Tour-sites Recommendation Mechanism for Navigation System

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Abstract

This work proposed a hierarchical tour-sites recommendation mechanism based on tourist group which is context, location, and time awareness. This mechanism includes two parts, Inter-site and Intra-site. We adopted the Artificial Fish Swarm Algorithm (AFSA) to build this two parts tour-sites recommendation mechanism. In the Inter-site recommendation, we combined Co-occurrence concept to predict the interest of tourists. We formulate the problem of choosing the paths among the vehicles in the same region by using non-cooperative game theory, and find out the solution of this game which is known as Nash equilibrium. This mechanism determined on reducing the average waiting time of tourist and balancing the congestion degree of sites in a city and presents a recommendation mechanism for vehicle-sharing. Moreover, it took the demand of tourists into consideration. The experimental results showed that the mechanism we proposed improve the tourism experience for tourist groups.

Keywords: Recommendation mechanism, Swarm intelligence, Co-occurrence, AFSA

1 Introduction

Recently, the cultural tourism becomes part of people's life. The quality of tourism is much important now. There are many researchers interested in improving the quality of tourism using recommendation systems. Researchers concentrated on personal navigation systems [1, 10] and congestion reducing topic of tourism recommendation [5-8, 16-17]. However, these researches are mainly focus on personal guidance.

Our method includes two parts which are Inter-site and Intra-site recommendation mechanism. There are three main problems in two parts of our mechanism respectively. In Intra-site: (1) The congestion problem: According to this problem, each scene has its capacity. The quality may drop as the scene's tourists exceed its capacity. Then, the tourist would experience unhappiness. (2) The time delay problem: According to this problem, we recommended groups to the next scene that less congestion and less waiting time [3]. (3) The massive multi-group problem: According to this problem, in most studies, the user is the single tourist.

That is to say, the visitors usually go to or leave each location together if they are in the same group. In Inter-site: (1) The context problem: According to this problem, the method we proposed considering the tourists' interest, the congestion degree of sites, and the popularity of sites to recommend the best next site for user. (2) The distance problem: According to this problem, each group will start their visit from different place. (3) The time problem: According to this problem, visitors would planned how long to stay in a city.

The rest of this paper is organized as follows. Section 2 introduces the background knowledge and related work. Section 3 describes the problem and our goals. Section 4 discusses our environment and assumptions; proposes the system architecture and mechanism details. Section 5 demonstrates the simulation results of the proposed method. Section 6 concludes this work and future work.

2 Related Work

2.1 Tourism Recommendation Mechanism

Many researchers studied on the personal tourism navigation system, which navigate users by displaying routes to given destinations [1, 10] A. Maruyama, N. Shibata, Y. Murata, K. Yasumoto, and M. Ito, "A personal tourism. Furthermore, some researchers were interested in congestion-aware scheduling methods for multi-destination travels [5-8, 18]. Those navigation systems focused mainly on guidance for personal use. Besides, some research concerned other factor such as the POIs (Point of Interests), available time of tourist, the location of tourist to recommend the tour path for user [4]. The adaptive recommendation mechanism used ACO to update the path pheromone which indicates the popularity and crowd degree of each scene in a single site [3].

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2.2 Artificial Fish Swarm Algorithm

AFSA is proposed by Li Xiao-Lei in 2002, the basic idea of the AFSA is to imitate the fish behaviors such as preying, following and swarming with local search of fish individual for reaching the global optimum, [9, 19]. These algorithms now applied in many research fields generally [12]. For example, control, Image processing, Network and scheduling, [2, 11, 14-15]. The details of three behaviors are described as follows.

Preying is the basic biological behavior that fish tends to the food [12]. Figure 1 shows the pseudo code of AFSA preying behavior.

$$X_j = X_i + Visual()$$
If $f(i) < f(j)$ *in the maximum problem, it goes forward a step in this direction;*
$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_j - X_i^{(t)}}{\|X_j - X_i^{(t)}\|} . Step().$$

Figure 1. AFSA preying behavior

Swarming behavior describes the fish will assembles in groups naturally in the moving process [12]. Figure 2 describes the following behavior. Fish take the center of neighbor into consideration and compare the objective value. Then move toward the better position according to the objective value.

X_c *is the center of neighbor* $(d_{ij} < Visual)$
$$\text{If } \left(f(c) > f(i) \;\&\; \frac{nf}{n} < \delta \right)$$
$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_c - X_i^{(t)}}{\|X_c - X_i^{(t)}\|} . Step().$$

Figure 2. AFSA swarming behavior

Figure 3 shows the following behavior. First, fish choose some neighbor to evaluate the objective value of them. Then, determine the target position based on the comparison of objective value [12]. Finally, move toward to the target position.

X_j *is a neighbor* $(d_{ij} < Visual)$
$$\text{If } \left(f(j) > f(i) \;\&\; \frac{nf}{n} < \delta \right)$$
$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_j - X_i^{(t)}}{\|X_j - X_i^{(t)}\|} . Step().$$

Figure 3. AFSA following behavior

2.3 Co-occurrence

GEOSO, a geo-social model has presented [13]. Figure 4 shows the idea of GEOSO. We can see that person a visit place 2 at t_1 and t_2, then visit place 3 at t_4 and t_5. Another person c visit place 2 at t_1 and t_2, and visit place 3 at t_4 and t_5 as well. These two persons both visit place 2 and 3 at the same time. It is possible that these two persons are social connected, which means they know each other, maybe even they are friends.

