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THE APPLICATION OF ANT COLONY OPTIMIZATION ALGORITHM IN TOUR ROUTE PLANNING

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ABSTRACT

Traditional tour route planning mostly depends on the planner's experience. However, whether tour route planning is appropriate or not has a considerable impact on the time and cost of the tour. Good planning can save unnecessary waiting time, avoid wasted operating costs, and contribute to the enhancement of the quality of tourism. Therefore, this study applied the ant colony optimization algorithm to build a tour route planning model. As the empirical results have shown, the proposed tour route planning model can effectively and rapidly complete route planning and achieve the objectives of optimum route and minimum cost.

Keywords: *Ant Colony Optimization algorithm, Tour Route, Planning*

1. INTRODUCTION

Previously, tour route planning mostly depended on Rules of Thumb. Such a planning method can easily result in wasted tourism costs. Therefore, this study applies the Ant Colony Optimization Algorithm (ACO) in building a tour route planning model, expecting to achieve the objectives of the optimal route and the minimum cost. The concept of ACO, first proposed by Dorigo et al. [1, 2], is derived from the foraging behavior of an ant colony, and was known as the Ant System (AS). After many modifications, AS for the processing of Optimization Problems is now known as the Ant Colony Optimization algorithm [3-5], and was first used to solve the traveling salesman problem (TSP) [5-8]. TSP means: a salesperson wants to visit n cities and seeks a route with minimum cost that includes all cities and returns to the starting point (the shortest route of total distance). Afterwards, many studies applied ACO in solving the Quadratic Assignment Problem, Vehicle Routing Problem, Network Routing Problem, and Job Scheduling Problem [8-13]. In everyday life, an ant colony transports Food and returns to Nest on the same path. The ant colony finds a route between Nest and Food by relying on a secretion trail (known as Pheromone), rather than vision [3, 4]; ants rely on Pheromone to communicate food route information, the ant colony generally selects the route with high concentrations of Pheromone [1-4]; if an obstacle is encountered, the ant colony will attempt routes in various directions, leaving Pheromone on the routes. The following ants will determine which route to take according to the amount of Pheromone. The concentration of Pheromone of a route will increase as ant colonies pass by. However, as time goes by, the Pheromone on the route will gradually vaporize. In the more remote routes, Pheromone will gradually vanish due to vaporization. However, on some shorter routes, although the Pheromone may vaporize, the Pheromone continuously left by the ant colony will build up an accumulation of Pheromone on the route. As a result, the ant colony will follow the same route [5,6]; as shown in Figure 1, (A) is the shortest route between Food and Nest and the ant colony transporting Food back to the Nest; (B) an obstacle is encountered on the route, the ant colony has to look for a new route; (C) the ant colony walks along the both sides of the obstacle. Thus, the shortest route will have the higher concentration of Pheromone, as it is more used by the ant colony; (D) the ant colony selects the shortest route for transporting food [7-9].

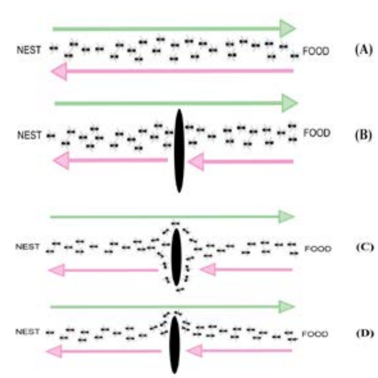

Figure 1: The method for determining the optimal route by the ant colony [7-9]

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2. RESEARCH METHOD

By imitating the behavior of an ant colony looking for the shortest route, ACO is a heuristic solution of artificial intelligence that searches for an approximate solution. Therefore, we apply ACO in building tour route planning models, including the Ant system, Ant-quantity system, Ant-density system, Antcycle system, and the Rank-Based version of the ant system.

2.1. Ant system

The core architecture of the Ant Colony Optimization algorithm is based on AS [1-4], which is the first proposed optimization model of ACO, and has been successfully applied in the Traveling Salesman Problem. Transition Probability and Pheromone updating of the AS algorithm are as shown below:

2.1.1. Transition probability (Eq. 1)

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{s\in allowed_k}\tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)}, & if\ j\in allowed_k\\ 0, & otherwise\end{cases} \tag{1}$$

t is No. t iteration, p_{ij}^{k} is the transition probability of Ant k from Node i to Node j, τ_{ij} represents the amount of pheromone on route (i,j), η_{ij} is the reciprocal of the distance from Node i to Node j, allowed k={0,1,2….., n-1} represents the next node that ant k can select. α and β are parameters that determine the relative importance between Pheromone and η_{ij}.

