Ant Colony Optimization Implementation on Traveling Salesman Problem to Achieve the Shortest Logistic Route

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Abstract. Transportation refers to the movement of everything from raw materials to finished goods between various facilities in the supply chain. In transportation, the exchange between responsiveness and efficiency is manifested in the choice of transportation modes. Because transportation costs can be as much as one third of the supply chain operating costs, the decision made here is very important. Traveling Salesman Problem is one of the best-known NP-hard problems where there is no precise algorithm to solve it in polynomial time. The ACO algorithm has good potential for problem solving and recent research that has attracted a lot of attention, in particular is the case of solving NP-Hard problems. One of the earliest best works is completing TSP using ACS (Ant Colony System). Ant System is the first ACO algorithm with its main characteristics being that at each iteration, the pheromone values are updated by all (m) ants who have built a solution in the iteration itself. From the arrangement of the shipping routes that have been implemented by the Ant Colony Optimization on the Traveling Salesman Problem, the amount of savings in the transportation mode of trucks to mileage is 37%.

1. Introduction

Transportation refers to the movement of everything from raw materials to finished goods between various facilities in the supply chain. In transportation, the exchange between responsiveness and efficiency is manifested in the choice of transportation modes. Because transportation costs can be as much as one third of the supply chain operating costs, the decision made here is very important. The objective of the transportation system aims to minimize the distance and cost. ensure that all vehicles are not allowed to carry more than their capacity, and choose better route for transportation process. So that the transportation system running with optimal and efficient condition to meet right place, right time, right quantity, right quantity [1]. Due to various modes of transportation and location of facilities in the supply chain, managers need to design routes and networks to move products. Route is the path where the product moves and the network consists of a collection of lines and facilities that are connected by that path. As a general rule, the higher the value of a product (such as electronic components or drugs), the more the transportation network must emphasize responsiveness and the lower the value of a product (such as bulk commodities such as grain or wood), the greater the network must emphasize efficiency [2].

The main components of transportation that must be analyzed by the company when designing and operating a Supply Chain [3].
• Transportation Network Design
• Transportation Mode Alternatives

Traveling Salesman Problem is one of the best known NP-hard problems where there is no precise algorithm to solve it in polynomial time. TSP is defined as a permutation problem with the goal of finding the path with the shortest length or minimum cost. The TSP was then studied by mathematicians Karl Menger at Vienna, Harvard and Hassler Whitney and Merrill Flood at Princeton in 1930 and wrote their general form. Because the growth of the algorithm is increasing from year to year, starting in 1950 the completion of the CSR program was solved by computers. In 1954 the important growth of CSR was researched by researchers namely: Dantzig, Fulkerson and Johnson who continued to develop new methods for solving CSR problems [4]. The Ant Colony Optimization (ACO) Heuristic Method is inspired by the behavior of real ants in finding the shortest path between nests and food. This is achieved by a substance called pheromone which shows ant traces. In its search, the ant uses heuristic information which is its own knowledge about where the smell of food comes from and other ant's decisions about the path to food with pheromone information [5].

ACO-TSP research like Dorigo, Stutzle and Birattari in the year applied the shortest route determination using ACO-TSP theoretically. Research on fuel costs (fuel cost) from public vehicles to get satisfactory results from ACO-TSP in vehicle efficiency [6]. ACO can also be used to improve the performance of a TSP in minimizing the transportation costs of the resulting route. [7]

The ACO algorithm has good potential for problem solving and recent research that has attracted a lot of attention, in particular is the case of solving NP-Hard problems. One of the earliest best works is completing TSP using ACS (Ant Colony System). ACS algorithm is used to solve TSP and claimed that ACS outperforms other algorithms inspired by nature such as simulated annealing and evolutionary computation [8]. Ant System is the first ACO algorithm with its main characteristics being that at each iteration, the pheromone values are updated by all (m) ants who have built a solution in the iteration itself [9,10]. Traveling Salesman Problem is well known in operations research to minimize travel costs or distance. Some linear programming concepts used with MATLAB, researchers have previously described the implementation of primal infeasible double interior point algorithm for large-scale linear programming under the MATLAB environment [11].

2. Research Methodology

2.1. Ant System
Ant System is the first ACO algorithm with its main characteristics being that at each iteration, the pheromone values are updated by all (m) ants who have built a solution in the iteration itself. Updated Pheromone $\tau_{ij}$ can be seen in the following formulations.

$$\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij} + \sum_{k=1}^{m} \Delta \tau_{ij}^k$$  \hspace{1cm} (1)

Whereas :
\begin{align*}
\rho & = \text{Evaporation Rate} \\
m & = \text{The number of artificial ants} \\
\Delta \tau_{ij}^k & = \text{Pheromone quantity at edge (i, j) by ant k} \\
\end{align*}

$$\Delta \tau_{ij}^k = \begin{cases} 
\frac{Q}{L_k} & \text{if ant k uses the Track} \ ('i, j') \ "on the tour" \\
0 & \text{otherwise}
\end{cases}$$  \hspace{1cm} (2)