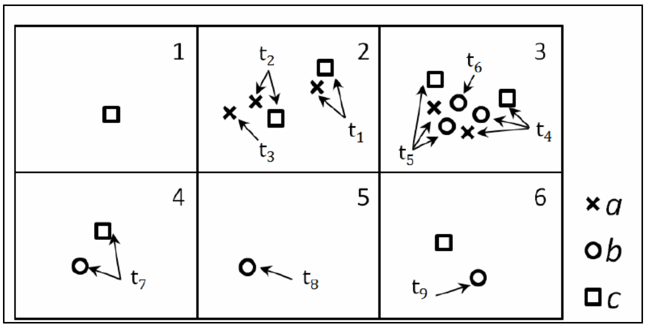


Figure 4. The idea of GEOSO [13]

3 Problem Description

3.1 Intra-site

There are three main problems in Intra-site part. First, the congestion problem means our mechanism should keep each scene’s number of visitor smaller than its visitor capacity; Second, the time-delay problem would be the less congestion scene shall remain relatively empty until the tourists arrive there; Finally, the massive multi-group problem considering a tourist group since visitors will usually go to or leave each location together if they are in the same group [3].

Figure 5 presents a schematic diagram of sightseeing environment using the Tainan Confucius Temple Map. There are seven scenes, four groups, and some scattered visitors. System may recommends group G4 to visit scene S1, which reflects the fact that the scene’s tourists do not exceed the scene’s capacity, that is to say, congestion do not happen. However, a situation in which group G2 and group G3 go to scene S4 at the same time causes a decline in the quality of the tourist visit experienced by the tourist visitors because the number of tourists at the scene exceeded its capacity.

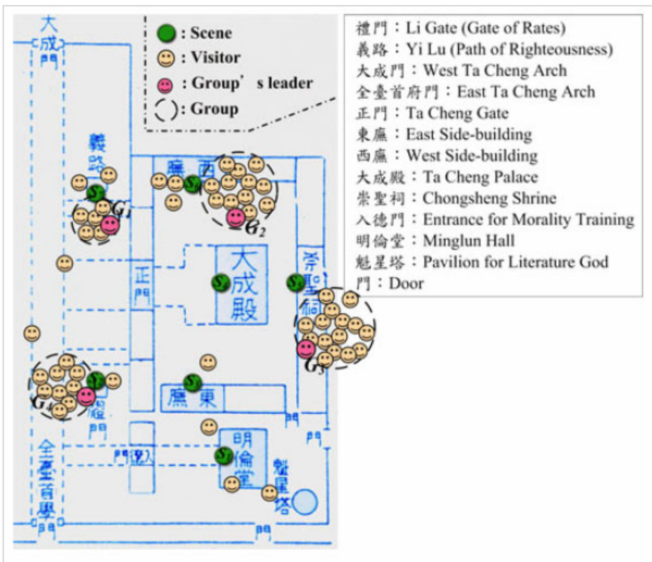


Figure 5. Scenario of Intra-site [8]

We could assume $G = \{G_1, G_2, \ldots, G_m\}$ as the tourist group in our environment, and the scenes in site represents as $S = \{Sc_1, Sc_2, \ldots, Sc_n\}$. Let $wt(Sc_i)_j$ be the waiting time which group *j* spent for visiting scene *i*, and $wt(avg)_j$ is the average waiting time of group *j*.

$$wt(avg)_j = \frac{\sum_{i=1}^{n} wt(Sc_i)_j}{n} \quad \textbf{(1)}$$

Our goal is to minimize the average waiting time of all groups:

$$wt_{avg} = \frac{\sum_{j=1}^{m} wt(avg)_j}{m} \quad \textbf{(2)}$$

3.2 Inter-site

There are three main problems in Inter-site as well. First, the context problem means to recommend a sightseeing site considering its popularity, congestion degree, and the tourist interest of it. Then, the distance problem is that our method would take the distance between tourist and recommended site into account. The site which is too far may not recommend. Last, this part also give thought to the time problem, in other words, the available visiting time of tourist and the anticipated visiting time of each site should be take care severely.

Figure 6 is a schematic diagram of scenario in Tainan city, Taiwan. There are four (red) groups already started their sightseeing. Now, there comes a new (green) group which has 10 persons at Tainan Train Station. We may probably recommend this new group to visit Chih Kan Tower or National Cheng Kung University first since the group is near to the site, and there is not congestion at all.

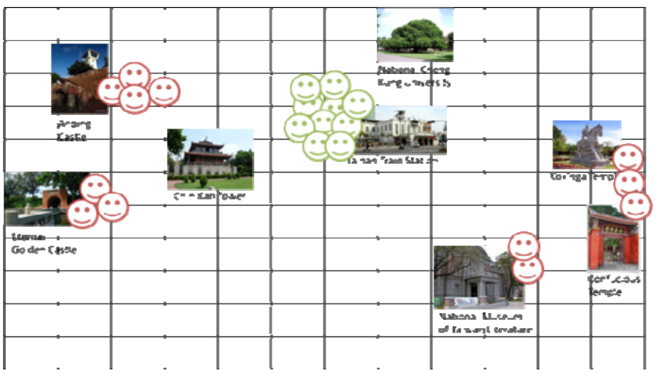


Figure 6. Scenario of Inter-site

In Inter-site part, we use a graph G=(V, E) to represent a city, the number of nodes is |V| = n, $V=\{V_1, V_2, \ldots, V_n\}$ is a set corresponds sightseeing sites in this city. The edge of graph E_{ij} is Manhattan distance between V_i and V_j. Each site (V_i) maintains its own information such as, c_i congestion degree, vt_i anticipated visiting time, and h_i popularity.

Table 1 is the candidate table of all sites; left side is the best candidate and the worst at right sight. The length of each element (candidate sight) depends on the anticipated visiting time of the site. The candidate sights V_i 's order would change according the principles below.

