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Optimization Model and Algorithm Design for Rural Leisure Tourism Passenger Flow Scheduling

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ABSTRACT A constrained optimization model and an iterative optimization algorithm based on PSO are designed for rural leisure tourism passenger flow scheduling. Compared with the traditional tourist dispatching scheme, this model maximizes the overall tourist experience and operation profit of the whole region on the base of protection of tourists' travel experience and the interests of operators in the dispatching spots. Simulations and comparisons are taken to evaluate the feasibility and effectiveness of the model and the optimization. The simulation results show that compared with the shortest-distance-based traffic scheduling scheme and the gravity-model-based scheme, the new model and optimization could meet the requirements of the rural leisure tourists dispatching and bring better tourist experience and tourism profit.

INDEX TERMS Adaptive algorithm, optimization model, particle swarm optimization, rural leisure tourism, tourist scheduling.

I. INTRODUCTION

At present, the rural leisure tourism is developing rapidly. The travel destinations of this new kind tourism are usually individual tourism operation spots in a village. These spots are mainly household-run small businesses or individual farmsteads [1]–[3]. Compared with traditional tourism, the rural leisure tourism does not rely on selling tickets to tourists. On the contrary, the management attaches importance to the overall reputation of a region, and the food as well as the accommodations with rural characteristics are regarded as the main source of income. Under these circumstances, most spots have similar resources, but they scatter in a relatively large and distributed region, such as a town or county, rather than the places like traditional scenic spots. Therefore, almost every weekend or holiday, most tourists are gathered in a few hot spots. However, very few tourists are attracted to other spots which are usually not far from the hot spots and have similar tourism resources.

For the unbalanced distribution of tourists, the tourism resources in the gathering areas may be consumed excessively [4], [5], which results in a serious decrease of the tourist experience in these areas. In other areas where tourists are scarce, the tourism operating efficiency is low. So this problem must be seriously considered to improve overall regional tourism profit and efficiency.

However, it is quite a challenge to design a reasonable dispatching scheme to solve the problem. For the tourists, the scheme should provide the same or better travel experience after the diverting. For the operators in hot spots, the scheme should guarantee that the operating profit loss be limited to an acceptable degree after the dispatching. Moreover, for regional tourism regulators, the scheme should provide all tourists with best experience and maximize the overall operating profit of the whole region. Therefore, this problem has become a major issue for the regulation of leisure tourism in a region to affect the further sustainable development [6].

Facing the challenge of passenger scheduling, some solutions have been brought out by now. Generally, these solutions can be concluded into two categories:

(1) Optimization models with single constraint factor.

This kind of model are often designed from the perspective of the tourism operators. The model selects a single factor, such as time, distance or price, as a constraint to achieve the average tourists flow distribution at a reasonable cost [7]–[9].

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This kind of scheme only takes the average distribution of total passenger flow in the whole area as the main objective, without considering the changes of tourist experience and the overall operating profit in the whole region caused by passenger diversion. Therefore, these models are not suitable for passenger scheduling optimization problem in rural leisure tourism.

(2) Comprehensive optimization models with multiple factors.

In the research of multi-factor tourist scheduling model, Zhang *et al.* take the model of Logit as basis to balance the loads of scenic spots. In the model, two factors are considered: the distance between the scenic spots and the influence to the tourist experience caused by the wait time [9], [10].

Based on the gravity model, Xiao *et al.* constructed a shunt-scheduling algorithm with the priority of balancing the loads, in this model, the tourists satisfaction punishment factor due to waiting is considered [11].

This kind of model takes into account a variety of factors, including not only the load of scenic spots, but also the road distance, tourist experience and its losses. Therefore, it is more reasonable than the first one. However, the primary goal of these models is still how to meet the balance of tourist load in each scenic spot to increase the overall capacity of the scenic area.

To sum up, the scheduling optimization models mentioned above are designed for traditional tourism applications. All of them are just based on the micro-scheduling of a tourist attraction operator. They do not consider how to promote the overall tourist experience and whole operator profit based on the micro-benefits. So far, there is still a lack of research on the tourist scheduling model and its optimization algorithms for rural leisure tourism, which has seriously affected the development of related fields. The problem needs to be solved as soon as possible.

In this paper, a new optimization model for rural leisure travel flow scheduling is proposed. This model considers factors of all stakeholders in rural tourism so as to protect the interests of most tourists, operators and the destination management organization. In order to obtain a reasonable scheduling scheme, we design an iterative optimization algorithm based on PSO, which aims to maximize the overall travel experience and operating profit. After the iteration, a scheme is determined and it explains the number of tourists in an over-loaded spot need to be transferred and the carrying capacity of under-loaded spots. The model pays more attention to the quality of the whole region. Under the guidance of calculation results, the destination management organization can obtain tourist information of all spots and make a proper dispatch scheme in time.

The remainder of this paper is organized as follows. Section 2 describes the constrained optimization model. The iterative optimization algorithm based on PSO are presented in section 3. Section 4 presents the experimental results and evaluations. Section 5 discusses the conclusion and the further works.

II. OPTIMIZATION MODEL DESIGN

Assuming that A is a collection of n tourist operation points in the region, then the tourist load rate of the tourism operation spot i at the t_0 moment $r_i^{t_0}$ is defined as follows, just as in [10]:

$$r_i^{t_0} = \frac{N_i^{t_0}}{c_i} \quad (i \in A; r_i^{t_0}; i = 1, 2, \ldots, n) \tag{1}$$

where $N_i^{t_0}$ is the number of tourists of spot i at the t_0 moment and c_i is the tourist capacity of the spot i.

In order to consider the interests of tourists and operators in the scheduling, two variables are defined: the tourist experience $E_i^{t_0}$ and the operator profit $P_i^{t_0}$.

