Volume 8 Number 2, May 2023, 345-358

ANT COLONY OPTIMIZATION ALGORITHM FOR TRAVELING SALESMAN PROBLEM IN DISTRIBUTING FERTILIZER

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ABSTRACT

Fertilization sometimes takes a long time due to the selection of mileage traveled in fertilizer distribution and coupled with the condition of plantation roads that are partially damaged. The path taken is usually only a path that is memorized and is considered the shortest and optimal. The journey from one location to another by considering the shortest path is included in the problem of graph theory. To determine the shortest path to be traversed, you can use the Ant Colony algorithm. because it is optimal in determining short distances and can measure the minimum accumulated travel time close to optimal. This is a Traveling Salesman Problem (TSP) problem, which is visiting all location points starting from the starting point and ending at the starting point again. This research was conducted on oil palm plantations of PT. Socfindo Bangun Bandar in fertilizer distribution. The sample used is 6 location points which are then solved using the Ant Colony algorithm where this algorithm adopts the workings of ants to get the shortest route. The use of the Ant Colony algorithm in this case is limited to one cycle or one iteration (NC=1) so that the best route is obtained while the first cycle is the fertilizer warehouse (V_1) to block 55 (V_4) then block 63 (V_6) to block 61 (V_5) then block 51 (V_2) to block 52 (V_3) and back again to the fertilizer warehouse (V_1) , and from this route can be modified again to the opposite route with a distance of 15.71 km. Because the resulting distance is shorter than the usual route, this can speed up the time used by trucks to distribute fertilizer so that trucks can be used by workers to transport harvested palm fruit. Keywords: Ant Colony Algorithm, Fertilizer Distribution, Traveling Salesman Problem, Shortest Path

How to Cite: Hazizah, S., Lubis, R. S., & Cipta, H. (2023). Ant Colony Optimization Algorithm for Traveling Salesman Problem in Distributing Fertilizer. *Mathline: Jurnal Matematika dan Pendidikan Matematika*, 8(2), 345-358. http://doi.org/10.31943/mathline.v8i2.388

PRELIMINARY

One of the most famous agricultural country is Indonesia because it is population mostly works in agriculture. Palm oil is one of the largest agricultural crops in Indonesia which is a primadonna crop producing palm oil and palm kernel as a source of non-oil and gas foreign exchange for Indonesia (Hoffmann et al., 2020). The large number of palm trees that are of productive age, makes fertilizer an important thing in fulfilling nutrients for the growth of palm fruit so as to achieve maximum results (Sunarpi et al., 2020). To support high crop productivity, fertilization of palm oil must be carried out in a sustainable

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manner. The fertilization process in PT. Socfindo Bangun Bandar is done by mechanical and manual means. Fertilization by mechanical means is carried out with one of the heavy equipment, namely Bepalo, while manual fertilization is carried out by humans or workers.

Fertilization by manual means is carried out if heavy equipment cannot reach the intended land (Nasrullah & Ovitasari, 2022). The main cause of manual fertilization is that in the block there are plantation land conditions such as ditches, swamps, and peat soils so that it is difficult to reach using heavy equipment (Ginting, 2019). Usually fertilizing manually in one day can move points, a minimum of four blocks in one day of fertilization work time. Fertilization sometimes takes a long time because of the selection of mileage in the distribution of fertilizer itself to move from one block to another, coupled with the condition of the plantation road which is partially damaged (Guampe et al., 2022). The path taken is usually just a memorized path that has been planted and is considered the shortest, even though it is not necessarily the more optimal path (Hariati et al., 2021).

Travelling Salesman Problem (TSP) is one example of a problem in optimization (Zhang et al., 2022). TSP is an activity carried out by a salesman in search of the shortest route or minimum distance from the city of origin of departure to city-n and will return to the city of origin of departure on exactly one trip (Cipta & Widyasari, 2020). In delivering goods, a salesman will determine the place to be visited first to the final place of departure, and can only be visited once a trip in each place taking into account the smallest distance and travel time.

