Adaptive Ant Colony Optimization using Individual Preference Factors

Kannita Sombatsricharoen, and Kritsada Sriphaew

***Abstract*—**Finding shortest route in a road network is a well known problem called Travelling Salesman Problem (TSP). Various proven algorithms such as Dijkstra, A* and Genetic Algorithms are extensively studied and implemented. Ant Colony Optimization (ACO) is another algorithm to solve such problem rightly since it is a meta-heuristic solution of artificial intelligence to use in solving many combinatorial optimization problems. However, the main objective of such problem is to find the shortest route of total distance but take no other factors such as favor or convenience into consideration. Therefore, this paper presents the difference between comparing algorithms in the traditional ACO and AACO models for food tasting planning. The results of traditional ACO provide the top candidate recommended routes based on shortest geometric distance in ascending order. On the other hand, the results of AACO model provide the top candidate recommended routes based on individual preference factors in descending order. The individual preference factors will be employed for user's consideration concerning route selection, and determined to be the weight applied in AACO model. In each retrieved route of both models is graphically shown on Google Map API Services. Furthermore, the results of experiments are evaluated by using TOP N in order to reflect on ranking accuracy. As a result, the performance of AACO model is mainly measured by using percent ranking accuracy. The results of 4 scenarios were shown on the average ranking accuracy rate of sampled population at 10, 20, 30 and 40 were 96.67%, 90.00%, 88.33% and 96.67% respectively. They are better than traditional ACO about 31.67%. For this reason, they indicate AACO model is adapted by itself according to individual preference factors effectively.

***Keywords*—**TSP Problem, ACO, AACO, Individual Preference Factors, Weight

I. Introduction

TRAVELLING Salesman problem (TSP) is the problem to find the best possible way of visiting all the cities exactly once and returning to the starting point. This problem has been grouped into NP-hard problem since the large amount of combinatorial optimization [1]. The ACO is another algorithm to produced better results on many NP-hard problems compared to other evolutionary algorithms such as Genetic Algorithm (GA) [2]. The concept of ACO was introduced by M. Dorigo since 1991 [3], [4]. It was developed to solve complexity of discrete combinatorial optimization problems. The ACO algorithm is inspired from the natural behavior of trail laying and following by ants. When exploring a region, ants are able to find the shortest path between their nest and a food source. It can be possible since the ants communicate with each other indirectly via pheromone deposits left behind as they travel. The pheromone deposited by one ant influences the selection of the path by the other ants. A high pheromone concentration increases the probability that the path will be selected. The pheromone deposits work as a form of positive feedback, reinforcing good path choices and guiding the ants to better paths. The first ACO algorithm was the Ant System (AS), which was designed to solve the TSP [5]-[8]. For this study, we choose the Ant System (AS) algorithm building the comparative food tasting planning models between the traditional ACO and the ACO with modification. It is a suitable algorithm since each ant must update pheromone on its trail every iteration after it has already built trail completely. That provides the top candidate recommended routes for ranking the routes. However, the traditional ACO focuses on the shortest route only regardless of other factors. Nevertheless, food tasting planning still has other individual preference factors such as favor, convenience, etc., used to consider selecting the route. Therefore, the modification of ACO is constructed for the comparative hypothesis testing that individual preference factors will have influence to consider route selection in user experience. Therefore, we combine individual preference factors with ACO algorithm to consider the issue of balance between them. Thus, we apply the individual preference factors to various routes as average weight for accumulation. They are adapted to AS algorithm during process of building trail. The optimized route is retrieved that makes users feel much more satisfactory [9]-[13]. Both of models illustrate direction and route via online Google Map. In addition, we determine Bangkok's Chinatown as a case study for food tasting planning since it is a popular tourist attraction and a food heaven for new generations.

II. Research Methodology

A. Ant System

The Ant Colony Optimization (ACO) is inspired by the behaviors of real ants. An ant leaves some pheromone at the amount of τ on ground when it travels and marks the path by

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a trail of this substance. The pheromone would evaporate at a certain rate ρ as time goes by. The next ant will smell the pheromone remained on the different routes and chooses one with probability proportional to the amount of pheromone. The ant that follows the path will leave its own pheromone. This pheromone is considered as a positive feedback process which could be treated as knowledge sharing through collaborative efforts. Based on previous knowledge, ants progressively construct their tours. This algorithm reported every touring route according to distance in ascending order. The results reflect the attempt to optimize TSP objective. The components of ACO that are used to build up the system are α, β, ρ and Q. The α and β control the relative importance of pheromone trail and distance between the cities in TSP. ρ refers to the rate of pheromone evaporation. Q is the constant value. The traditional ACO and the associated parameters [14]-[16] are can be represented algorithmically by the following pseudocode.

