the test data. The default values of the parameters are as follows: information heuristic factor $\alpha = 1$, expected heuristic factor $\beta = 4$, pheromone volatilization coefficient $\rho = 0.3$, maximum iteration times of the algorithm $N_{c-\max} = 100$, and number of ants $m = 25$. Select the pheromone strength $Q = \{1, 10, 100, 1000\}$, solve it 10 times, and calculate the mean value. The solution results are shown in Figure 4.

It can be seen from Table 4 that there is an optimal solution when the pheromone intensity is $Q = 100$, and other cases fall into the same local optimal solution. The research results of [21, 22] show that pheromone intensity Q has little impact on the algorithm, but pheromone intensity is generally set as $Q = 100$ in small-scale traveling salesman problems.

This section proposes a solution to the traveling salesman problem based on an improved weighted algorithm. On the basis of the weighting algorithm, the path selection probability is improved by random factors; after completing one cycle, the optimal path will be searched locally; only the pheromone on the optimal path is used to update, and the threshold of the pheromone is set at the same time value; optimize the algorithm solution process; determine the reasonable parameters of the algorithm. Through performance simulation analysis, compared with the particle swarm weighted hybrid algorithm, although the algorithm in this paper is lacking in search accuracy, the solution speed is faster, and it has good practical value for solving the problem of tourist route planning.

3.2. Steps and Process of Improving Weighting Algorithm to Realize Traveling Salesman Problem. The steps of improving the weighting algorithm to realize the traveling salesman problem are as follows:

Step 1. Initialization of parameters. Set the number of cycles $N_c = 0$, set the maximum number of cycles $N_{c-\max}$, clear the taboo table $tabu_k$, make each edge (i, j), the initialization pheromone is $\tau_{ij}(0) = \tau_{\max}$, and the increment of pheromone at the initial time is $\Delta\tau_{ij}(0) = 0$.

Step 2. Number of cycles: $N_c = N_c + 1N_c = N_c + 1$.

Step 3. Place m in n cities, and then add the city of k to the taboo table $tabu_k$ of weighted kk.

Step 4. Weighted number $k = 1k = 1$.

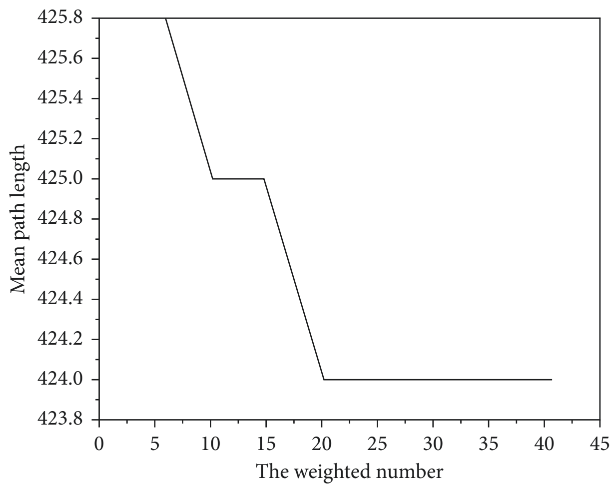

FIGURE 4: Relationship between ant colony number m and average path length.

TABLE 4: Relationship between pheromone intensity Q and average path length.

Pheromone intensity Q	1	10	100	1000
Average path length	424.16	424.13	424.32	424.44

Step 5. Calculate the path selection probability $P_{ij}^k(t)$ according to equation (4), judge to move to the next city J according to the random factor, and then add it to the taboo table $tabu_k$ of weighted K to calculate the current path length of k: $L_k = (k = 1, 2, \cdots, m)$. If the current path length is $L_k > L_{\text{best}}$, the search will stop.

Step 6. Weighted number $K = K + 1$.

Step 7. If $K > m$, execute Step 5. Otherwise, perform Step 8.

Step 8. Calculate the weighted path length $L_k = (k = 1, 2, \cdots, m)$, and record the current optimal solution L_{best}. If the optimal solution is updated, update the sign $Y = 1$ and cycle sign $C = C + 1$. Otherwise, update $Y = 0$ and $C = 0$.

Step 9. If the sign is updated as $Y = 1$, conduct a local search for the current optimal solution to determine whether the optimal solution L_{best} needs to be updated.

Step 10. Update the path pheromone according to equations (3) and (4), and determine the pheromone $\tau_{ij}(t)$ of each side (i, j) after updating. If it is greater than $\tau_{\max}$, then correct $\tau_{\max}$, and if it is less than $\tau_{\min}$, then correct $\tau_{\min}$.

Step 11. If $N_c \geq N_{\max}$ or $C \geq 10$ is satisfied, execute Step 12. Otherwise, clear the taboo table L_{best} and perform the step.

Step 12. Output the shortest path, and end.

The program flow of the improved weighting algorithm is shown in Figure 5.