Table 1. Recommendation mechanism table

Best	V_1	V_2	V_3	……	V_n	Worst

- *If* $[(h_i - c_i)] > [(h_j - c_j)]$, *then recommend* h_i *first than* h_j
- *If* $[(h_i - c_i)] = [(h_j - c_j)]$ *and length*(h_i) > *length*(h_j), *then recommend* h_i *first than* h_j

Let R_i represents the sites we already recommended to a tourist group, and $T(R_i)$ corresponds to the total visiting and routing time the tourist group spent to finish the visit of R_i. $Cong(V_i)^{(t)}$ means the congestion degree of site V_i at time t.

$$Cong(avg)^{(t)} = \frac{\sum_{i=1}^{n} Cong(V_i)^{(t)}}{n} \quad \textbf{(3)}$$
$$st.\, t \le T_{available}$$

Our target in Inter-site part is to minimize $Cong(avg)$, the average congestion degree of whole sites.

$$Minimize\ Cong(avg) = \frac{\sum_{i=1}^{t} Cong(avg)^{(i)}}{t} \quad \textbf{(4)}$$

It is note that our mechanism guaranteed $T(R_i)$ must smaller than $T_{available}$, the available time that a group can spend on the tourism of a city.

4 System Model and Assumption

4.1 Environment and Assumptions

We considered a city having several sightseeing sites, and each site has several scenes in there. There are some assumptions in our environment:

(1) Each scenes and sites has its specific tourist capacity. When the tourists' amount exceeds the capacity of the site/scene, congestion happens.

(2) The road of the city is grid-liked. We use Manhattan distance to represent the path length between two locations.

(3) Each group has a mobile device. Our recommend results could be fetched by user's mobile device directly.

(4) Each scene has a sensor to sense if tourist group

approach. Through the message exchanged, scene sensor could know which group is visiting now.

(5) Super PC could maintain the information such as round trip time and the amount of group in the scene now.

(6) There always is a path between any two scenes. The diagram of environment in site is show in Figure 8.

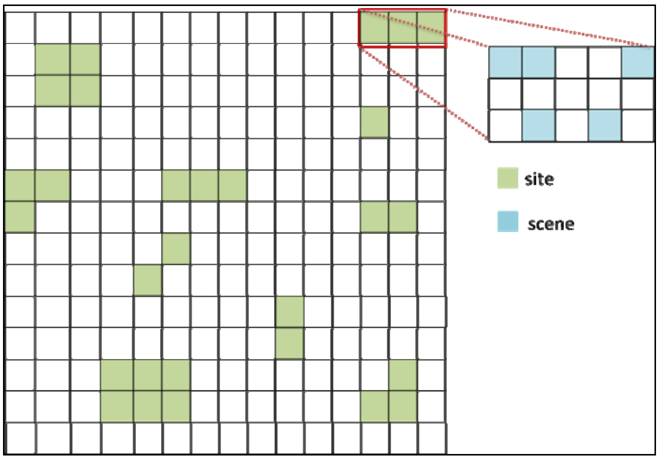


Figure 7. Grid-like city road and its sites and scenes

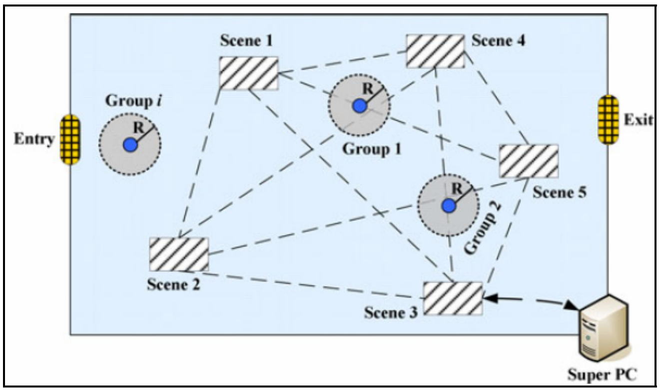


Figure 8. Environment in a site [3]

(7) Each Super PC connected to cloud server through network which without the bandwidth limit.

(8) Each group visits all scenes in one site before goes to another site.

4.2 AFSA Recommendation Mechanism

Figure 9 shows the system architecture of our system. Each site has sensor to sense whether there are groups visit the scene or not. Intra-site recommendation mechanism runs on the super PC of each site.

Figure 10 is the flow chart of our mechanism. In Intra-site module, we use raw data which comes from the simulation historical logs as the initial estimated data. After compute the best "next location" through Intra-site recommendation method, user moves toward the recommended location. Then, movement collecting module gets the information about the user movement. The system compute the best "next site" using the objective function and artificial fish swarm algorithm.

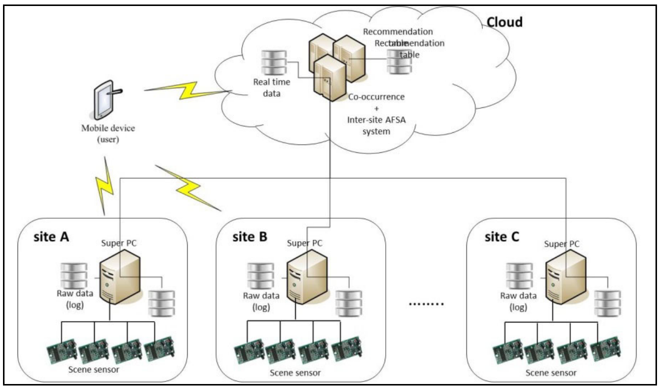


Figure 9. System architecture of AFSA Recommendation System

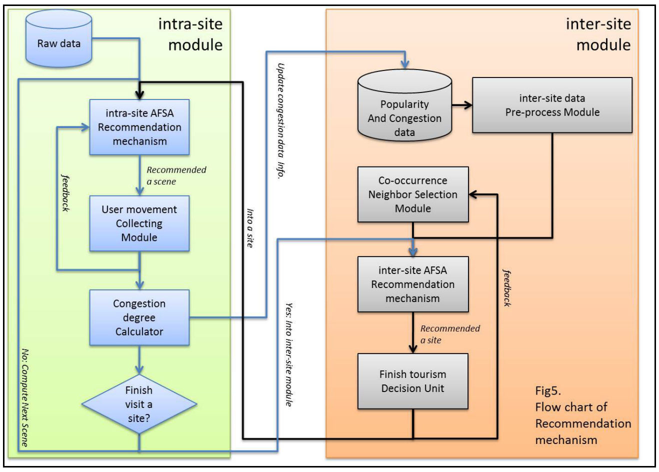


Figure 10. Flow Chart of AFSA Recommendation System

At the end, system should judge if this group finish its tourism or not. When user arrives at the recommended site, the Intra-site recommendation module would be start up.