1. Set the parameters: Initialized amount of pheromones for each edge; the value of relevant parameters i.e., α, β, ρ, Q
2. Repeat
   2.1 For each ant do
   2.1.1 Randomly select a starting node
   2.1.2 Repeat
   2.1.2.1 Move to Next node according to the node transition probability formula, given α, β
   Until all ants build trail
   2.1.3 Repeat each edge do
   2.1.3.1 Update the pheromone intensity using global pheromone or local pheromone, given ρ, Q
   Until the pheromone between all pairs of cities are updated
   End For
Until maxTime run is attained
3. Sort distance in ascending order

The formulas for each factor's next generation are transition probability, global and local pheromone updating are defined as in (1), (2) and (3), respectively.

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta}}{\sum\limits_{r \in Table_k} (\tau_{ir}^{\alpha} \times \eta_{ir}^{\beta})}, & if\ j \in Table_k \\ 0, & otherwise \end{cases} \tag{1}$$

$$\tau_{ij} = (1-\rho).\tau_{ij} \tag{2}$$

$$\tau_{ij} = (1-\rho).\tau_{ij} + \Delta\tau_{ij} \quad , \quad \text{where} \quad \Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3}$$

Assume that there are m cities with i and j as the city in the colony, the distance between city i and city j is d_{ij}. The ant chooses a city to visit according to two factors [17]: τ_{ij}, the pheromone placed on the route between city i and city j; η_{ij}, the heuristic information of ant's moving from city i and city j, which in TSP is defined as $\eta_{ij} = 1/d_{ij}$. Therefore, the probability of ant k moving from city i to city j is defined as in (1) where $Table_k$ is a set of cities in which ant k can visit in the next step, it will dynamically change with movement of ant k.

After an ant has visited all the cities, the pheromone τ_{ij} will evaporate as time goes by, and the evaporation rate is denoted as ρ. ρ is a coefficient such that $(1-\rho)$ represents the evaporation of trail where (2) is a global pheromone updating and (3) is a local pheromone updating. $\Delta\tau_{ij}^{k} = Q / L_k$ is the quantity per unit of length of trail substance laid on edge (i, j) when ant k move city i to city j.

According to such pseudocode, a repetitive step in 2.1.2 refers to the process of building the trail by using (1). Furthermore, a repetitive step in 2.1.3 refers to the visited route or visited route updating pheromone formulas by using (2) or (3), respectively.

B. Adaptive Ant System

Our proposed concept is to modify ACO to consider individual preference factors besides distance called AACO: Adaptive Ant Colony Optimization. AACO aims to employ $\bar{w}_{ij}$, which is the average weight regarding the individual preference factors. Therefore, the transition probability ($p_{ij}'^{k}$) formula is modified as in (4).

$$p_{ij}'^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta} \times \bar{w}_{ij}}{\sum\limits_{r \in Table_k} (\tau_{ir}^{\alpha} \times \eta_{ir}^{\beta} \times \bar{w}_{ij})}, & if\ j \in Table_k \\ 0, & otherwise \end{cases} \tag{4}$$

In this work, the traditional ACO to find shortest route for TSP problem is compared with the AACO applying user preferences to show which method is more suitable for user satisfaction.

III. Experimental Setting

A. Scenario Setting

We determine Chinatown food shop in Thailand for food tasting planning, which consists of meat dish/dessert food shops that are popular. The objective of this study is searching the recommended route, which must be pleased to most users.

B. Step of Experiments

Step1 experts determine the quantity of meat dish/dessert food shops, which are employed in experiments searching recommended route.

Step2 M users are given to choose the combination of all possible routes, and rank the routes in descending preference order in each scenario.

Step3 Weight ($\bar{w}_{ij}$) as individual preference factors applied to AACO model with regard to (4).

Step4 AACO model is executed for suggesting the quantity of best N routes.

C. User Survey

The sampled population, which are used for preference survey, are general people 40 persons. The sampled population will give a rank to each recommended route according to their preference. These results will be used to calculate the weight as in (4) for AACO Model. In our preliminary survey, we found that the preference of food tasting planning is mostly relied on the kind of food and the order of tasting the food. For example, some of people prefer to eat more meat dishes than dessert, but the others do not prefer so. Therefore, we divide the condition given to the user in selecting the preferred route into 4 scenarios as in TABLE I

TABLE I
SCENARIOS

Scenarios	Number of meat dish restaurants	Number of dessert restaurants
1	2	1
2	1	2
3	3	0
4	0	3

However, user survey should specify in the expert sampled population. It makes inter-rater agreement with multiple raters better. The average weight in each route will have term of values, which are divided obviously. The results will have be lower swinging of the ranking accuracy rate. As a result, AACO model needs yet further optimizing.