The tourist experience represents the interest of visitors. It is influenced by many factors which can be summarized in two aspects according to the length of affecting time. From a short-term perspective, the number of tourists has a great impact on the tourist experience. If the number reaches a certain threshold, the tourist experience begins to reduce. From a long-term perspective, tourism resources, such as spot reputation, traffic environment and quality of service, are the key to guaranteeing the good tourist experience [12]–[14]. Among the resources, a good reputation is the prerequisite of attracting tourists [15], [16]. There are three terms determining the spot reputation, identity, brand and image. Argenti and Druckenmiller [17] give an illustration on the difference of these terms, that is, identity addresses the scenic assessment of itself; brand reflects the future development direction and image replies the public impression of the spot. Darwish and Burns [18] propose a model of tourist destination reputation definition which considers the experiences and emotions of internal, peripheral and external stakeholders. The above terms as well as the model give an accurate perception of a spot reputation and help minimise the risk of unsatisfactory tourist experience. As for other resources, if a spot has convenient traffic conditions and can provide tourists with comfortable accommodation and delicious food, it also can improve the tourist experience. Thus, the spots with such resources usually attract more tourists and make more profits.

The tourist experience function of the tourism operation spot i can be defined as:

$$E_i^{t_0} = f_i(r_i^{t_0}) = \begin{cases} 0, & r_i^{t_0} < 0 \\ L_i \cdot \dfrac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_i^{t_0} - x_0)^2}{2\sigma^2}}, & r_i^{t_0} \geq 0 \end{cases} \tag{2}$$

$$L_i = w_1 res_1 + w_2 res_2 + w_3 res_3 \tag{3}$$

As shown in formula 2 and formula 3, L_i is related to the tourism resources of the operating spot. res_1, res_2 and res_3 separately represent the spot reputation, the traffic environment, the quality of service, and w_i is the weight of each kind of tourism resource. Generally, L_i is set to a constant because tourism resource will not be changed a lot over a long period of time. Except for L_i, the rest part of function describes the relationship between tourism experience and the number of tourists, where σ is the standard deviation of

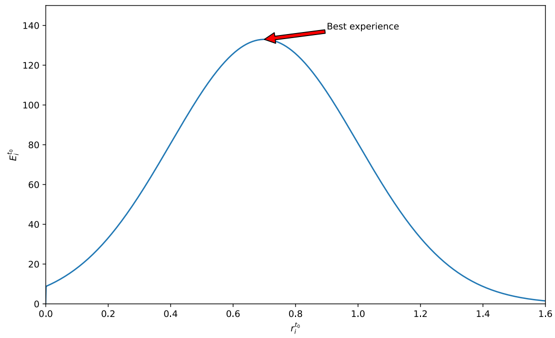


FIGURE 1. Tourist experience function ($L_i = 100, x_0 = 0.7, \sigma = 0.7$).

tourism experience value and x_0 is the best experience load rate.

Figure 1 is an example of the tourist experience function where the best experience load rate is 0.7 and the value decreases when the load rate becomes higher or lower than x_0.

For rural leisure tourism, the operator profit mainly depends on offering food and accommodations with local characteristics for tourists. So, the profit is closely related to the number of tourists. When the tourists are in a suitable amount, the individual operators have the ability to provide high quality service and they can make profit in an efficient way. However, the food and accommodations they can prepare are limited. If the number of tourists continues to increase, these resources will be quickly exhausted. Meanwhile, the profit will begin to decline. When the number exceeds the load rate, the operators have no conditions to make more profit.

So, the operator profit function of spot i is also defined as a function of tourist load rate:

$$P_i^{t_0} = \begin{cases} k_1 r_i^{t_0}, & r_i^{t_0} < \tau \\ k_1 \cdot \tau + k_2 ln(r_i^{t_0} - \tau + 1), & \tau \le r_i^{t_0} < \omega \\ k_1 \cdot \tau + k_2 ln(\omega - \tau + 1), & r_i^{t_0} \ge \omega \end{cases} \tag{4}$$

This function reflects the trend of the tourism profit of the operating point with the increase of the load rate. k_1, k_2 are tourism profit increment parameters and their values may be different in every operation point. τ is the tourist load rate when tourism profit begins to fade. ω is the tourist load rate when tourism profit reaches the maximum. An example of tourism profit function is shown in Figure 2.

$E_a^{t_0}$ and $P_a^{t_0}$ represent the total tourist experience and total tourism profit of the area A at the t_0 moment respectively, which are defined as:

$$E_a^{t_0} = \sum_{i=1}^{n} \frac{E_i^{t_0}}{E_m} \tag{5}$$

$$P_a^{t_0} = \sum_{i=1}^{n} \frac{P_i^{t_0}}{P_m} \tag{6}$$

where E_m and P_m are the max values of E_i and $P_i (i \in A)$, respectively.

To ensure the profit of tourism operation spots, the scheme seeks the maximization of the whole regional tourist experience and economic profit, while keeping the tourist load rate in a reasonable range. Based on different values of load rate $r_i^{t_0}$, the set A of tourism operation spots can be divided into three subsets:

$$\begin{aligned} A_{in} &= \{i \in A | r_i^{t_0} < \alpha\} \\ A_{out} &= \{i \in A | r_i^{t_0} > \beta\} \\ A_0 &= \{i \in A | \alpha \le r_i^{t_0} \le \beta\} \end{aligned} \tag{7}$$

Operation points in A_{in} have low tourist load rates where tourists can be diverted in. Operation points in A_{out} have high tourist load rates where tourists need to be diverted out. Operation points in A_0 have moderate tourist load rates.

Here $\alpha, \beta (0 \le \alpha \le \beta \le 1)$ are thresholds which affect not only the tourist experience and operation profit of the specific spot, but also the overall tourist experience and profit of the whole region.

From the point of view of the visitors, it is necessary to limit the experience loss to an acceptable level after dispatching. From the point of tourism operators, it is also necessary to keep the load rate in a reasonable range after scheduling to ensure the profit.