4.3 Feedback Handling in AFSARM

We handle the feedback information using aging concept, which means older information are much less reliable. The estimated value changed according to formula 5. D_{orig} is the current estimated value, $D_{feedback}$ represents the data feedback to system. We could get the new estimated value D_{new} simply by multiplying two values to different weights. It is note that ω_1 should small than ω_2 to reflect the aging concept.

$$D_{mew} = \omega_1 \times D_{orig} + \omega_2 \times D_{feedback}, \quad \text{st.}\ \omega\_1 < \omega 2 \tag{5}$$

4.4 Intra-site AFSARM

We adopted the swarming behavior of AFSA in Intra-site recommendation mechanism. This behavior reflects our goal in Intra-site recommendation mechanism, that is, reducing the waiting time of each tourist group.

AFSA using the objective function to determine that which position to go next. The objective function in our method is listed as follows:

$$f(x) = \alpha \times rtt(current, x) + \beta \times Nofs(x) \times Ewt(x) + \gamma \times \frac{N(x)}{Cap(x)}$$

This objective function considers the round trip time between current scene and candidate scene, the estimated waiting time of candidate scene, and the present congestion degree of candidate scene. The input of this function x is the candidate scene. First, $rtt(current, x)$ indicates the estimated time need to spend that a group walk from current scene to candidate scene x. Second, $Nofs(x)$ means the amount of group now visiting the scene x, and $Ewt(x)$ represents the estimated visiting time of a group at scene x, which would change according to the feedback information. In more detail, $Nofs(x) \times Ewt(x)$ shows that how much time the group needs to wait for the previous group finish their visit. At the end, $N(x)/Cap(x)$ represents the congestion degree of scene x, $N(x)$ is the number of persons visiting the scene x, and $Cap(x)$ is the capacity of scene x.

This paragraph shows how a group chooses its candidate position. The swarm behavior has been used.

Let SetC =
{V_c, *c is the scene that group doesn't visit yet*}
For each (V_j *from SetC*)
{
  $If\,(Cong(c) < \delta\ \&\&\ f(j) > f(i))$
  $\{V_c = V_{jJc};\}$
}
$$V_i^{(t+1)} = V_i^{(t)} + \frac{V_c - V_i^{(t)}}{\| V_c - V_i^{(t)} \|} \cdot speed();$$

Figure 11. Swarming behavior of Inter-site AFSARM

As said, we compare the congestion degree of candidate scene, that is, $Cong(c)$ with the crowd factor δ to estimate whether the target scene is too crowd or not.

$$\delta = \frac{\Sigma cong(k), k \in SetC}{|SetC|} \quad \textbf{(6)}$$

4.5 Inter-site AFSARM

In the Preying behavior, we use objective function to estimate the worth of the candidate site. The objective function also be used in Following behavior.

$$f(x) = \alpha \times h_x - b \times c_x - c \times E_{ix} + d \times vt_x \quad \textbf{(7)}$$

Formula (7) is the objective function of Inter-site recommendation mechanism. First, h_x means the popularity of candidate site, which can be obtain from the social network. Secondly, c_x expresses the congestion degree of candidate site, which is evaluated from the super PC in each site. Thirdly, E_{ix} represents the Manhattan distance between current site and candidate site. Finally, vt_x indicates the estimated visiting time of candidate site, which is calculated from super PC as well.

The pseudo code of Preying behavior is as Figure 12. For each element in the set, we compare the objective value of it. According to the design of objective function, we make the site as target if it has the maximum objective value. The maximum objective value reflects the target site is popular, near, less congestion, and need less waiting time to visit. It is emphasized that visiting time should be controlled in the available time of tourist group.

For each (V_j in *Visual* ()) {
  If ($E_{ij} <$ *Visual* (), $f(j) > f(i)$, $T_{current} + vt_j \leqq T_{available}$)
  {V_c=V_j ;}
}
$$\{V_i^{(t+1)} = V_i^{(t)} + \frac{V_c - V_i^{(t)}}{\| V_c - V_i^{(t)} \|} \cdot speed();\}$$

Figure 12. Preying behavior of Inter-site AFSARM

The Following behavior, represents in Figure 13, is similar with Preying. The significant difference between Preying and Following behavior is candidate set. We proposed a co-occurrence neighbor selection method to choose the candidate sites in Following behavior.

For each (V_j from candidate set using *cooccurrence. neighbor.selection*())
{
  If ($f(j) > f(i)$, $T_{current} + vt_j \leqq T_{available}$)
  {V_c=V_j ;}
}
$$\{V_i^{(t+1)} = V_i^{(t)} + \frac{V_c - V_i^{(t)}}{\| V_c - V_i^{(t)} \|} \cdot speed();\}$$

Figure 13. Following behavior of Inter-site AFSARM

At the last step of Inter-site recommendation mechanism, we measure two results from Preying and Following behavior. We made the final decision simply by selecting the one that has bigger objective value.

4.6 Co-occurrence Neighbor Selection Method

The visiting event can be represented as *<g, v, t>,* it shows that a groups (g) visited a site(v) and stay for how long(t). The argumentations are listed as follows.