D. Weight Calculation

Assume that W^u_{route} is the weight of a route from particular user. N is the number of all possible routes and R is the ranking from particular user u. For Example, user gives a rank of route as number 1, therefore R^u =1 is the weight of route W^u_{route} can be calculated as (5).

$$W^u_{route} = \frac{N+1-R^u}{N} \tag{5}$$

During executing AACO model, W^u_{route} is distributed on each pair of cities in path within route, $i, j \in path(route)$. That is called w^u_{ij}, which is the weight between city i to city j given by user u. However, there are many w^u_{ij} that are produced from all users. Therefore, AACO model has to employ the average weight of w^u_{ij} called $\bar{w}_{ij}$. The result from executing AACO Model provides the new weight for such route as shown in (6). Note that $|route|$ is the number of cities in route. The W'_{route} will be used for ranking the search result.

$$W'_{route} = \frac{\sum_{i,j \in path(route)} \bar{w}_{ij}}{|route|-1} \tag{6}$$

IV. EXPERIMENTS AND RESULTS

The parameters used for both traditional ACO and AACO models. Our preliminary study notes that there is not much difference for varying the parameters as shown in TABLE II.

TABLE II
DEFINED PARAMETERS IN ACO MODELS

Parameters	Values
Maximum Number of iterations in ACO process	10^3
Number of ants used in ACO algorithm within each iteration	Number of nodes x 2
α	1
β	5
ρ	0.7
Q	1

Both traditional ACO and AACO model use the same setting of parameters. The maximum number of iterations is 10^3, which refers to the total number of the evolutionary process for all sets of ants. The number of ants used in ACO algorithms is twice the number of nodes. α, β, ρ and Q are 1, 5, 0.7 and 1, respectively. Both of models are implemented with all relevant parameters without changing during runtime.

User survey is clustered using inter rater agreement with multiple raters, Fleiss' Kappa [18], which is employed to report measure of the sampled population at 10, 20, 30 and 40 persons in ascending order to classify these users into cluster. The degrees of agreement are interpreted in TABLE III.

TABLE III
INTERPRETATION OF KAPPA

Kappa	Agreement
< 0	Less than chance agreement
0.01-0.20	Slight agreement
0.21-0.40	Fair agreement
0.41-0.60	Moderate agreement
0.61-0.80	Substantial agreement
0.81-1.00	Almost perfect agreement

The results of agreement degrees with Fleiss' Kappa for each cluster of sampled population as shown in TABLE IV, the 4 scenarios produce different agreement values in each size of sampled population at 10, 20, 30, 40. They are likely to decrease when the size of sampled population becomes bigger as shown in Fig. 1.

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TABLE IV
INTER-RATER AGREEMENT OF KAPPA IN 4 SCENARIOS

Sampled Population (*M*)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
10	0.529	0.711	0.653	0.578
20	0.395	0.417	0.297	0.297
30	0.294	0.247	0.151	0.175
40	0.206	0.145	0.074	0.096

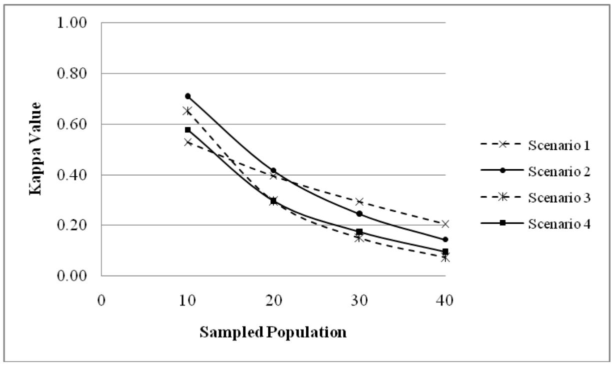

Fig. 1 Kappa Values vs. Sampled Population

The empirical experiments consist of comparison in 2 sections between traditional ACO and AACO models to examine hypothesis that the shortest route may not be the optimized route for users. The results of experiments provide the recommended route in effective order. Therefore, this study will evaluate the results by TOP N evaluation. This method measures retrieval effectiveness based on the number of relevant routes at TOP N where N = 1, 2, 3, 4 or 5 ranked retrieved routes. Note that N = 1 means the first retrieved route.

The results of traditional ACO model in each scenario is derived from comparing TOP N evaluation between routes based on ACO and routes based on weight from user survey using the similar data. On the contrary, the results of AACO model in each scenario is derived from comparing TOP N evaluation between routes based on AACO and routes based on weight from user survey using the similar data. The results of evaluation at the sampled population are 10, 20, 30 and 40 are shown in percent ranking accuracy in each scenario as in TABLE VI, VII, VIII, IX.