Therefore $N_{i,out}$ represents the number of tourists who need to be diverted out from spot i and it is defined as follows:

$$N_{i,out} = \begin{cases} 0, & r_i^{t_0} < \alpha \\ \theta \cdot (r_i^{t_0} - \alpha) \cdot c_i, & \alpha \le r_i^{t_0} < \beta \\ \theta \cdot (\beta - \alpha) \cdot c_i + (r_i^{t_0} - \beta) \cdot c_i, & r_i^{t_0} \ge \beta \end{cases} \tag{8}$$

As shown in this formula, the tourism operation spot needs no adjustment when its tourist load rate is less than α. Tourists in an operation spot should be diverted out with the proportion of θ when tourist load rate lies between α and β. When tourist load rate is higher than β, the exceeding part needs to be diverted out completely.

Therefore, considering the individual operators and the overall tourist experience and operating efficiency of the region, the optimization model of this scheduling program is:

$$\begin{aligned} &\max z = E_a^{t_1} \cdot P_a^{t_1} \\ &s.t.\ E_j^{t_1} - E_i^{t_0} > -\delta \\ &\quad \alpha \le r_i^{t_1} \le \beta \quad (i \in A) \end{aligned} \tag{9}$$

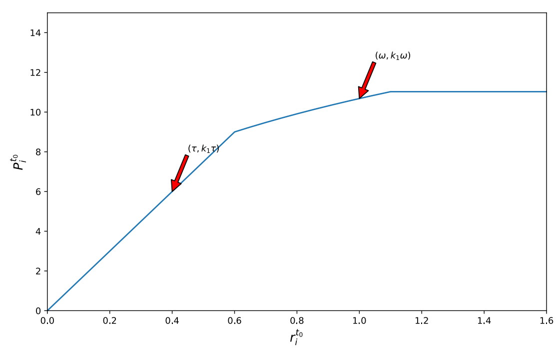


FIGURE 2. Tourism profit function ($\tau = 0.6, \omega = 1.1, k1 = 15, k2 = 5$).

where t_1 is the moment after the scheduling, $i \in A_{out}, j \in A_{in}$, $\delta \geq 0$, δ is a constant, which determines how much the tourism experience loss can be accepted after the scheduling.

III. OPTIMIZATION ALGORITHM DESIGN

In order to get the optimization result of the tourism travel scheduling, an iterative optimization algorithm based on PSO is constructed to find the Pareto solution.

A. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is an evolutionary algorithm inspired by the movement of the bird flocks in nature, which is proposed by Eberhart and Kennedy [19] and Kennedy and Eberhart [20]. In PSO, a number of particles are initialized and moving in the search space to find the best solution. PSO was mathematically defined as follow:

$$v_i^{t+1} = \omega v_i^t + c_1 \times rand \times (pbest_i - x_i^t) + c_2 \times rand \times (gbest_i - x_i^t) \tag{10}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{11}$$

where v_i^t is the velocity of particle i at iteration t, ω is the inertia weight parameter, c_1 and c_2 are acceleration constants, which are respectively self-experience weight and group-experience weight, respectively. $rand$ is a random number between 0 and 1. x_i^t is the current position of particle i at iteration t. $pbest_i$ is the best value achieved by particle i while $gbest_i$ is the best one achieved by the population so far.

Compared with traditional optimization algorithms such as gradient descent method [21], linear programming [22], dynamic programming [23], using PSO for optimization, there is neither need to construct a complex functional relationship between the objective function and the decision variable, nor need to make the objective function differential. The PSO has been widely used in many fields today, because it is suitable for the optimization problem of complex scenes.

In this paper, we also apply PSO to optimize the scheduling of passenger flow. However, considering the restrictive factors of the decline in tourist experience and the decline in operators' interests, we need to carefully consider the design of the optimization algorithm.

B. ITERATIVE OPTIMIZATION ALGORITHM BASED ON PSO

In this paper, an Iterative optimization algorithm based on Particle Swarm Optimization Algorithm (IPSO) is designed to complete the tourist scheduling scheme.

As a heuristic optimization algorithm, PSO cannot be directly applied to constraint optimization problems such as the optimization of tourist scheduling problems. It should also be combined with constraint processing methods in application.

In the optimization of rural leisure tourist flow scheduling, the decision variable is the specific number of tourists transferred from an overloaded operating point to each under-loaded point. The scheduling objective function is defined in Equation 9.

The goal of the scheduling is to maximize the product of the regional tourism experience value and regional tourism revenue after scheduling. However, the realization of this goal is based on a prerequisite to ensure that the constraints can be met. In the scheduling, an under-loaded operating point accepts tourists from multiple overloaded operating points, which may be difficult to meet the load rate constraints of the under-loaded operating point. At the same time, after the scheduling, the experience value of the tourists in the under-loaded area is related to the number of original tourists and the number of transferred people. Because tourists are transferred from multiple overloaded points, these overloaded points will have different experience values. However, it is a reasonable scheduling result that the value of the tourist experience of the under-loaded point is higher than the highest tourist experience value of all the call-out points.

Therefore, it is quite significant to design a suitable tourist scheduling optimization algorithm. In this paper, the PSO based on iterative optimization method is designed to deal with the scheduling problem. In this algorithm, the operating points in A_{out} are first sorted according to the number of people who need to be dispatched. From high to low, for each overloaded point, the method selects destinations that can be scheduled based on the distance between the current overloaded point and other under-loaded points, the scheduling capacity of the under-loaded points, and other factors. Then the PSO calculates the numbers of dispatched tourists from the overloaded point to each under-loaded points. In this process, the above-mentioned constraints are considered to be satisfied at each iterative step. The feature of the algorithm is that the overall schedule optimization process of the region is decomposed into an iterative process. In each iteration, the optimization is performed only for one overload point and its corresponding acceptable scheduling operation points. This method can simplify the constraints and reduce the impact of scheduling among operating points.

The main process is described as follows:

(1) Determine A_{in} and A_{out}.

