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# OLYMPIC TORCH RELAY ROUTE PLANNING BASED ON ANT COLONY OPTIMIZATION

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Abstract. *Planning plays an important role in modern society for dealing with economic development and the issues of competitiveness. To increase competitiveness, the costs of personnel and time must be effectively controlled by minimization of unnecessary expenditure and wasted time. Planning is critical in every aspect of every kind of business. The ant colony optimization algorithm (ACO) was used as the core tool in this study. To test the theory, a torch relay map was downloaded from the official web site of the Olympic Games. The distances between the 77 cities marked on the map were obtained from their coordinates, acquired from the geographic information system database. The overall relay route was then optimized by calculation using the ACO programs. The method used in this study can also be applied to many problems such as route planning, allocation, combination, scale, where risk and expenditure of manpower and resources need to be effectively reduced, and clearly visible final results are expected. The performance and efficiency of management, both individual and overall, can be also greatly enhanced.*
**Keywords:** Ant colony optimization algorithm (ACO), Olympic Games, Torch relay

1. **Introduction.** The Olympic flame originated in Greek mythology in which the Greek God Prometheus deceived both Zeus and Apollo, and stole the seed of fire to save human kind from starvation and cold. Once on earth, fire could not be returned to Heaven. So Zeus mandated the lighting of the Olympic flame in his honor. The ancient Olympic Games were a large event steeped in religious connotation. Before the opening ceremony, a grand fire lighting ceremony was carried out. The Olympic flame was carried throughout Greek cities to signal that each city must enact a truce and forget hatred and war like a supreme and solemn command. The flame relay represents inheritance, continuation, light, unity, friendship, peace, and justice. The five colors of the Olympic rings represent the unity of the five continents, blue for Europe, Black for Africa, Red for the Americas, Yellow for Asia, and green for Oceania [1].

The path planning in this study is as defined in the traveling salesman problem (TSP) [2-4]. There are $n$ number of cities. One salesman leaves from a certain city, and visits each city only once for the shortest route. The popular algorithms include particle swarm optimization (PSO) [5], ant colony optimization (ACO) [6], and the genetic algorithm (GA) [7]. This study initially used PSO, which was proposed by Kennedy and Eberhart in 1995 after observing birds foraging. Using this algorithm on multiple path choices can easily result in limited solutions, and convergence and its parameter selections must be analyzed [8]. To obtain superior results and produce a more accurate choice, PSO must be used with other algorithms to obtain the optimal solution. The GA is a core method derived from Darwin's theory of evolution. The core of GA is the survival of the fittest, elimination of the unfit and continued reproduction of the genes. This increases the adaptability of the individual and prevents environmental impact. Application of this algorithm to engineering problems can process data with large scope, and obtain an optimal solution. The other genes will continue to mate, mutate, replicate, and reproduce. Although time can be controlled, the computing cost is very high. Thus, using this method to search for an optimal solution requires an element of luck, and it is not possible to be certain convergence has been reached. This method poses both instability and uncertainty. The PSO and GA methods have many commonalities [9], the most significant being that there is no guarantee of finding an optimal solution and so they are not used in this study.

Instead, ACO [10] as proposed by Dorigo, Maniezzo, and Colorni is very similar to that used here. This type of algorithm has been in development for the past 20 years, and many improvements have been made over time. These improvements allow faster convergence, and the goal is to obtain an optimal solution. This algorithm is widely used not only for TSP, but also for PID controller parameters [11], sequencing [12], allocation [13], multi-scale [14], and missile path or robot movement path [15] problems. This algorithm can be combined with others to help in the search for other optimization solutions. In this paper, each ant will pick the shortest path after each pheromone update, based on the concentration of each pheromone iteration. The number of ants will change with time, and the pheromone concentration of the shortest path will become stronger. Conversely, the pheromone concentration of the longer paths will become weaker with time. This algorithm not only obtains all the optimal solutions within a reasonable time, but has also proved to be superior to GA and PSO for TSP. Thus, we can search for a high stability optimal solution without spending too much time.

2. **Ant Colony Optimization.** ACO is an algorithm based on natural phenomena. The principle behind this algorithm is that ants cannot see and must rely on special information given off by other ants as a chemical trail to determine where they should go. During the initial stage of a search, ants will move randomly and leave an information chemical trail. After a while, ants will tend to move toward areas of high concentration. As the ants move, they also strengthen the original chemical trail so that the likelihood of other ants choosing the shortest path becomes higher as shown in Figure 1 [6,16-18].