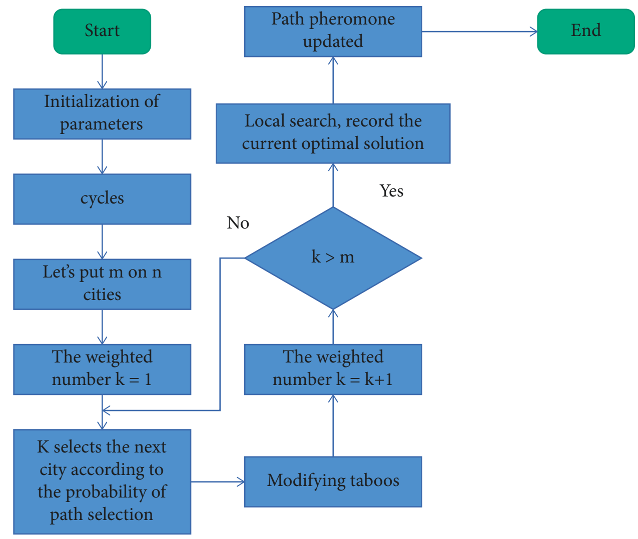

FIGURE 5: Program flow of improved weighting algorithm.

Comparing the best solutions of the algorithms in this paper and other algorithms, the algorithms in this paper can get the best solution, while the ant colony algorithm will fall into the local perspective. Costs and errors can be seen, but the best areas are less likely to fall.

4. Modeling and Solution of Intelligent Tourism Route Planning

4.1. Problem Description and Analysis. The problem of smart business planning is explained as follows. A traveler can travel by various means of transportation and travel to many beautiful places. How to create a travel guide gives travelers the best value and offers a unique travel plan [23].

The planning of smart tourism route shall include the following steps:

(1) Choose a time to visit the natural sights and all the sights according to the traveler's plan.

(1) According to the location of tourists and scenic spots, calculate the distance between tourists and scenic spots and the distance between scenic spots and scenic spots.

(3) According to the relevant location and distance, comprehensively consider the travel cost, select the appropriate means of transportation, determine the smart tourism route, and give the specific smart tourism route planning.

The specific smart tourism route planning should include the following seven aspects: (1) the starting place of each day; (2) specific transportation mode; (3) travel time; (4) driving mileage; (5) scenic spots visited; (6) time of scenic spot tour; (7) travel expenses.

The selection of scenic spots in smart tourism can be realized through big data analysis. Through big data analysis, we can recommend suitable scenic spots for tourists and analyze the appropriate travel time of each scenic spot. Similarly, according to travelers, through big data analysis in itinerary arrangement, recommendations including hotels, restaurants, and shopping can also be provided. In view of the limited space of the paper, this section focuses on the route planning of smart tourism.

According to the above analysis, we find that the core of smart route planning lies in how to select appropriate means of transportation, determine the route of smart tourism, and ensure the rationality of the smart tourism route. The process of solving the intelligent tourism route planning problem by mathematical modeling is shown in Figure 6.

In terms of considering various modes of transportation, three modes of transportation are considered: automobile, train, and aircraft. Although ship tourism may have more prominent aspects in the tourism experience, it is reasonable not to consider it. The factors of travel cost include the cost of transportation and the cost of travel and accommodation. Compared with the mathematical model of self-driving travel route planning, the model is more complex.

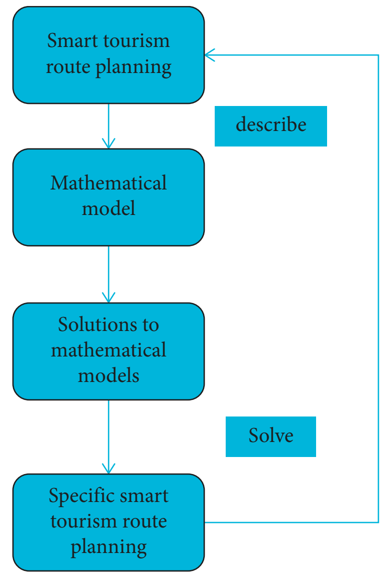

Figure 6: Solution process of intelligent tourism route planning problem.

4.2. Establishment of the Weighted Data Algorithm Model. The problem with smart business planning is that it needs to be simplified for a number of reasons.

It is important to plan a self-guided trip. The accommodation fee is simplified to 200 yuan/person/day for provincial capital cities and scenic spots, 150 yuan/person/day for prefecture-level cities, and 100 yuan/person/day for counties. The driving cost is simplified to the average fuel consumption plus the toll of an expressway is 1.00 yuan/km, and the average fuel consumption on an ordinary highway is 0.60 yuan/km.

From the above definition of travel experience, we can see that we consider linking travel experience with travel time. Through the analysis, we can see that the tourism experience F we define is in line with the actual situation.

In general, a multitask programming solution is to turn multiple goals into a single task problem with the appropriate tools. We consider setting the comprehensive objective as P and then solving the single objective; then

$$\min P = M \times (1 - F), \tag{7}$$

where M refers to all the expenses of a trip, F is the satisfaction of a trip, and $1 - F$ is the dissatisfaction of a trip. Therefore, P can be understood as the expenses spent by tourism enthusiasts on dissatisfied activities during a trip. The lower the value P, the better the comprehensive evaluation. The higher the value P, the worse the comprehensive evaluation.