As described in Equation 7, according to the parameters α, β and the current load rate in each point, the set of overloaded point A_{out} and the set of under-loaded points A_{in} are determined. For each operation point in A_{out}, the max number of tourists that need to be exported is calculated, then the spots are sorted based on this number.

Suppose A_{out} contains M operating points, for each point, the upper bound of the tourists number that needs to be dispatched, which is donated as $O_i (i \in A_{out})$, can be calculated by the following formula:

$$O_i = (r_i - \alpha) \times c_i, \quad i \in A_{out} \tag{12}$$

Here, α is the lower limit of the load rate after the overload operation point is scheduled. The result of $r_i - \alpha$ shows the maximal proportion of tourists needed to be dispatched. And c_i is the tourist capacity of the spot i. The concrete dispatching number of each over-loaded spot can be calculated according to formula 7 and the result can not be greater than O_i in the above formula. O_i guarantees that the tourism revenue will not be excessively reduced due to the transfer of too many tourists.

In the iterative scheduling method, operating points with more overloaded people are given priority for scheduling, therefore, the elements in A_{out} are sorted based on O_i.

(2) For each overloaded point in A_{out}, the most suitable k operating points are selected as scheduling targets.

In the dispatching of tourists, every under-loaded operating point can be taken as the dispatching target. However, such calculations will make it difficult to reasonably consider factors such as scheduling distance, which may cause the total scheduling distance of the final solution to rise. And when there are many under-loaded operating points, the calculation time will also be affected.

Therefore, by defining a new gravitational function, we evaluate the under-loaded operating points, screens out the k most matching under-loaded operating points, and uses them as the scheduling target.

The development of the gravitational function is to calculate whether the overload and under-loaded points in the tourist distribution can be matched [24], [25]. When expanding the model, this paper not only considers the matching of the number of dispatchers, but also considers resistance factors such as distance and the decrease of tourism experience.

Our new gravity model is shown as follows:

$$F_{ij} = G\frac{r_i^{t_0} \cdot k_j^{t_0}}{z_{ij}^{t_0}} \quad (i \in A_{out}, j \in A_{in}) \tag{13}$$

F_{ij} represents the matching degree between operating point i and j, in the above formula, G is gravitational constant, $r_i^{t_0}$ and $r_j^{t_0}$ are the tourist load rates in overloaded spot i and under-loaded spot j, respectively, $k_j^{t_0} = (r_j^{t_0})^{-1}$ and Z_{ij} is designed as the dispatch resistance factor between spot i and j:

$$z_{ij} = \mu \cdot d_{ij} \cdot \rho_{ij}^{t_0} + \varphi(E_i^{t_0} - E_j^{t_0} + E_m) \tag{14}$$

where μ and φ are weights of distance cost and tourist experience respectively, $\rho_{ij}^{t_0}$ is the dispatch cost of unit distance, d_{ij} is the physical distance between two spots. To ensure the value of Z_{ij} is positive, max value of experience E_m is added.

Then the above calculation is performed on the overloaded operation point i, the k points with the largest F_{ij} values are selected as the scheduling targets. These targets set is recorded as D_i, and the specific number of people transferred into the k points is calculated to find the best scheduling solution.

(3) Constraints processing

At each step of the iterative process, constraints are taken into account.

Constraint 1: For the overloaded operating point i and its target D_i, the number of people who need to be dispatched from i is equal to the total number of people who are dispatched into D_i, that is:

$$N_{o,i} = \sum_{j \in D_i} N_{i,j} \tag{15}$$

$N_{o,i}$ represents the number of people dispatched from operation point i, and $N_{i,j}$ indicates the number of people dispatched from operation point i to operation point j.

Constraint 2: In scheduling, it is necessary to ensure the tourist experience value does not decrease too much, that is:

$$E_j^{t_1} - E_i^{t_0} \geq -\delta, \quad \text{if } N_{ij} \geq 1,\ j \in D_i \tag{16}$$

In this paper, take $\delta = 0.1$.

Constraint 3: For the place where tourists are transferred out, it is necessary to ensure that the value of local tourism revenue will not be excessively reduced due to the transfer of too many tourists. So, we have the following constraints:

$$r_i^{t_1} \geq \alpha \tag{17}$$

In this paper, α is set to 0.8.

Constraint 4: For the transfer destination of tourists, the number of transferred tourists needs to be controlled to avoid new scheduling requirements. So, we have:

$$r_j^{t_1} < 1, \quad j \in D_i \tag{18}$$

Therefore, for each overload point i in A_{out} and its corresponding destination D_i, the number of tourists dispatched to the candidate spots is used to construct a k-dimensional decision variable. Then the following decision matrix can be constructed:

$$Q = \begin{pmatrix} Q_1^1 & \cdots & Q_k^1 \\ \vdots & \ddots & \vdots \\ Q_1^N & \cdots & Q_k^N \end{pmatrix} \tag{19}$$

Q_j^i represents the number of tourists transferred from the i-th overload point to the j-th target point.

In each step, the objective function max $z = E_a^{t_1} \cdot P_a^{t_1}$ and the PSO algorithm is used to determine the dispatch plan.

The whole specific process of the algorithm is as follows and shown in Algorithm 1.

C. COMPLEXITY ANALYSIS OF OPTIMIZATION ALGORITHM

Suppose N_i, N_o represents the number of people who need to be dispatched, M is the population particle number and T is the maximum number of iterations. D is the dimension of each particle, which is equal to the value of selected top k spots. Therefore, the complexity of PSO is $O(M \cdot T \cdot D)$. The calculation of matching degree and the process of sorting are parallel with PSO, the complexity of which are $O(N_i)$ and $O(N_i \cdot logN_i)$ respectively. The whole complexity can be defined as $O(N_o \cdot (M \cdot T \cdot D + N_i + N_i \cdot logN_i))$. Considering that $O(M \cdot T \cdot D)$ is much greater than the other two items, so the final complexity of the algorithm is $O(N_o \cdot M \cdot T \cdot D)$.