Where Q is constant and Lk is the length of the tour trip by ant k. In the stage of finding a solution, the ant chooses the prospective city to be traversed using a stochastic mechanism. Where ant k is in city i and builds a partial solution $Sp$ so that the probability to visit city j can be formulated as follows:

$$p_{ij}^k = \begin{cases} 
\frac{\tau_{ij}^\alpha \eta_{ij}^\beta}{\sum_{c \in N(Sp)} \tau_{ic}^\alpha \eta_{ic}^\beta} & \text{if } i \in N(Sp), \\
0 & \text{otherwise}
\end{cases}$$  \hspace{1cm} (3)
Where N (sp) is a set of feasible components, where in nodes (i, l), l is a city that has not been visited by ants k. The parameters of α and β are control variables that are relatively dependent on how important the pheromone value is, which is inversely proportional to the heuristic information $\eta_{ij}$, so the formulation is as follows:

$$\eta_{ij} = \frac{1}{d_{ij}}$$  \hspace{1cm} (4)

Where $d_{ij}$ is the distance between city i and city j.

2.2. Parameter Any Colony Optimization

The ACO algorithm involves a number of parameters that need to be set precisely. Of these, the α and β parameters are used to weigh the relative influence of pheromones and heuristic values in the construction of ant solutions. The role of these parameters in refactoring the search for ants. Higher α values emphasize differences in pheromone values, and higher β values have the same effect on heuristic values. The initial value of the pheromone, $\tau_0$, has a significant effect on the convergence speed of the algorithm.

However, the recommended settings depend on the specific ACO algorithm. The evaporation rate parameter, $\rho$, $0 \leq \rho \leq 1$, regulates the rate of decline in the pheromone pathway. If $\rho$ is low, the effect of pheromone values will last longer, while a high $\rho$ value allows quick forgetting of choices that were previously very interesting and resulted in allowing more rapid focus on new information entered into the pheromone matrix. Another parameter is the number of ants in the colony (m). For a given computing budget, such as the maximum calculation time, the number of ants is an important parameter to determine the exchange between the number of iterations that can be made and how extensive the search is in each iteration. Ant Colony's performance is very dependent on its intensity parameter settings. To find the appropriate settings for the algorithm parameters is considered a nontrivial task. Traditionally, parameter settings are mostly done by Trial and Error.

3. Result and Discussion

3.1. Measurement of Ant Colony Parameter Intensity

The next step is to test the intensity of parameters such as the ant trail intensity control parameter (Pheromone) (α), the visibility control parameter (β) and the evaporation parameter (ρ). Where the value of each parameter has an influence on the performance of the results obtained at Ant Colony, so to determine the effect of these parameters determined the range of values of each of these variables.

- Parameter $\alpha \in \{0; 0.2; 0.4; 0.6; 0.8; 1; 1.2; 1.5; 1.8; 2\}$
- Parameter $\beta \in \{0; 0.4; 0.8; 1; 2; 4; 6; 8; 10; 20\}$
- Parameter $\rho \in \{0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$

The parameters α and β, which are used to weigh the relative influence of pheromones and heuristic values in the construction of ant solutions. The parameter $\rho$, $0 \leq \rho \leq 1$, adjusts the rate of decline in the pheromone trace. If $\rho$ is low, the effect of pheromone values will last longer, while the high $\rho$ value allows the ant to quickly forget the previously very interesting choice. The test results can be seen in Figure 1.
Figure 1. Parameter testing $\alpha$

Figure 1. above shows with the value of $\alpha = 1$ the best performance results obtained with the best tour length 1.3034 and the worst performance obtained with a value of $\alpha = 0.4$ with the best tour length 1.3862. The best tour fluctuations produced based on the intensity of the ant colony ($\beta$) Ant Colony first week of first delivery can be seen in Figure 2.

Figure 2. Parameter testing $\beta$

Figure 2. shows the value of $\beta = 5$ obtained the best performance results with the best tour length of 1.2021 and the worst performance obtained with the value of $\beta = 0.4$ with the best tour length of 4.6669. The best tour fluctuation produced based on the intensity of the Ant Colony pheromone evaporation ($\rho$) the first week of the first shipment can be seen in Figure 3.

Figure 3. Parameter testing $\rho$

Figure 3. shows the value of $\rho = 0.3$ obtained the best performance results with the best tour length of 1.2497 and the worst performance obtained with the value of $\rho = 0.5$ with the best tour length of 1.3604.

| Testing of $\alpha$ | Testing of $\beta$ | Testing of $\rho$ |
|---------------------|---------------------|---------------------|
| Value $\alpha$     | Tour                | Value $\beta$       | Tour                | Value $\rho$     | Tour                |
| 0                   | 1.3140              | 0                   | 4.6669              | 0.1               | 1.2856              |
| 0.2                 | 1.3762              | 0.4                 | 4.2638              | 0.2               | 1.2688              |
| 0.4                 | 1.3862              | 0.8                 | 3.6845              | 0.3               | 1.2497              |
| 0.6                 | 1.3668              | 1                   | 3.3549              | 0.4               | 1.3219              |
| 0.8                 | 1.3388              | 2                   | 2.182               | 0.5               | 1.3604              |
Of the three parameters mentioned above, there is the best combination to obtain results that are close to optimal. Each of the three parameter values is as follows.