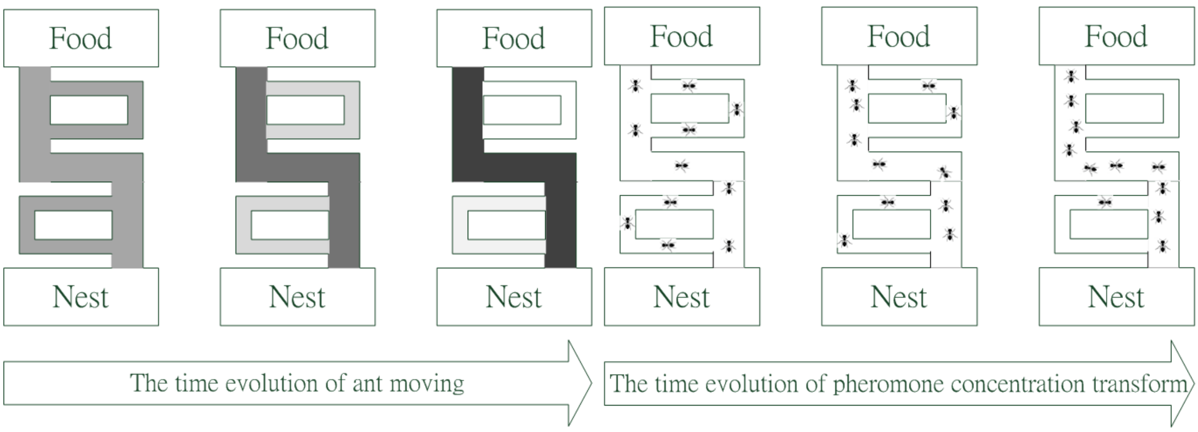


FIGURE 1. Path evolution for ants searching for food

In this study, $m$ ants are assumed to be in the search. When they meet a node, the probability of them choosing another path is determined according to Equation (1):

$$p_{ij}^{s}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \times (\eta_{ij})^{\beta}}{\sum\limits_{u \in J_s(i)} [\tau_{iu}(t)]^{\alpha} \times (\eta_{iu})^{\beta}}, & \text{if } j \in J_s(i) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $\alpha$ and $\beta$ are the parameters for determining the pheromone and distance reciprocal. $p_{ij}^s(t)$ is the probability of $s$ ant on segment $(i,j)$ during $t$ iteration. $\eta_{ij}$ is the reciprocal of the distance for $(i,j)$. $\tau_{ij}(t)$ is the pheromone concentration for segment $(i,j)$ during $t$ iteration. $J_s(i)$ is $s$ ant gathering after passing neighboring nodes through node $i$. In Equation (3), it can be seen that the greater value of the numerator will obtain the greater probability of ants choosing that path. Each time an ant walks that path, the pheromone concentration should be adjusted, as shown in Equations (2) and (3):

$$\tau_{ij}(t) = (1-\partial) \times \tau_{ij}(t) + \sum_{s=1}^{m} \Delta\tau_{ij}^s \tag{2}$$

$$\Delta\tau_{ij}^s = \begin{cases} \dfrac{Q}{A_s}, & \text{if } s\text{th ant uses edge } ij \text{ in its tour} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$\partial$ is the pheromone evaporation coefficient. $Q$ is the size of the pheromone, and this parameter's convergence speed will be somewhat affected. $A_s$ is the total path length obtained for $s$ ants. Whenever time $t$ completes an iteration, the pheromone on paths with few or no ants will be attenuated. When the number of iterations reaches stability, this means that the ants almost all take the same path. At this time, the optimization calculation can be terminated. The overall flow chart is shown in Figure 2.