- The more sites two groups visited together, the more likely they are interested close
- The more sites two groups visited together and stayed for almost same time period, the more likely they are interested connected

We assume there were group A and B, which already finished their tourism. Their visiting table can be represented as Table 2. The table element shows the time that group stay more than estimated visiting time. For instance, group A stayed at site V_1 more 15 minutes than the estimated visiting time 15 minutes.

Table 2. Visiting table of group A and group B

	$V_1(15)$	$V_2(15)$	$V_3(30)$	$V_4(20)$	$V_5(15)$	$V_6(35)$
Group A	15	0	-5	20	10	0
Group B	-5	0	15	0	30	0

Now there is a group C just finished the visit of one site. The visiting table of group C is shown in Table 3.

Table 3. Current visiting table of group C

	$V_1(15)$	$V_2(15)$	$V_3(30)$	$V_4(20)$	$V_5(15)$	$V_6(35)$
Group A	15	0	0	0	0	0

After the interested sites candidate set has been choose, the following behavior measures the objective value of these sites and select a final target site. We simply use the historical visiting data of groups to analysis the interest of user and predict the candidate interested set to our mechanism.

4.7 Non-cooperative Game Model for Group Recommendation

The main objective of the recommendation problem is to maximize the profits of the vehicles in the same region by utilizing the concept of equilibrium. As the concept mentioned above, a non-cooperative game model can be formulated as follows. The strategy of each vehicle is the choice of route. The payoff of each vehicle is the profit related to probability for a visitor and the cost born by the vehicle. The commodity in the scenario is recommendation routes.

Firstly, we assume there are N vehicles in the same region with the request of recommendation at time t. Path s_i for recommendation is considered a strategy of vehicle i in the system model. $\mathbb{S}$ denotes the set of strategies of all vehicles in the region (i.e. $\mathbb{S} = \{s_1, \ldots, s_N\}$).

Based on the assumption described above, we represent the function to calculate the cost which vehicles need to bear according to the selections of strategies. This cost function is given by

$$c(\mathbb{S}) = \eta_1 \times [\Sigma_{S_i \in \mathbb{S}} (s_{i.d} + s_{i.t})^{\tau} \quad \textbf{(8)}$$

where η_1 is a normalized factor to adjust the cost, $s_{i.d}$ and $s_{i.t}$ is the distance and travel time for strategy s_i, τ is a non-negative constant, and $\tau \geq 1$ (so that the cost function is convex i.e., there exists the extreme value in this function), and $\mathbb{S}$ denotes the set of strategies of all vehicles in the same region.

Let $\mathbb{S}_{-i}$ denote the set of strategies adopted by all vehicles except vehicle i (i.e. $\mathbb{S}_{-i} = \{s_j \mid j = 1, \ldots, N; j \neq i\}$ and $\mathbb{S} = \mathbb{S}_{-i} \cup \{s_i\}$). The optimal recommendation of routes to each vehicle depends on the strategies of other vehicles. Nash equilibrium is regarded as the solution of the game. Nash equilibrium of a game is a strategy profile (e.g. lists of strategies in the form of one for each other). The property of Nash equilibrium is that no player can increase his payoff by choosing another strategy according to other players' strategies. It means that no player is willing to change his action for more profit, given the others' actions.

The Nash equilibrium in this case is obtained by using the best response function which is the best strategy of one player, given others' strategies. The best response function of vehicles i given the strategies of the other vehicles s_j, where $j \neq i$, is defined as follows:

$$BR_i(\mathbb{S}_{-i}) = \arg\max s_i \pi_i(\mathbb{S}_{-i} \cup \{s_i\}) \quad \textbf{(9)}$$

The set $\mathbb{S}^* = \{s_1^*, \ldots, s_N^*\}$ denotes the Nash equilibrium of this game if and only if $s_1^* = BR_i(\mathbb{S}_{-i}^*)$, $\forall i$, where $\mathbb{S}_{-i}^*$ denotes the set of the best responses for vehicle j for $j \neq i$. We can obtain the Nash equilibrium by solving the following equation

$$\frac{\partial_{\pi_i}}{\partial_{s_i}} = \eta_2 \{ \frac{p_{s_i}}{M(s_i)} - \eta_1 [\Sigma_{s_i \in \mathbb{S}} (s_{i.d} + s_{i.t})]^{\tau} \} \\ -\mu_1 s_i \tau [\Sigma_{s_i \in \mathbb{S}} (s_{i.d} + s_{i.t})]^{\tau - 1} \} \quad \textbf{(10)}$$

Therefore, the optimization problem with the objective can be defined as follows:

$$\text{Minimize} \sum_{i=1}^{N} | s_i - BR_i(\mathbb{S}_{-1}) | \quad \textbf{(11)}$$

For example, minimize the sum of the difference between decision variable s_i and corresponding best response function. The algorithm reaches the Nash equilibrium while the minimum value of the objective function is zero. As a result, the server determines the route recommendation for each vehicle in the same region at arbitrary time.

5 Performance Analysis

We implemented the AFSARM using Matlab, which comparing with Ant Colony Optimization Algorithm and Opportunistic scheme. The environment is shown in Table 4. We setup a city for tourist groups coming to visit. We use Poisson distribution to simulate the group arrival interval. The biggest Poisson distribution λ value indicates that tourist group arrived in environment with a longer time period, which mean the group arrived much scattered. Others parameters of each scene, site, and group are shown in Table 5.