TABLE V
THE PERCENT RANKING ACCURACY AT SAMPLED POPULATION IS 10

TOP	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
N	ACO	AACO	ACO	AACO	ACO	AACO	ACO	AACO
1	66.67	100	66.67	100	66.67	100	66.67	100
2	33.33	100	33.33	100	33.33	100	33.33	100
3	66.67	100	33.33	100	66.67	66.67	33.33	100
4	66.67	100	33.33	100	66.67	100	66.67	66.67
5	100	100	66.67	100	100	100	100	100
Avg.	66.67	100	46.67	100	66.67	93.33	60.00	93.33

TABLE VI
THE PERCENT RANKING ACCURACY AT SAMPLED POPULATION IS 20

TOP	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
N	ACO	AACO	ACO	AACO	ACO	AACO	ACO	AACO
1	66.67	100	66.67	100	66.67	100	66.67	66.67
2	33.33	66.67	33.33	100	33.33	66.67	33.33	100
3	66.67	100	33.33	100	66.67	66.67	66.67	100
4	66.67	100	33.33	100	66.67	66.67	66.67	66.67
5	100	100	66.67	100	100	100	100	100
Avg.	66.67	93.33	46.67	100	66.67	80	66.67	86.67

TABLE VII
THE PERCENT RANKING ACCURACY AT SAMPLED POPULATION IS 30

TOP	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
N	ACO	AACO	ACO	AACO	ACO	AACO	ACO	AACO
1	66.67	100	66.67	100	66.67	100	66.67	66.67
2	33.33	100	33.33	100	33.33	66.67	33.33	100
3	66.67	66.67	33.33	100	33.33	66.67	66.67	66.67
4	66.67	100	33.33	100	66.67	66.67	66.67	66.67
5	100	100	66.67	100	100	100	100	100
Avg.	66.67	93.33	46.67	100	60	80	66.67	80

TABLE VIII
THE PERCENT RANKING ACCURACY AT SAMPLED POPULATION IS 40

TOP	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
N	ACO	AACO	ACO	AACO	ACO	AACO	ACO	AACO
1	66.67	100	66.67	100	66.67	100	66.67	100
2	33.33	100	33.33	100	33.33	100	33.33	100
3	66.67	100	33.33	100	66.67	66.67	66.67	66.67
4	66.67	100	66.67	100	66.67	100	66.67	100
5	100	100	66.67	100	100	100	100	100
Avg.	66.67	100	53.33	100	66.67	93.33	66.67	93.33

TABLE V, VI, VII and VIII point out traditional ACO and AACO model produce ranking accuracy percentage that is not depended on size of sampled population, and the percent ranking accuracy of AACO model are greater than or equal to ACO model on TOP 1-5 in each scenario. For this reason, they indicate AACO is much more effective performance.

The best average ranking accuracy rate on overview of all scenarios in each sampled population is shown on TABLE X.

TABLE IX
PERFORMANCE COMPARISON OF ACO AND AACO

Sampled Population (*M*)	ACO	AACO
10	60	96.67
20	61.67	90
30	60	88.33
40	63.33	96.67
Avg.	61.25	92.92

The TABLE IX shows the overall results, which are generated by 8 empirical experiments for each size of sampled population. The average ranking accuracy rate concerning AACO model is better than traditional ACO model for all sampled population size about 31.67%. These results indicate AACO model surpassing over the traditional ACO model in terms of ranking accuracy rate. In addition, it denotes AACO model is adapted by itself according to weight using individual preference factors. They are shown obviously on Fig. 2.

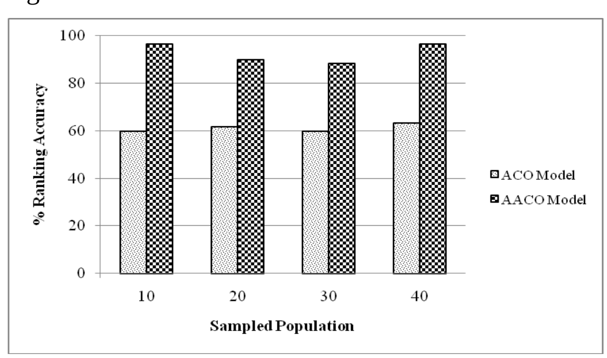

Fig. 2 Bar Chart Comparison of the average percent ranking accuracy between ACO and AACO Models

V. Conclusion

This work proposed AACO Model in which it adapts the optimization problem based on the weights according to individual preference factors. The experiments show that AACO model can improve the search result according to users' preferences efficiently comparing to ACO model. ACO model may be better in the search result of the shortest route but some scenarios may have the other factors using the route selection such as favor, convenience, traffic on route, etc., which AACO model can provide better support such other factors. However, this model experiment was designed for food tasting planning by sidewalk, it can be further improved better for driving scenario, which concerns real-time traffic information.

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