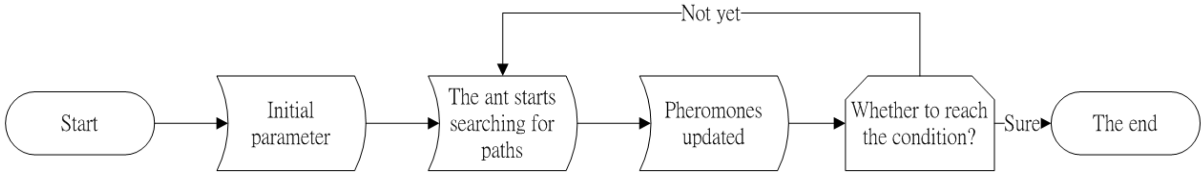


FIGURE 2. Ant movement flow chart

3. **Test Result.** First, a simple example is used to verify this scheme. This case is considered the ten colleges and universities in Yunlin and Chiayi regions of Taiwan as punctuations. The Yunlin county's government is as a starting point. The path will bypass the other schools and then return to the Yunlin county's government. All the parameters were set according to Liu [19]. The distance matrix placed in this study's simulation test system. The resulting optimal paths were 1→2→4→10→11→5→6→9→8→7→3→1 and the minimal total length was 121.56. The test time was approximately 0.933 per time, and the optimal solution appeared about 41 times per 100 calculations, as shown below. Figure 3 shows the coordinate path of this study. The $x$-axis represents the longitude and the $y$-axis represents the latitude. The convergence after each iteration is shown in Figure 4. The $x$-axis represents the number of iterations; the $y$-axis represents the distance (km).

The 2012 London Olympic Games relay includes Greece and England. In Greece there were 500 torch bearers and in England there were 8000 torch bearers. The total length was 15775km, of which, 2900km were in Greece and the remaining 12875km were in England. The scope of this study was the torch relay route within England. Cities passed in the torch relay (obtained from Wikipedia) were used as nodes. Coordinates were obtained from the Google geographical information database. Online coordinate distance calculations were used to obtain the distance matrix between cities, which was then placed in this study test system. Because there were a large number of cities, the optimal solution was obtained from 100 tests. The values of parameters in the simulation are shown in Table 1. The resulting optimal path was obtained in Figure 5 as follows: 1→2→11→38→15→42→45→49→41→33→32→34→36→35→44→46→48→63→64→60 →61→3→4→5→8→6→56→70→74→75→71→72→55→47→57→65→59→62→58→7→

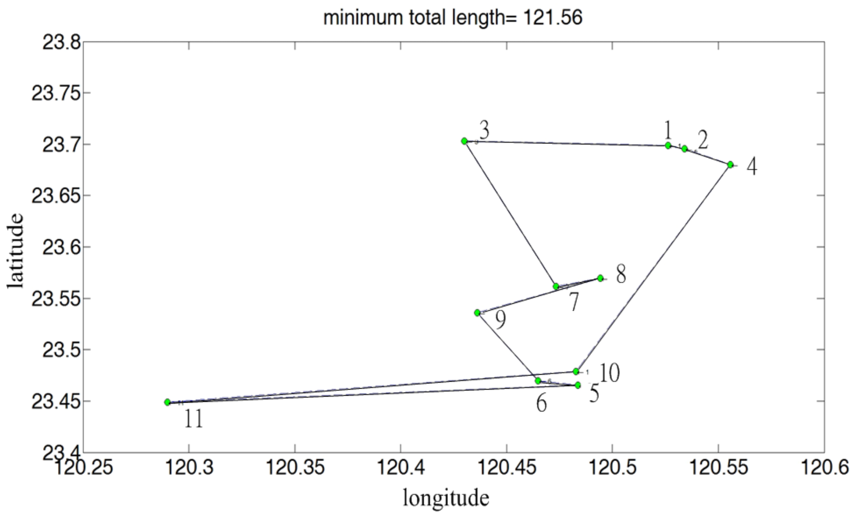


FIGURE 3. Coordinate path

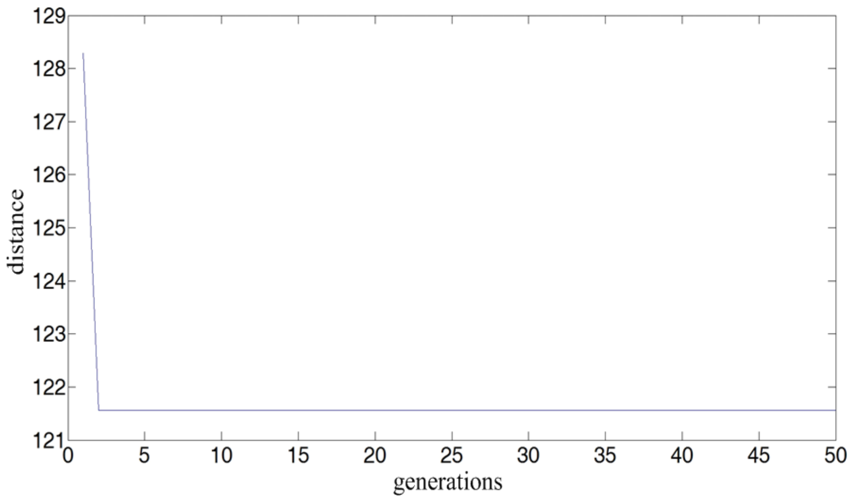


FIGURE 4. Convergence after each iteration

TABLE 1. Parameter values

| Name | Parameter setting |
|---|---|
| $\alpha$ | 1 |
| $\beta$ | 4 |
| $\partial$ | 0.15 |
| $m$ | 100 |
| $n$ | 77 |
| Miter | 100 |

Note: $n$ is the number of cities, $m$ is the number of ants, and Miter is the number of iterations.