Table 4. Environment setup

	value
City	$8 \times 10\ km^2$
Number of Site	5 or 10
Number of Scenes in a Site	3 to 7
Group arrival interval	Poisson distribution with rate λ
Group arrival time	8 hour
Simulation time	12 hour

Table 5. Parameters of each group, scene, and site

Parameters of each group		
	notation	value
Number of person in group i	$NofG(i)$	10-45
Arrival time of group i	$T_{arrival}(i)$	0-28800(seconds)
Moving velocity of group i	$Velocity(i)$	11 m/s (= 40 km/hr)
Parameters of each scene		
	notation	value
Round trip time between scenes i, j	$Rtt(i, j)$	60-180 (seconds)
Estimated waiting time of scene i	$Ewt(i)$	60-300(seconds)
Capacity of scene i	$Cap(i)$	60-100(persons)
Parameters of each site		
	notation	value
Number of scenes in site i	ns_i	3 to 7
Location of site i	$Loc_i = (Loc\_x, Loc\_y)$	(0-800, 0-1000)
Popularity of site i	h_i	0-1
Congestion degree of site i	c_i	0-1

Table 6. Weight values of Intra-site and Inter-site objective functions

Weight value of Intra-site objective function	
α	0.4
β	0.3
γ	0.3
Weight value of Inter-site objective function	
a	0.3
b	0.2
c	0.2
d	0.3

5.1 Average Waiting Time in Intra-site Environment

Proposed mechanism presents better than two others methods. The results in Figure 14 and 15 shows that proposed mechanism, AFSARM, reducing average waiting time from two other methods even in a small group arrival interval rate. Proposed mechanism considering the round trip time and congestion degree of scenes, which distribute the tourist groups to different scenes and reducing the waiting time of each group.

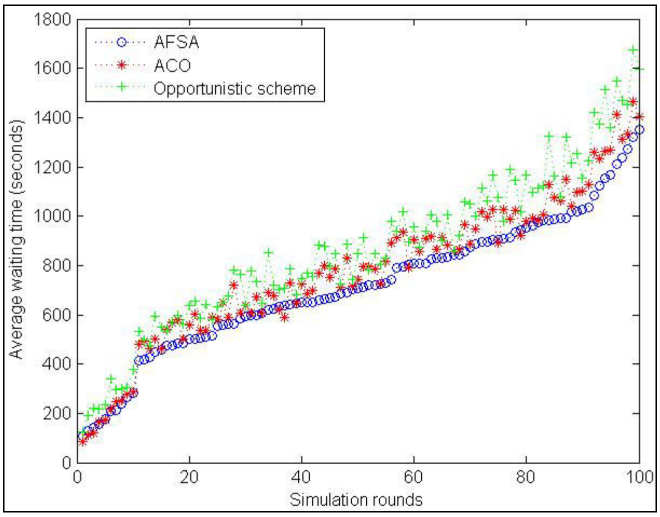


Figure 14. Average waiting time of each group in Intra-site

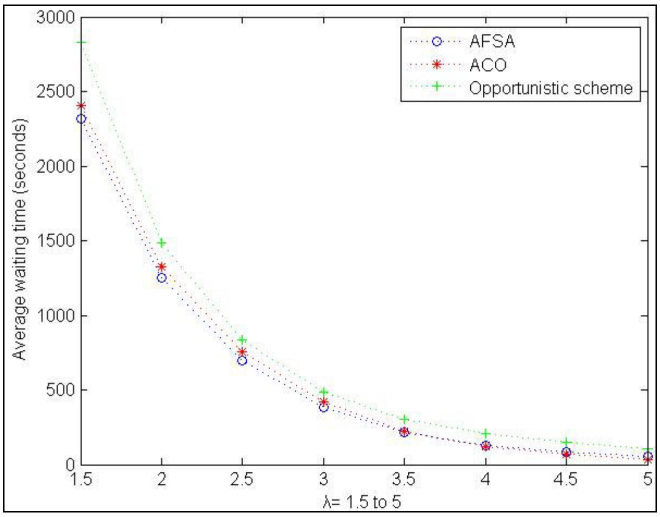


Figure 15. Average waiting time with different arrival interval rate in Intra-site simulation

5.2 Average Waiting Time in Inter-site Environment

Trough Inter-site AFSARM, the congestion degree of each site can be balanced. Figure 16 shows that AFSARM reduce the waiting time of tourist groups effectively and the noticeable than the results of Intra-site AFSARM. In Figure 17(a) and Figure 17(b), which shows the waiting time of AFSARM is the least in average. Besides, AFSARM could remain the better performance with different group arrival interval rate, which shown in Figure 18. Moreover, the waiting time using AFSARM is less than ACO during the rush hour, which shown in Figure 19.