In the actual solution, we found that it is difficult to get the solution result when the aircraft, high-speed rail, and self-driving are completely mixed together. The improved weighted mining algorithm is used to solve each region, and the shortest path and required days of each region are obtained.

The definition of tourism value is the definition of the tourism product as a result of the value of tourism product of the main force of education. In terms of the value of the natural tourism landscape, the objectification of the vital force of tourism education and the subjectivity of tourism products are the basis of its value. The former is an indirect source and creates intrinsic value, while the latter is a direct source and creates real value; the first determines the interest rate, and the second determines the validity of the value. The theme of its benefits for landscape tourism culture is the integration of the concept of studying the vital force of tourism education and tourism equipment. Therefore, the meaning of tourism products is the key to tourism spending, and the content is the impact of tourism products on the main force of education.

4.3. Solution Results. According to the shortest path of each region, the specific itinerary of smart tourism route planning can be sorted out. The number of travel days, total travel expenses, and scenic spots visited in each area are shown in Figure 7. Sort out the specific itinerary of smart tourism according to the regional browsing plan.

According to the rationalization assumption of the mathematical model, the total number of trips per year shall not exceed 30 days, and the total number shall be less than 4. Through a reasonable combination of the days spent on tourism in each region, we can visit all regions in fewer years. The annual tour area plan is shown in Table 5.

The specific itinerary of the intelligent tourism route planning problem given is the optimal route in theory, but whether it is reasonable should be tested according to the actual situation, such as whether the road is unobstructed. At the same time, it can also be classified according to the characteristics of the actual scenic spots so that tourists can choose the types of scenic spots they are interested in for recommendation.

Compared with the simple self-driving tour, the travel plan formulated by comprehensively considering various modes of transportation has significantly improved in time.

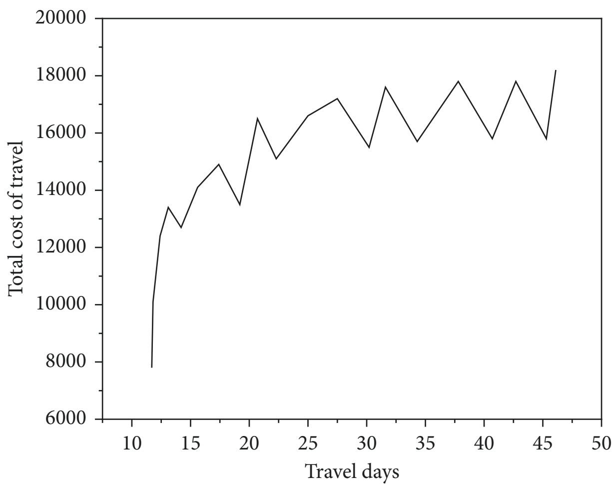

Figure 7: Travel days, total travel expenses, and the number of scenic spots visited in each region.

Table 5: Regional plan for visiting 201 5A scenic spots in China.

Year	Area number browsed	Total travel days
1	1, 2	20
2	3, 4, 5	35
3	6, 7, 8	40
4	9, 10, 11	30
5	12, 13, 14	30
9	15, 16, 17	20
10	18, 19, 20	28

The tourist routes of regions 1, 3, 20, 26, and 27 are a combination of aircraft and self-driving. Their corresponding tourist provinces are mainly far away from Xinjiang, Tibet, Hainan, and Yunnan. In addition to the above five regions, the solution results of the remaining 22 regions are only self-driving. The price data of air tickets and train tickets are from question F of the 2016 National Postgraduate Mathematical Modeling Competition. In fact, the prices of air tickets and train tickets given in the annex are relatively high, which has a certain impact on the solution results of the model to a certain extent. At the same time, the case considers the situation of a family of three. Compared with the plan of traveling alone, self-driving travel has certain cost advantages when many people travel together.

Regardless of the travel time limit, the travel plan of "poor travel" can be formulated. The travel plan of "rich tour" can be formulated without considering the restriction of travel expenses. Considering the travel time and cost, the travel plan of "economic tour" can be formulated. Different plans are suitable for people with different needs.

Based on the problem of smart travel route planning, a mathematical model with the dual goals of optimal travel cost and optimal travel experience is established by considering multiple modes of transportation. When solving, the dual objective is reasonably transformed into a single objective, and the model is solved by comprehensively considering the travel cost and travel experience. For multiple traffic modes, the optimal solution results are determined by comparing each traffic mode separately. Finally, the specific itinerary is given according to the optimal solution result.

5. Conclusion

This paper provides mathematical models for heavy data mining for intelligent brigade planning. The best solution is determined by comparing and resolving all types of vehicles for different types of traffic. The best solution was to move to smarter tourism industry in the planning area and eventually develop a smart business plan. Compared to the current state of tourism and natural attractions, the travel plan given in this form has the following advantages: Good results indicate importance and can serve as a basis for research in tourism planning. Smart marketing is always seen in ready-made, accessible, and popular information services. Encouraged by public demand, some industrial service companies continue to promote self-service and develop specialized products. Smart tourism integrates a wealth of tourism information based on the principles of consumer-friendly tourism and makes this information relevant to all travelers through intelligent management.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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