Algorithm 1 The Pseudo Code for IPSO

Determine A_{in} and A_{out} according to Equation 7
for each overloaded spot i, $i \in A_{out}$ **do**
  Determine the number of people (O_i) need to be scheduled
  for each under-loaded spot j, $j \in A_{in}$ **do**
    Calculate matching degree F_{ij} between operating spot i and j according to Equation 13
  end for
  Sort the under-loaded spots by the matching degree in descending order
  Select the top k spots as dispatching targets D_i
  Use PSO to find a scheduling solution for overloaded spot i with Equation 9 as objective function
  Delete the spots from A_{in} that are not under-loaded after dispatch
end for
Combine the dispatching results and get the final dispatch plan

IV. SIMULATION AND EVALUATION

A. SIMULATION ENVIRONMENT AND EXPERIMENTAL DATA

Simulation environment is described in Table 1.

TABLE 1. Simulation environment.

CPU	3.2 GHz Intel Core i5
Memory	8 GB 1333MHz DDR3
System	CentOS 7
Language	Python 3.6
Libraries	Numpy/Pandas/Matplotlib

As the tourist diversion scheme is still in the research stage, it cannot be implemented until it is mature, so at present, only simulation data can be used to prove the effectiveness of the scheme. Table 2 shows the initial tourist flow data of 20 spots, which is randomly generated.

In this paper, it is assumed that the actual geographical distribution among different places is ignored and the distances among spots are Euclidean Distance. Based on this assumption, simulation has been made to prove the feasibility of the scheduling model.

In this section, our scheme is compared with two other schemes, a scheme that based on gravity model [10] and a scheme in which distance is the only consideration.

The parameters in Table 2 are described as following:

- **ID** is the identifier of a spot.
- **Coordinates** is the coordinates of a region, which is used to characterize the actual geographical location.
- **Capacity** is the maximum of tourist number a spot can serve.
- N_i is the current amount of tourists.
- r_i is the tourist load rate of the tourism operation spot i before shunting.
- E_i is the tourism experience value of a operation spot, which is calculated through formula 2, where $L_i = 100$.
- σ is the standard deviation of tourism experience value in formula 2.
- P_i is the operation profit which is calculated through formula 4, where $k_2 = 1$, $\tau = 0.8$.
- k_1 is the parameter in formula 4.
- ω is the tourist load rate when spot tourism profit reaches the maximum in formula 4.

B. EXPERIMENTAL RESULTS AND ANALYSIS

As described in Table 2, The spots are divided into 3 subsets according to its current load rate.

- **The spots that have low tourist load rate.** These spots can receive the diverted tourists, and the maximum of their load rate will be limited to β.
- **The spots that have over load rate.** In our scheme, they have to dispatch out some tourists.
- **The spots with proper load rate.** These spots do not need to make any scheduling.

In Table 2, the overloaded spots include spot 2 (load rate is 1.460), spot 8 (load rate is 1.166), spot 9 (load rate is 3.250), spot 12(load rate is 1.586), spot 13 (load rate is 2.210), spot 14 (load rate is 1.814), spot 15 (load rate is 1.119).

The concrete scheduling scheme is generated via the iterative calculation of the overall load rate and tourist experience under the constraints discussed above. The simulation results of the scheduling scheme are shown in Table 3.

The simulation results of shortest distance scheme and gravity model are shown in Table 4 and Table 5.

In the simulation, the filtering of the tourist dispatch destination is completed by gravitational model. The parameter k was set to 5. The reason that the number of dispatch destinations in the dispatch result less than 5 are:

- The number of under-loaded spots is less than 5.
- After the optimization process of PSO, the number of people dispatched to certain spots is 0.

Simulation results show that the above scheduling strategies can play the role of scheduling diversion at macro level and make the load of tourists balanced in the whole leisure travel area. However, due to their different scheduling optimization goals, the final scheduling solutions are obviously different. The shortest-distance-based traffic scheduling scheme and the gravity-model-based scheme only take the traffic load balancing in the area as the optimization goal. While the scheme proposed in this paper not only consider the balanced distribution of the load of tourists in the whole region, but also consider the overall business interests of the region and the maximization of the overall travel experience.

Taking the high-load spot 13 as an example, it can be seen from the tables that the shortest distance-based traffic dispatch solution selects only the point 0 and 3 for diversion so as to pursue a balanced distribution of all the tourists in the area, gravity model based dispatch solution select only the

TABLE 2. Simulation data.

ID i	Coordinates	Capacity	N_i	r_i	σ	k_1	ω	Experience E_i	Profit P_i
0	(103, 125)	1149	718	0.625	1.38968	15.08	1.16	28.480772	9.425
1	(2, 14)	1309	179	0.137	3.99531	15.92	0.97	9.848722	2.18104
2	(68, 39)	1228	1793	1.46	1.58048	15.64	0.95	23.134162	12.65176
3	(27, 13)	1472	207	0.141	1.31643	15.25	0.91	26.735968	2.15025
4	(25, 83)	1270	221	0.174	6.24293	15.66	1.14	6.358259	2.72484
5	(116, 59)	1344	999	0.743	8.23017	15.43	1.18	4.847199	11.46449
6	(116, 78)	757	365	0.482	6.4261	15.81	1.00	6.200559	7.62042
7	(58, 76)	1153	674	0.585	5.84932	15.04	0.97	6.815713	8.7984
8	(125, 98)	637	743	1.166	9.70776	15.33	0.91	4.1066	12.36836
9	(18, 132)	567	1843	3.25	7.80521	15.83	1.04	4.865531	12.87911
10	(82, 52)	914	861	0.942	6.08896	15.81	1.11	6.550114	12.78078
11	(52, 60)	535	424	0.793	8.53404	15.1	1.18	4.674716	11.9743
12	(129, 58)	1083	1718	1.586	7.88851	15.92	0.97	5.032216	12.893
13	(65, 146)	711	1571	2.21	7.81728	15.79	1.11	5.020996	12.90203
14	(67, 46)	1052	1908	1.814	5.67604	15.82	1.07	6.917267	12.89502
15	(109, 133)	706	790	1.119	2.68584	15.94	1.06	14.749141	12.98311
16	(19, 112)	1479	232	0.157	7.45051	15.49	0.93	5.33466	2.43193
17	(62, 44)	1311	423	0.323	9.75031	15.4	1.15	4.086692	4.9742
18	(57, 76)	1413	892	0.631	1.38922	15.71	1.01	28.505291	9.91301
19	(84, 49)	1410	1399	0.992	7.32397	15.54	1.18	5.445206	12.60763

TABLE 3. Simulation results of passenger flow scheduling ($\alpha = 0.8, \beta = 1, \theta = 0.3$).