2.1.2. Pheromone update (Eq.2 and 3)

After time period n, the ant completes a search of the optimum route. The concentrations of Pheromone on various routes can be adjusted according to Eq. 2 and Eq. 3:

$$\tau_{ij}(t+1)=\rho\tau_{ij}(t)+\Delta\tau_{ij}(t,t+1) \tag{2}$$

$$\Delta\tau_{ij}(t,t+1)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1) \tag{3}$$

$\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1)$ represents the amount of Pheromone of No. k ant on route (i,j) at time period $(t,t+1)$; $\Delta\tau_{ij}(t,t+1)$ represents the increase of Pheromone; $(1-\rho)$ is the vaporization coefficient of the Pheromone.

According to different algorithms, the expression of $\Delta\tau_{ij},\Delta\tau_{ij}^{k},p_{ij}^{k}(t)$ may be different. Relevant studies [1-5] have proposed the Ant-quantity system, Ant-density system, and Antcycle system.

2.2. Ant-quantity system and ant-density system

The difference between the Ant-quantity system and Ant-density system is $\Delta\tau_{ij}^{k}(t,t+1)$. In the Ant-density system, the amount of Pheromone released by an ant colony on route (i,j) is Q per unit length. In the Ant-quantity system, the amount of Pheromone released by an ant colony on route (i,j) is Q/d_{ij} (d_{ij} is the distance between i and j) per unit length.

In the Ant-density system, when an ant colony moves from i to j, the increased Pheromone strength on route (i,j) has nothing to do with d_{ij}. However, in the Ant-quantity system, when an ant colony moves from i to j, the increased Pheromone strength on route (i,j) is inversely proportional to d_{ij}. In other words, in the Ant-quantity system, the short route is more attractive to ants, thus, Eq.1 η_{ij} value is increased.

2.3. Antcycle system

The difference of the Antcycle system and Ant-quantity system; the Ant-density system lies in $\Delta\tau_{ij}^{k}$. In the Antcycle system, $\Delta\tau_{ij}^{k}(t,t+n)$ indicates the amount of increased Pheromone, $(t,t+n)$ means that the ant colony completes a cycle after time period n, and the updated value is as shown in Eq. 4:

$$\Delta\tau_{ij}^{k}(t,t+n)=\frac{Q}{L_k} \tag{4}$$

L_k is the length of the route covered by No. k ant.

In the Ant-density system and Ant-quantity system, the ant colony will release Pheromone when looking for the optimal route by taking advantage of the partial updating method. The Antcycle system releases Pheromone after establishing the complete route by taking advantage of the overall updating method. Pheromone is updated according to Eq. 5 and Eq. 6:

$$\tau_{ij}(t+n)=\rho_i\tau_{ij}(t)+\Delta\tau_{ij}(t,t+n) \tag{5}$$

$$\Delta\tau_{ij}(t,t+n)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+n) \tag{6}$$

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2.4. Rank-Based version of the ant system (ASrank)

ASrank expands the ranking concept of the Genetic Algorithm for application in the ant colony algorithm system [14-16]. The algorithm design is to sort the values of m ants after completing each iteration, and before updating the Pheromone of the ants ranking W=σ−1. The ant with the higher ranking has the more increased amount of Pheromone.

The algorithm's Transition Probability is Eq. 1, Pheromone Updating is as shown in Eq. 7:

$$\tau_{ij}(t+1)=\rho\tau_{ij}(t)+\Delta\tau_{ij}+\Delta\tau_{ij}^{*} \qquad (7)$$

$\Delta\tau_{ij}=\sum_{\mu=1}^{\sigma-1}\Delta\tau_{ij}^{\mu}$ represents the updating of Pheromone No. $\sigma-1$ ant between (i,j) according to the ranking; μ is the sequence of ants; $\Delta\tau_{ij}^{\mu}=(\sigma-\mu)\frac{Q}{L^{\mu}}$, $\Delta\tau_{ij}^{*}=\sigma\frac{Q}{L^{*}}$, $\Delta\tau_{ij}^{\mu}$ represents the amount of increased Pheromone of No. μ ant on route (i,j) ; L^{μ} is the length of the optimal route of No. μ ant; $\Delta\tau_{ij}^{*}$ represents the amount of increased Pheromone on the route (i,j) formed by the elite ants; σ is the number of elite ants; L^{*} is the length of the route of the determined optimal solution.

3. MODEL TEST AND APPLICATION

3.1. Model test

This study takes advantage of the examples (Table 1) of relevant studies [7,17] to test the proposed model, with parts of the testing results as shown in Table 2. The optimal solutions obtained by using the established Ant system, Ant-quantity system, Ant-density system, Antcycle system, and Rank-Based Version of the Ant System are as shown in Table 3. It can be seen from the table that, in the case of $\alpha=1$, $\beta=5$, $\rho=0.5$, the times of iteration above 250 and number of ants above 25, the resulting 18979.35 is the same as the result of Shiu and Huang [7], and better than the result of the model proposed by Lin and Hsu [17]. This result suggests that the proposed route planning model can effectively complete route planning and achieve the objective of the optimal route planning.