The application of TSP can be done on a complete graph of weights that have a minimum total side weight, where there weight on the sides is the distance (Alani et al., 2020). In the TSP route load all points on the graph exactly once. Solving TSP problems can use a variety of optimization methods, including Ant Colony Optimization (ACO) (Stodola et al., 2022). The ant colony algorithm is a probabilistic search algorithm and is one of the algorithm in solving optimization problems that are heuristic (Ramya et al., 2019). The ant colony algorithm is adopted from the behavioral characteristics of ants that search for good sources and carry theis groups efficiently through the same path following the footsteps of other ant ants. Ant colonies are able to find the shortest route naturally from the location of their nest to the source of food. During the course of each ant emits pheromone a kind of signal to fellow ants. The greater the number of ants through the marked path, the deeper the pheromone scent will be so that there will be many ants going through the path (Li et al., 2022).

METHODS

Graph Theory

Graph *G* is defined as a pair of sets (*V*, *E*), writen with the notation G = (V, E), *V* is the set of non-empty vertices (nodes) and *E* is the set of sides (edges or arcs) connecting a pair of nodes (Stanković et al., 2019). Geometry in the presentation of the graph there are no specific provisions, such as where and how to present vertices and sections. We can see the presentation of the same graph and presented in another from graph G = (V, E) (Hendra Cipta, 2020):



Figure 1. Graph

There is *G*-directional graph consisting of the set *V* of the vertices and the set *E* of the edge such that the ribs of $e \in E$ connect the pairs of sequential vertices. And the *G*-undirectional graph consisting of the set *V* of the vertices and the set of *E* of the edges is such that each egde of $e \in E$ corresponds to a pair of non-consecutive vertices.

According to (Mordeson & Mathew, 2019) a weighted graph is a graph whose each side is given a value or weight in the from of a non-negative number. Weighted graphs can also use directional graphs or unguided graphs. Another term weighted graph that is often associated is with labeled graphs. However, the labeled graph actually has a broader meaning. Not only on the sides, but labels are also given to the vertices. The sides are labeled as non-negative numbers, while the vertices are labeled with other data. For example, in the graph that models cities, the labels on the vertices are named cities, while the labels on the sides express the distance between cities.



Figure 2. Weight Graph

Optimization

Optimization is a branch of science that has long developed in the form of techniques and applications that can be described definitively as a numerical method and set of mathematical formulas to find and identify the best option of several alternatives without having to calculate and evaluate all possible alternatives (Deng et al., 2022). The optimal value is the value obtained from a process and is considered to be the best answer solution from all existing choices. In general, in solving the problem of finding the shortest route there are two methods, namely conventional and heuristic (Mykel J. Kochenderfer, 2019). Conventional methods can use calculations mathematically ordinary, while heuristic methods are applied with the calculation of the approach system.

Travelling Salesman Problem (TSP)

The Travelling Salesman Problem (TSP) is a combinatorial optimization problem that is usually found in mathematical and computer applications (Y. Wang & Han, 2021). The problem with TSP is how to determine the most optimal travel route from one city to all other cities visited. The cities visited each time are only once and must return to the hometown..

TSP can be applied in a complete weighted graph and the goal is to find a Hamilton trajectory, that is, a trajectory that passes through all points of the graph with the minimum total weight. In TSP, Hamilton's trajectory is commonly referred to as a journey or route. Thus, what is done is to form a journey (X. Li et al., 2022). Handling this TSP problem is the same as finding the shortest Hamilton trajectory from several existing solutions, namely with a greedy algorithm with its formula which is $\tau_{ij} = \tau_0 = \frac{k}{c_{aready}}$.

Ant Colony Optimization (ACO)

ACO is a seeking algorithm with probabilistic and is one of the algorithms in solving optimization problems that are heuristic. The algorithm first introduced by Moyson and Manderick and later developed by Marco Dorigo (Alani et al., 2020). This algorithm is inspired by the behavior of a group of ants while searching for a food source, where the ants can search for the shortest trajectory from their nest to food source (X. Wang et al., 2020).