Dispatch out spot (i)	Dispatch in spot (j)	Number of dispatched people ($N_{i,j}$)	Distance from i to j (d_{ij})	Load rate before dispatching ($r_i^{t_0}$)	Load rate after dispatching ($r_i^{t_1}$)	Experience before dispatching ($E_i^{t_0}$)	Experience after dispatching ($E_j^{t_1}$)
9	4	361	49.497	3.25	0.822	4.86553081	6.380724
	3	694	119.34				29.9974
	1	322	119.08				9.931025
13	0	191	43.417	2.21	0.819	5.0209963	28.70689
	18	145	70.456				28.68461
	4	406	74.626				6.390266
	7	247	70.349				6.820319
14	18	79	31.623	1.814	1.399	6.91726671	28.71625
	3	357	51.856				30.27842
12	6	241	23.854	1.586	0.82	5.03221607	6.208155
	16	589	122.54				5.351669
2	18	297	38.601	1.46	1.013	23.1341622	28.42094
	3	178	48.549				30.03523
	0	74	92.849				28.68419
8	17	125	82.976	1.166	0.821	4.10659975	4.088447
	1	95	148.946				9.948106
15	0	41	10.000	1.119	1.061	14.749141	28.64601

nearest operation spot 3 for diversion. The scheduling scheme proposed in this paper chooses more operation spots 16, 0, 1, 18, and 7 for diversion considering not only the balanced distribution of the load, but also the overall regional business interests, as well as the overall tourist experience.

In order to evaluate the performance of our tourists scheduling scheme, the following indices are defined or used for a comprehensive comparison and analysis.

- z. The optimization objective of the scheduling, which is the product of the regional overall tourism experience value and the tourism profit value, is calculated according to formula 9.
- $\boldsymbol{E_a}$. The total tourist experience of the region, which is calculated according to formula 5.
- $\boldsymbol{P_a^{t_0}}$. The total tourism profit of the region, which is calculated according to formula 6.

TABLE 4. Simulation results of passenger flow scheduling based on shortest distance.

Dispatch out spot (i)	Dispatch in spot (j)	Number of dispatched people $(N_{i,j})$	Distance from i to j (d_{ij})	Load rate before dispatching $(r_i^{t_0})$	Load rate after dispatching $(r_i^{t_1})$	Experience before dispatching $(E_i^{t_0})$	Experience after dispatching $(E_j^{t_1})$
9	16	1247	20.025	3.25	1	4.865531	5.33466
	4	29	49.497				6.358259
13	0	431	43.417	2.21	1	5.020996	28.48077
	7	429	70.349				6.815713
14	17	856	5.385	1.814	1	6.917267	4.086692
12	5	345	13.038	1.586	1	5.032216	4.847199
	6	290	23.854				6.200559
2	17	32	7.81	1.46	1	23.13416	4.090919
	19	11	18.868				5.445206
	10	53	19.105				6.550114
	11	111	26.401				4.674716
	7	50	38.328				6.817863
	18	308	38.601				28.50529
8	6	102	21.932	1.166	1	4.1066	6.207838
	18	4	71.47				28.69914
15	18	84	77.156	1.119	1	14.74914	28.69689

TABLE 5. Simulation results of passenger flow scheduling based on gravity model.

Dispatch out spot (i)	Dispatch in spot (j)	Number of dispatched people $(N_{i,j})$	Distance from i to j (d_{ij})	Load rate before dispatching $(r_i^{t_0})$	Load rate after dispatching $(r_i^{t_1})$	Experience before dispatching $(E_i^{t_0})$	Experience after dispatching $(E_j^{t_1})$
9	16	124	20.025	3.25	1	4.865531	5.33466
	4	29	49.497				6.358259
13	3	860	138.322	2.21	1	5.020996	26.73597
14	17	856	5.385	1.814	1	6.917267	4.086692
12	6	392	23.854	1.586	1	5.032216	6.200559
	5	243	13.038				4.847199
2	18	521	38.601	1.46	1	23.13416	28.50529
	3	44	48.549				30.25572
8	0	106	34.828	1.166	1	4.1066	28.48077
15	0	84	10.000	1.119	1	14.74914	28.65634

- $\boldsymbol{E_\Sigma}$. The general tourist experience, which is calculated as following:

$$E_\Sigma = \sum_{i=0}^{19} E_i \cdot N_i \tag{20}$$

- $\boldsymbol{S^2}$. The differences of the number of tourists of all spots, which is the variance of the tourist load rate after dispatching. The smaller the value, the better the scheduling scheme.
- $\boldsymbol{N_{i,j}}$. The number of people scheduled from point i to j. $\sum_{i,j\in A} N_{i,j}$ is the total number of people been scheduled in the area.
- $\boldsymbol{C_r}$. The relative cost during the dispatch. Dispatching cost C is defined as below. C_0 is the cost of gravity-model-based scheme as the standard value which is 1 as shown in Table 6. d_{ij} below is the distance from spot i to j.

$$C = \sum_{i,j\in A, i\neq j} d_{ij} \cdot N_{i,j} \tag{21}$$

$$C_r = \frac{C}{C_0} \tag{22}$$

To avoid the influence of randomness, 5 simulations were carried out for each group of parameters, and the average value was used as the final result.