Table 1. Examples for testing the model [7, 17]

No.	X	Y
1	1049	422937
2	1791	841
3	3463	2729
4	3938	5336
5	4475	2388
6	1665	2547
7	4635	5311
8	4297	734
9	3029	3007
10	3363	1501
11	3712	2263
12	801	4685
13	3558	2986
14	2905	2317
15	2946	3806
16	762	4334
17	1937	2453

Table 2: Parameter testing results

α	β	ρ	Iteration	Number of ants	Best Solution
1	2	0.1	250	25	20128.72
1	2	0.2	250	25	19609.15
1	2	0.3	250	25	19221.00
1	2	0.5	250	25	19109.35
1	2	0.7	250	25	20125.00
1	2	0.9	250	25	19891.92
1	3	0.1	250	25	19779.85
1	3	0.2	250	25	19308.46
1	3	0.3	250	25	19179.15
1	3	0.5	250	25	19755.74
1	3	0.7	250	25	19358.97
1	3	0.9	250	25	20119.13
1	4	0.1	250	25	19193.84
1	4	0.2	250	25	19220.96
1	4	0.3	250	25	19193.84
1	4	0.5	250	25	19110.35
1	4	0.7	250	25	19383.49
1	4	0.9	250	25	20520.37
1	5	0.1	250	25	19082.57
1	5	0.2	250	25	19193.84
1	5	0.3	250	25	19182.68
1	5	0.5	250	25	18979.35
1	5	0.7	250	25	19226.17
1	5	0.9	250	25	19703.87
1	5	0.5	250	25	18979.35
1	5	0.5	500	25	18979.35
1	5	0.5	1000	25	18979.35
1	5	0.5	250	1	20447.77
1	5	0.5	250	2	19612.56
1	5	0.5	250	5	19408.26
1	5	0.5	250	10	19085.94
1	5	0.5	250	25	18979.35
1	5	0.5	250	50	18979.35
1	5	0.5	250	100	18979.35

Table 3: Model testing results

System	Best solution
Ant system	18979.35
Ant-quantity system	18979.35

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Ant-density system	18979.35
Antcycle syste	18979.35
Rank-Based Version of Ant System	18979.35
Shiu and Huang[7]	18979.35
Lin and Hsu[17]	21954.40

3.2. Model application

3.2.1. Eco-tour route planning

This study selected eight tourist sites and four coastal recreational areas in Taiwan for eco-tour route planning (Figure 2), with information regarding the 12 scenic spots as shown in Table 4. The ACO parameter settings are the optimized algorithm parameters. The tour length of the best route is 737 unit lengths.

Table 4: Information regarding eco-tourism scenic locations

No.	Scenic Spot	Coordinates X	Coordinates Y
1	Sun Moon Lake National Scenic Area	120.9030	23.8521
2	Maolin National Scenic Area	120.6502	22.8807
3	Jialeshuei Scenic Spot	120.8491	21.9900
4	Siraya National Scenic Area	120.4838	23.3517
5	Southwest Coast National Area	120.1562	23.3798
6	17 Kilometers Coastline Scenic Area	120.9213	24.8412
7	Gangnan Coastal Scenic Area	120.9167	24.8216
8	Dapeng Bay National Scenic Area	120.4796	22.4574
9	Cigu Lagoon	120.0780	23.1237
10	Shi-Hzuwan(Bay)	120.2638	22.6260
11	Hsinfeng Scenic Area	120.9763	24.9134
12	Guandu Scenic Area	121.4692	25.1193

Figure 2: Best route of eco-tour planning

3.2.2. Forest recreational tour route planning

This study selected nine forest recreational areas for tour route planning (Figure 3), with the information regarding the scenic spots as shown in Table 5. The parameter settings are the optimized algorithm parameters. The tour length of the best route is 638 unit lengths.

Table 5: Information regarding forest recreational region scenic locations

No.	Scenic Spot	Coordinates X	Coordinates Y
1	Nanren Mountain ecological protection area	120.8204	21.9573
2	Xinwei Forest Park	120.6223	22.8949
3	Dongshi Forest Garden	120.8721	24.2826
4	Sicao Lake	120.0702	23.0460
5	Mautu Discovery Forest	120.8000	23.6700
6	Shuangliou National Forest Recreation Area	120.7843	22.2518
7	Tengzhi National Forest Recreation Area	120.7801	23.0710
8	Eighteen Peaks Mountain	120.9000	24.7900
9	Basianshan Forest Recreation Area	121.1581	24.2744

Figure 3: Best route of forest recreational region tour planning

4. CONCLUSION

Good tour route planning can save tour time and contribute to the enhancement of tourism quality. Hence, this study applied the Ant system, Ant-quantity system, Ant-density system, Antcycle system, and the Rank-Based Version of the Ant System in building a tour route planning model. As the empirical results have shown, the proposed route planning model can effectively and rapidly complete route planning, and achieve the objectives of determining the best route at the minimum cost.

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The proposed model can be a reference for tour planning.

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