The shortest trajectory the ants go through will leave a sharper pheromone scent than the longer trajectory. This happens because the pheromone left behind will evaporate. The ants will choose the trajectory based on the strong aroma of pheromone and the distance of the track. The more ants that travel the trajectory, the stronger the pheromone scent will be so that other ants will follow the same trajectory (Stodola et al., 2020).



Figure 3. Ant Journey to Find Food Sources

Shown in Figure 3.(a) there is a group of ants going on a trip. On the left side of the area where the ants and the right side the food source to which a group of ants go. Figure 3.(b) in the upper path of pheromone left by ants has undergone a lot of evaporation because the upper path is traversed by fewer ants than in the lower path. Where as pheromone is in the lower path, its evaporation tends to be longer because more ants go through the lower path than in the upper path seen in Figure 3.(c). Figure 3.(d) shows that eventually all the other ants decided to pass through the lower path because there was still a lot of pheromone left behind. Meanwhile, on the upper path, pheromone has evaporated a lot so that the ants do not choose this path (Stodola et al., 2022).

To find out the implementation of the ant colony algorithm in determining the shortest route required the following variables and steps (X. Wang et al., 2020), (Han, 2021) and (Y. Li et al., 2021):

Step 1: Set the values of the algorithm parameters. The parameters set are:

- 1) Pheromone intensity or state, namely traces of ants between cities (τ_{ij}) and changes (η_{ij}) must be set before starting the track. (τ_{ij}) used in the probability equation of the chances of the place to be visited. Many cities (n) involve coordinates (x, y) and distance between city *i* to city $j(d_{ij})$
- 2) Determine the city of departure and the city of destination
- 3) Ant travel trajectory settings (Q)
- 4) Ant trace intensity control (state) settings (α), value $\alpha \ge 0$
- 5) The visibility control setting or clarity of the observed state, here is the distance (β) , value $\beta \ge 0$

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6) Determining pheromones or traces of early ants by greedy algorithm, $\tau_{ij} = \tau_0 = \frac{k}{c_{\text{preserven}}}$

7) Visibility or change in distance between cities, $(\eta_{ij}) = \frac{1}{d_{ij}}$

- 8) Many ants (k)
- 9) Ant trace evaporation settings (ρ) , value ρ that is $0 \le \rho \le 1$ to it $\rho = 0, 10$. That is, the value most often used in the ant colony algorithm.
- 10) Fixed the algorithm is run for the maximum number of cycles (*NCmax*) while τ_{ij} will always be priced will always be updated in price (value) on each cycle of the algorithm starting from the first cycle (*NC=1*) until the maximum number of cycles (*NC=NCmax*) is reached or until convergence occurs (the same state). Set the first city of each ant. After setting x is done, then (k) many ants are placed on a certain first city at random.
- Step 2: Fill the first city into the taboo list. At this stage it produces the first element of the taboo list of each ant with a specific city index, which means that each *tabuk* (1) (list of other cities) can contain a city index between 1 and *n* as the result of the determination in step 1.
- **Step 3:** Arrange the route of each ant's to visit city. Groups of ants that are already distributed to a number or every city, will begin to travel from the first city as their respective hometowns and one of the other cities as the destination city. Then from the second city each group of ants will travel by choosing one of the cities that are not in $tabu_k$ as the next destination city. If the index of the order of visits is expressed by *s*, the city of origin is expressed as $tabu_{k_{(s)}}$ and the other cities are expressed as $\{N tabu_k\}$, then to determine the city of destination is used the equation of probability (chance) of the city to visit as follows:

$$P_{ij}^{k} = \frac{\left[\tau_{ij}\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{k' \in \{N-tabu_{k}\}} \left[\tau_{ij}\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}} \text{ for } j \in \{N-tabu_{k}\} \text{ and } P_{ij}^{k} = 0, \text{ for other } j.$$

Step 4: Calculation of the length closed tour or L_k for each ant is carried out after one cycle is completed by all ants. Then it will be calculated the improvement of

pheromone traces or changes in pheromone prices between cities. With the following equation: $\Delta \tau_{ij,k} = \frac{1}{L_k}$, jika $(i, j) \in T_k$

- **Step 5:** Calculation of pheromone traces between cities for the next cycle. The value of pheromone traces in all trajectories between cities is likely to change due to differences in the number of ants and the evaporation of pheromones. Further the pheromone value is calculated by the equation $\tau_{ij,k}(baru) = (1 \rho)\tau_{ij,k} + \Delta \tau_{ij,k}$
- **Step 6:** Clear the taboo list and repeat step 2. The taboo list needs to be emptied to be filled again with a new order of cities in the next cycle, if the maximum number of cycles has not been reached or convergence has not occurred. The algorithm in step 2 is repeated again at the price of the updated intercity ant footprint intensity parameter.