9→10→12→37→30→31→29→28→26→25→17→21→22→20→18→19→27→23→67→69→68→52→51→76→73→50→54→43→40→14→16→13→39→53→66→77. The convergence after each iteration is shown in Figure 6. The optimal solution was obtained from 100 tests and the time taken for each test was approximately 17.585 seconds, as shown below. Test results showed that the route in this study was shorter than the Olympic game route [12875km] by 19.5% ($\frac{12875-10352}{12875} \times 100\%$). This is equivalent to 2523km.

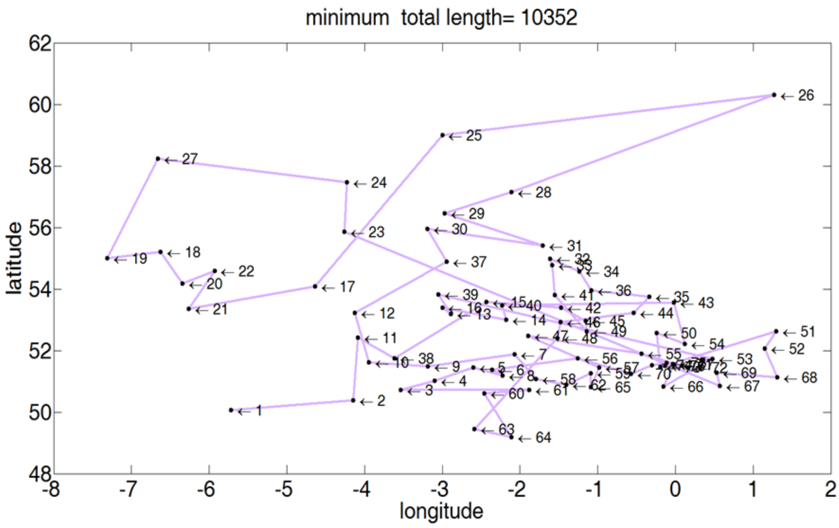


FIGURE 5. Coordinate path

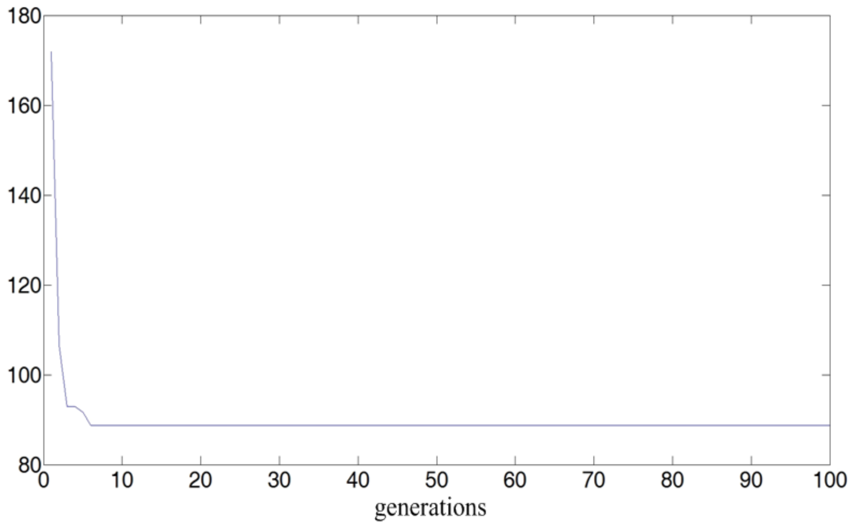


FIGURE 6. Convergence after each iteration

4. **Conclusion.** In this study, ACO was used to obtain path optimization. Pheromone concentration changes after each iteration was used to obtain the optimal route and most appropriate distance. Test results showed that the route in this study was shorter than the Olympic game route by 19.5%. This is equivalent to 2523km. The ACO was originally used in the TSP. It is firstly used in Olympic Torch Relay Route Planning in this study. In the future, we hope to consider the actual road conditions, weather, and obstacles, etc. We will try to modify the scheme of ACO to obtain an optimal path for computing path problems, which included some constraints in Olympic Torch Relay Route Planning.

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