The comparison result of different scheme is shown in Table 6 which indicates that our scheduling can achieve obviously the better z, the optimization objective, than other schemes. This means that our scheduling can greatly improve the regional tourist experience and tourism profit, whether from the scenario that a large number of visitors are scheduled (IPSO, $\alpha = 0.4, \beta = 1.0, \theta = 0.3$) or the one that relative

TABLE 6. Comparison of different scheduling schemes.

Algorithm	Parameters α	β	θ	z	P_a	E_a	E_Σ	S^2	$\sum_{i,j\in A} N_{i,j}$	C_r
Original data		-		99.57506	14.528	6.854009	5918.681	0.596351	-	-
Gravity model		-		123.514	17.50262	7.056887	6934.182	0.064772	4382	1
Shortest distance		-		118.5835	17.09547	6.936544	6273.763	0.089691	4382	0.372
IPSO $swarmsize = 100$ $\Omega = 0.5$ $PHIP = 0.5$ $PHIG = 0.5$ $MAXITER = 100$	0.8	1.0	0.1	125.075	17.75596	7.047925	7405.177	0.047533	4073.8	1.784
	0.8	1.0	0.3	126.494	17.72677	7.042909	7499.752	0.050746	4094.4	1.803
	0.8	1.0	0.5	126.843	18.00240	7.046019	7441.301	0.035812	4375.8	1.900
	0.8	1.0	0.7	126.261	17.94517	7.045895	7426.740	0.044920	4298.8	1.881
	0.8	1.0	0.9	127.685	17.92691	7.042768	7487.732	0.046461	4325.8	1.804
	0.6	1.0	0.3	127.135	17.87797	7.043099	7491.841	0.042589	4299.6	1.780
	0.4	1.0	0.3	127.291	18.02819	7.049724	7420.026	0.043239	4375.6	1.912
	0.8	1.2	0.3	124.588	17.65361	7.051712	7374.746	0.056926	3813.0	1.639
	0.8	1.4	0.3	122.385	17.38210	7.043376	7235.918	0.083391	3268.6	1.423

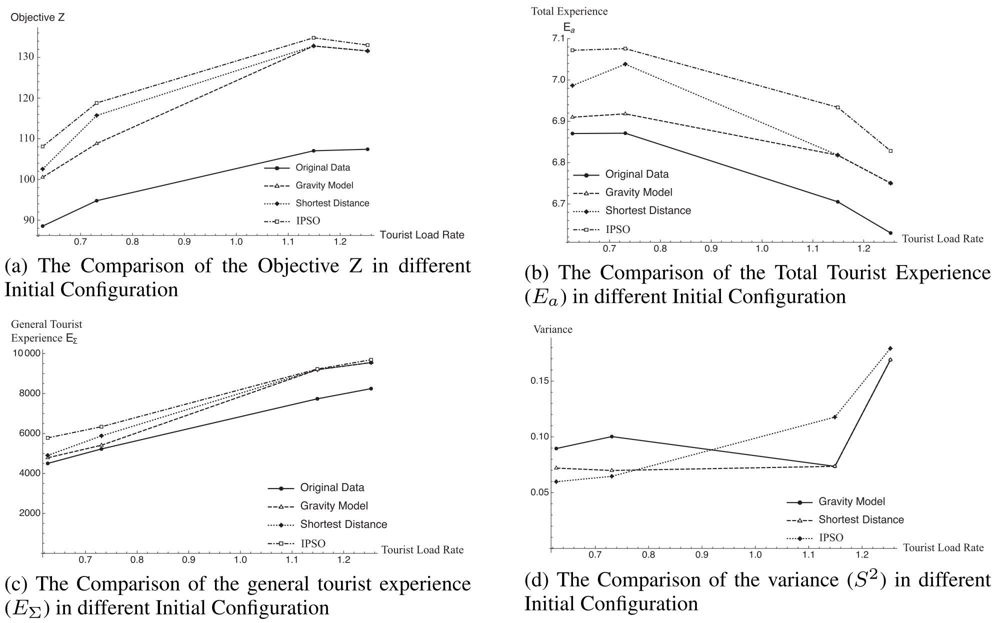
TABLE 7. Comparison of different parameters with high load rate.