- Parameters controlling the intensity of ant traces (Pheromone) \( (\alpha) = 1.0 \)
- Visibility controller parameters \( (\beta) = 5.0 \)
- Evaporation parameters (evaporation) \( (\rho) = 0.3 \)

### 3.2. Initiation of Parameter Ant Colony Optimization (ACO)

The next step is to calculate Ant Colony Optimization (ACO) to get the shortest path. The initiation of the parameter values was adjusted to the results of the previous test and trial in each shipping case. Example calculation as follows.

- Parameters controlling the intensity of ant traces (Pheromone) \( (\alpha) = 1 \)
- Visibility control parameter (\( \beta \)) = 5
- Evaporation parameters (\( \rho \)) = 0.3
- Many ants (\( k \)) = 8
- Initial Pheromone (\( \tau_0 \)) = 1 at each point

### 3.3. Updating Pheromone Rate

Every trip that the ant will do will leave a trail of pheromones on each route. However, before the addition of pheromone in each route, the initial pheromone (\( \tau_0 \)) will experience evaporation of value \( \rho = 0.3 \). So that the latest pheromone after pheromone has evaporated can be seen in Table 2.

#### Table 2. Matrix of pheromone update 1

| Matrix \( t_0 \) | Company | K-1 | K-3 | K-6 | K-9 | K-11 | K-17 | K-23 | K-27 | K-33 | K-37 | K-40 |
|------------------|---------|-----|-----|-----|-----|------|------|------|------|------|------|------|
| Company          | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-1              | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-3              | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-6              | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-9              | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-11             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-17             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-23             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-27             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-33             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-37             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |
| K-40             | 0.7     | 0.7 | 0.7 | 0.7 | 0.7 | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  | 0.7  |

Ants 1 who have completed the P-27-23-11-33-17-6-3-37-9-1-40-P tour with a total distance of 131.3 km will provide an additional pheromone of \( 1 / (\text{total distance} + \text{total time}) \) on each route traveled that is equal to 0.002023. Table 3. shows the total pheromone to be added by each ant on each route traversed.

#### Table 3. Matrix of pheromone update 1

| K Ant | Result Distance | Duration | Pheromone |
|-------|-----------------|----------|-----------|
| Ant 1 | 131.3 km        | 363.0 menit | 0.002023  |
| Ant 2 | 141.4 km        | 375.0 menit | 0.001936  |
| Ant 3 | 118.5 km        | 354.0 menit | 0.002116  |
| Ant 4 | 107.6 km        | 321.0 menit | 0.002333  |
| Ant 5 | 132.1 km        | 370.0 menit | 0.001992  |
| Ant 6 | 98.2 km         | 315.0 menit | 0.002420  |
| Ant 7 | 103.3 km        | 323.0 menit | 0.002346  |
| Ant 8 | 115.3 km        | 334.0 menit | 0.002226  |
3.4. Ant Colony Optimization Result with MATLAB

Then the Pheromone Update Ants 8 matrix becomes the final matrix for the iteration step 1. The MATLAB software results to produce the best route for each shipment from week 1 to week 4 of each shipment. The parameters inputted in processing using MATLAB software are as follows.

- Parameters controlling the intensity of ant traces (Pheromone) \( (\alpha) = 1 \)
- Parameters controlling visibility \( (\beta) = 5 \)
- Evaporation parameters \( (\rho) = 0.3 \)
- Maximum number of iterations (maxIter) = 500
- Laying the initial ant (current node) = \{3.520773,98.686744\}% Company Point
- Number of ants used = number of vehicles
- Probability of \( r = \text{rand}(), r \leq \text{cumsnp} \)

The table below shows the results of the recapitulation of the route order of each shipping case that has been calculated using MATLAB software.

| Route Combination | Pheromone | Best Tour |
|-------------------|-----------|-----------|
| **Table 4. Construction results using MATLAB software** |

| Iteration #100 | All Pheromones | Best tour (the queen) |
|----------------|----------------|-----------------------|
| 98.74          | 98.72          | 98.72                 |
| 98.74          | 98.72          | 98.72                 |
| 98.74          | 98.72          | 98.72                 |
| 98.74          | 98.72          | 98.72                 |

Etc...
The savings that can be saved in terms of distance are 37 percent compared to the actual condition of companies that do not make route improvements.

4. Conclusion
In the specifications required in this case to implement Ant Colony Optimization in Traveling Salesman Problem with the ant trail intensity control parameter (Pheromone) ($\alpha$) = 1.0, the visibility control parameter ($\beta$) = 5.0 and the evaporation parameter ($\rho$) = 0.3. From the arrangement of the shipping routes that have been implemented by the Ant Colony Optimization on the Traveling Salesman Problem, the amount of savings in the transportation mode of trucks to mileage is 37%. Of course the results of improvements that can occur savings, then of course it is proven that ACO-TSP effectively reduces the company's shipping routes.

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