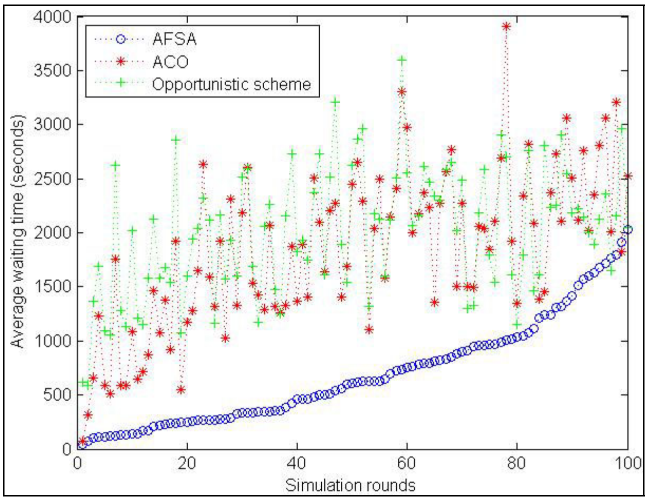
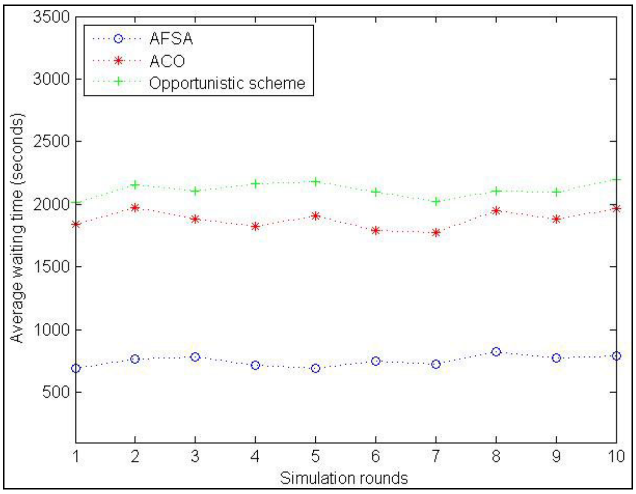
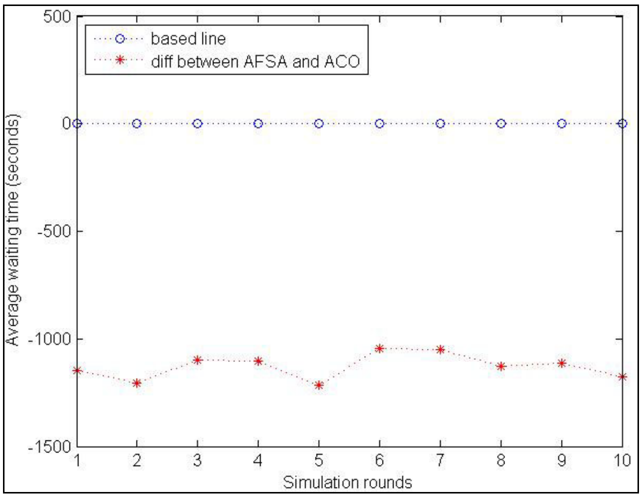


Figure 16. Average waiting time of each group in Inter-site



(a) Average waiting time of each group in Inter-site simulation



(b) Difference of average waiting time between AFSARM and ACO in Inter-site simulation

Figure 17.

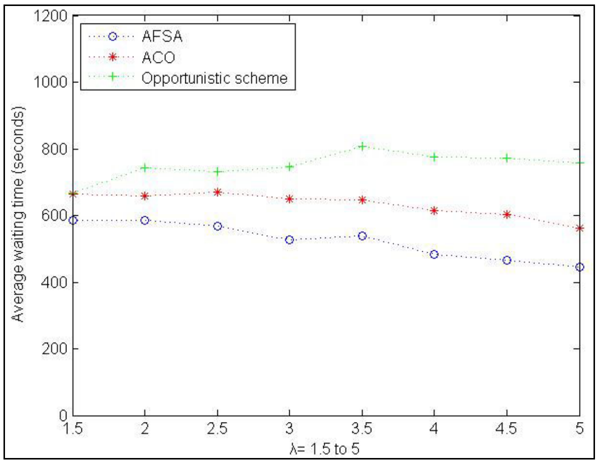


Figure 18. Average waiting time with different arrival interval rate in Inter-site simulation

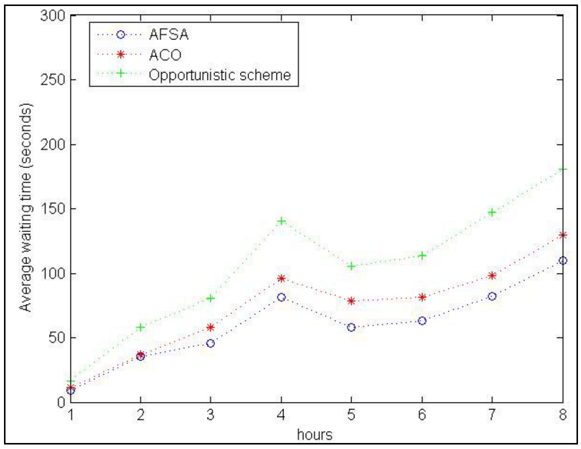


Figure 19. Stability of waiting time during rush hour in Inter-site simulation

5.3 Average Congestion Degree in Inter-site Environment

Figure 20 and Figure 21 shows that AFSARM reduce the congestion degree of each site about 20% comparing with ACO method. This is because ACO only consider the popularity and congestion factors, which could not distributed tourist groups well. Moreover, AFSARM could remain lower congestion degree with different group arrival interval rate.

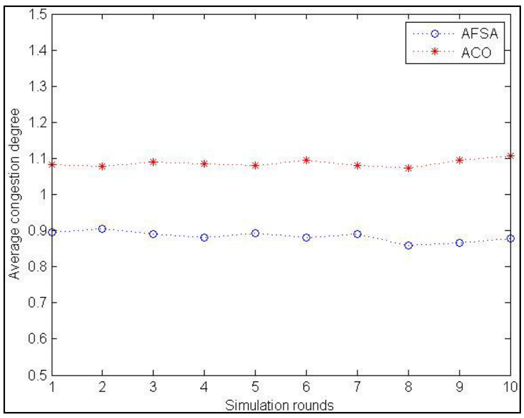


Figure 20. Average congestion degree of each site with same arrival interval rate in Inter-site simulation

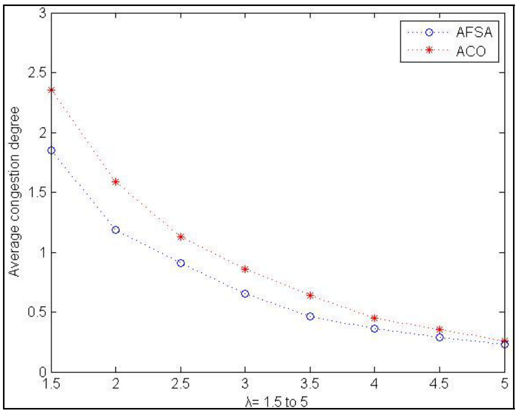


Figure 21. Average congestion degree of each site with different arrival interval rate in Inter-site simulation

Figure 21 shows the average waiting time of vehicles with and without recommendation respectively. The groups with recommendation had shorter waiting time than the ones without recommendation. The proposed method (with recommendation) had better performance due to 62 percent of waiting time reduced for groups on average.