ID i	Original data r_i	E_i	P_i	$\alpha = 0.6, \beta = 1.0$ r_i	E_i	P_i	$\alpha = 0.8, \beta = 1.0$ r_i	E_i	P_i	$\alpha = 0.8, \beta = 1.2$ r_i	E_i	P_i
0	0.519	28.4643	7.8222	0.772	28.6691	11.6406	0.947	28.2573	12.2012	1.092	27.5890	12.3200
1	1.277	9.8816	12.8930	0.615	9.9830	9.7869	0.982	9.9604	12.8930	1.047	9.9477	12.8930
2	0.396	24.7785	6.1898	0.670	25.2372	10.4723	0.961	24.8999	12.6518	1.133	24.3110	12.6518
3	0.872	30.0464	12.2698	0.909	29.9265	12.3032	0.884	30.0090	12.2810	0.949	29.7682	12.3044
4	0.720	6.3903	11.2703	0.781	6.3898	12.2373	0.904	6.3869	12.6272	0.924	6.3862	12.6453
5	0.312	4.8419	4.8219	0.785	4.8471	12.1109	0.990	4.8443	12.5182	1.158	4.8398	12.6500
6	1.518	6.1581	12.8303	0.939	6.2038	12.7785	0.989	6.2019	12.8213	1.199	6.1895	12.8303
7	0.860	6.8178	12.0906	0.628	6.8198	9.4473	0.974	6.8129	12.1890	1.036	6.8091	12.1890
8	1.520	4.0949	12.3684	0.898	4.1087	12.3572	0.870	4.1089	12.3316	1.132	4.1054	12.3684
9	1.741	5.0660	12.8791	0.625	5.1110	9.8878	0.986	5.1078	12.8347	1.018	5.1070	12.8610
10	0.686	6.5519	10.8456	0.811	6.5508	12.6585	0.919	6.5476	12.7607	1.117	6.5366	12.9180
11	1.359	4.6608	12.4021	0.782	4.6745	11.8111	0.805	4.6744	12.0847	1.041	4.6710	12.2960
12	0.236	5.0485	3.7632	0.902	5.0556	12.8329	0.934	5.0550	12.8617	0.941	5.0549	12.8682
13	1.930	5.0406	12.9020	0.986	5.0999	12.8029	0.942	5.1009	12.7646	1.012	5.0993	12.8244
14	0.986	7.0196	12.8264	0.670	7.0284	10.5965	0.887	7.0247	12.7397	1.009	7.0182	12.8454
15	0.190	14.5880	3.0254	0.845	14.8320	12.7957	0.817	14.8396	12.7684	1.109	14.6824	12.9831
16	0.865	5.3533	12.4548	0.941	5.3518	12.5142	0.893	5.3528	12.4805	0.848	5.3535	12.4391
17	0.617	4.0914	9.5031	0.973	4.0900	12.4791	0.935	4.0904	12.4464	1.052	4.0889	12.5446
18	1.389	25.3979	12.7586	0.797	28.6464	12.5279	0.922	28.3543	12.6827	1.110	27.4917	12.7586
19	0.721	5.4471	11.2086	0.775	5.4468	12.0399	0.804	5.4465	12.4365	0.835	5.4462	12.4661

little amount people are diverted (IPSO, $\alpha = 0.8, \beta = 1.0, \theta = 0.1$).

Our program always manages to keep or enhance the visitor travel experience after the diverting. So we can see from Table 6 that although the number of people dispatched in our plan and the total tourist experience of the region are all comparable to the other two plans, but our scheme can also get remarkably better performance in E_Σ than the scheme based on gravity model and distance-based scheduling scheme, which means more tourists can benefit from our scheme. It shows that our scheme can also get obviously better performance in S^2, which means better visitor load distribution balance.

In Table 2, the actual number of tourists in each spot is generated randomly, which represents a situation in a real scene. Beyond that, the tourist number will increase sharply when some popular holidays come. Therefore, a simulation with high load rate is taken to verify the performance of the optimization model and the result is shown in Table 7. It can be concluded that after the dispatching, the load rate of each spot is located in proper section. Comparing with the original data, the overall tourism experience and operator profit increase to some extent, which proves the performance of the model in such an extreme scene. In addition, the setting of the parameters counts a lot. If the value of α is too small, the number of under-loaded spots will decrease. It is possible



(a) The Comparison of the Objective Z in different Initial Configuration

(b) The Comparison of the Total Tourist Experience (E_a) in different Initial Configuration

(c) The Comparison of the general tourist experience (E_Σ) in different Initial Configuration

(d) The Comparison of the variance (S^2) in different Initial Configuration

FIGURE 3. Simulation results based on different initial conditions.

to select some spots far from the current spot so as to increase the dispatching cost. Similarly, if $\beta > 1$, some spots still maintain over-loaded after dispatching. Therefore, when the load rate of the whole region is high, the value of β is set to 1 as far as possible. As for α, its value can be increased to provide more under-loaded spots nearby.

However, IPSO has a higher value of C_r than the other two schemes. It can reach 1.912 when the parameters α, β, and θ are set to 0.4, 1.0 and 0.3. It means tourists needs to be scheduled to farther places. This is the cost of the dispatching. But it can be accepted in most circumstance because in rural leisure tourism, people usually prefer to driver a little further to get better experience.

The simulations above are all based on the same original data. To verify the generality of the scheme, we carried out a comparative experiment based on different initial conditions that having different tourist load rate in the region. The related results are shown in Figure 3.

From the results, we can see that in different visitor loads, our algorithm can get better and more stable scheduling result. The value of the objective function z is higher than the other two scheduling schemes. It shows that our algorithm can ensure that tourists will get better experience both in E_a and E_Σ after the scheduling, comparing with the other two algorithms. The Figure 3(d) also shows our algorithm can make tourists distribution more balanced than the others in low tourist load rate. However it is difficult for our algorithm to get further improvement in higher load rate situation, because the space that can be used to accommodate the diverted visitors become much smaller.

V. CONCLUSION

In this paper, a new traffic scheduling scheme for the problem of unbalanced distribution of tourists is presented. The purpose of our plan is to improve the overall business interests and tourism experience of the region on the basis of protecting the interests of tourists and operators. Simulation results show that our approach outperforms the shortest-distance-based traffic scheduling scheme and the gravity-model-based scheme in most common situations. For each over-loaded spot, the scheme can find the most suitable under-loaded spots to divert tourists and minimize the influence on tourist experience and operator profit. During the process of dispatching, although some tourists need to spend a little time driving to other under-loaded spots, they can avoid crowded conditions, even can get higher quality of service, which is meaningful for all stakeholders. In addition, it is proved that the scheme is also efficient under an extreme condition where most spots are over-loaded. However, the model also has some limitations that the parameters are difficult to be set properly. For example, if the value of α is too small, the under-loaded spots might be located in long-distance places, which takes more dispatching cost.

For the future work, it is considerable to follow the two aspects. First of all, the model proposed in this paper took an overall objective based on tourist experience and operator profit. The future research could consider multi-objective model which will regard tourist experience and operator profit as two individual objectives. It will be more convenient and flexible to calculate the optimal value of each objective. Secondly, our model provided suitable dispatching scheme for administrators and tourists with a low demand on real-time performance. For further study, the parallel computing will be a possible direction to improve real-time performance. The number of dispatching tourists of over-loaded and under-loaded spots will be calculated together to accelerate the entire dispatching process.

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