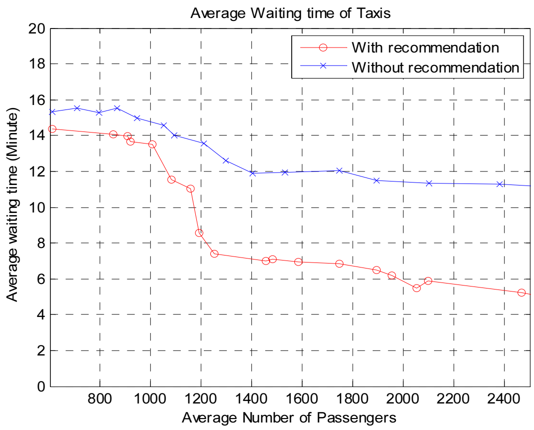


Figure 22. Average waiting time of vehicles

Figure 23 shows the average service time of groups in the conditions with and without recommendation respectively. As the result, the groups just needed to wait a little time for vehicle-sharing so that they could get more profit by saving their payment.

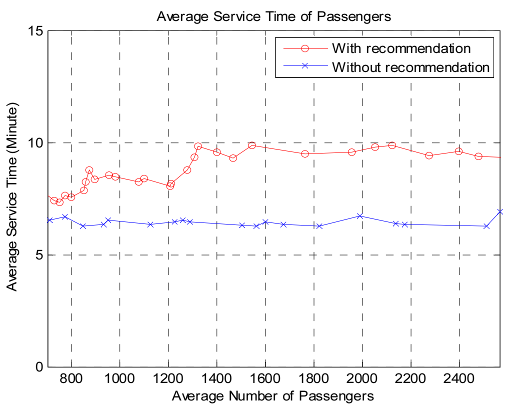


Figure 23. Average service time of groups

As Figure 24 shows, the curve with recommendation had less number of vehicles than the one with recommendation. The result indicates that a smaller number of vehicles can fulfill the service demands for groups by vehicle-sharing.

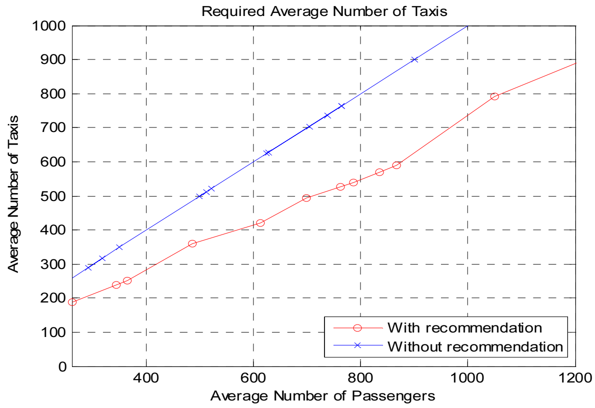


Figure 24. Required Average Number of Vehicles

Table 7. Units for Magnetic Properties

Symbol	Quantity	Conversion from Gaussian and CGS EMU to SI [a]
Φ	magnetic flux	1 Mx $\rightarrow 10^{-8}$ Wb = 10^{-8} V·s
B	magnetic flux density, magnetic induction	1 G $\rightarrow 10^{-4}$ T = 10^{-4} Wb/m^2
H	magnetic field strength	1 Oe $\rightarrow 10^3/(4\pi)$ A/m
m	magnetic moment	1 erg/G = 1 emu $\rightarrow 10^{-3}$ A·m^2 = 10^{-3} J/T
M	magnetization	1 erg/(G·cm^3) = 1 emu/cm^3 $\rightarrow 10^3$ A/m
$4\pi M$	magnetization	1 G $\rightarrow 10^3/(4\pi)$ A/m
σ	specific magnetization	1 erg/(G·g) = 1 emu/g $\rightarrow$ 1 A·m^2/kg
j	magnetic dipole moment	1 erg/G = 1 emu $\rightarrow 4\pi \times 10^{-10}$ Wb·m
J	magnetic polarization	1 erg/(G·cm^3) = 1 emu/cm^3 $\rightarrow 4\pi \times 10^{-4}$ T
χ, κ	susceptibility	1 $\rightarrow 4\pi$
χ_ρ	mass susceptibility	1 cm^3/g $\rightarrow 4\pi \times 10^{-3}$ m^3/kg
μ	permeability	1 $\rightarrow 4\pi \times 10^{-7}$ H/m = $4\pi \times 10^{-7}$ Wb/(A·m)
μ_r	relative permeability	$\mu \rightarrow \mu_r$
w, W	energy density	1 erg/cm^3 $\rightarrow 10^{-1}$ J/m^3
N, D	demagnetizing factor	1 $\rightarrow 1/(4\pi)$

Note. [a] Gaussian units are the same as cg emu for magnetostatics; Mx = maxwell, G = gauss, Oe = oersted; Wb = weber, V = volt, s = second, T = tesla, m = meter, A = ampere, J = joule, kg = kilogram, H = henry.

6 Conclusion

In this work, we proposed an Artificial Fish Swarm Algorithm Recommendation Mechanism (AFSARM) to improve the experience of tourism. AFSARM is a hierarchical mechanism which includes the Intra-site and Inter-site part. The simulation results proved that proposed mechanism reduce the waiting time effectively in Intra-site part. These two main achievements promote the tourism experience of tourists. This paper not only considers the congestion problem but also takes the popularity and the interest of user into account. This multi-consideration reducing the problem we mentioned above and improving the satisfactions of users. Moreover, AFSARM is the first work that using the concept of co-occurrence to predict the interested sites of users.

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