Figure 4. Research Flowchart

RESULT AND DISCUSSION

The selection of this research study is at several points of Division I in PT. Socfindo Bangun Bandar. The reason for taking this point is to implement the knowledge gained in the search for the shortest route in the distribution of fertilizers.



Figure 5. Working Map of Division I

Some of the locations for the distribution of fertilizer used:

 V_1 = Fertilizer Warehouse V_2 = Block 51 V3 = Block 52 V_4 = Block 55 V_5 = Block 61 V_6 = Block 63

The first step taken is to describe the points of the destination location into points in the graph, after that the side weight in the graph is the distance between the points of the destination.



Figure 6. Complete Graph of 6 Points of Destination Location

Based on the data obtained, the mileage between points (d_{ij}) is obtained and arranged in kilometers from each point in the table as follows:

Point Location (km)	V_1	\mathbf{V}_2	V 3	V_4	V_5	V_6
\mathbf{V}_1	0	1,14	0,94	3,85	4,05	6,05
\mathbf{V}_2	1,14	0	1,8	4,70	4,92	6,91
V_3	0,94	1,8	0	4,51	4,71	6,71
\mathbf{V}_4	3,85	4,70	4,51	0	0,2	2,2
V_5	4,05	4,92	4,71	0,2	0	2
V_6	6,05	6,91	6,71	2,2	2	0

Table 1. Mileage of Six Points

Each Antss Route of Visit to Each Point Exactly One Trip

The first step taken is to set the value of the algorithm parameters, the parameters used are $\alpha = 1,00$, $\beta = 1,00$, $\rho = 0,10$, and multiple ants (k) = 6. The initial pheromone is by using the greedy algorithm, so that the initial pheromone is obtained $\tau_{ij} = \tau_0 = \frac{6}{15,69} = 0,3824$

Then look for the change in the distance between points by using the formula $\eta_{ij} = \frac{1}{d_{ij}}$,

Then the change	in the	distance	between	points	is	obtained	as	follows:
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$\eta_{ij} = \frac{1}{d_{ij}}$	V ₁	V ₂	V ₃	V_4	V 5	V ₆
V ₁	0	0,877	1,064	0,260	0,247	0,165
\mathbf{V}_2	0,877	0	0,555	0,213	0,203	0,145
V 3	1,064	0,555	0	0,222	0,212	0,150
\mathbf{V}_4	0,260	0,213	0,222	0	5	0,455
V_5	0,247	0,203	0,212	5	0	0,5
\mathbf{V}_{6}	0,165	0,145	0,150	0,455	0,5	0

Table 2. Visibility Between Points

Distance Between Each Point Using Ant Colony Algorithm

The next step arrange ant travel route for each destination location point starting from their respective starting points as points of origin and other points as destination points. After that, the ants travel randomly with consideration of paths that have never been traversed before. The travel of ants lasts constantly until all points have been visited and formed a path. The probability calculation for one cycle (NC=1).

Table 3. First Travel of Ants

	Original			Prob	abiliy		Selected				
Ants	Point	V ₁	V_2	V_3	V_4	V_5	V_6	Point	Tabu List		
k_1	V_1	0	0,3356	0,4072	0,0995	0,0945	0,0632	V_4	$V_1 \rightarrow V_4$		
k_2	V_2	0,4400	0	0,2784	0,1069	0,1019	0,0728	V_6	$V_2 \rightarrow V_6$		
k_3	V_3	0,4830	0,2520	0	0,1007	0,0962	0,0681	V_4	$V_3 \rightarrow V_4$		
k_4	V_4	0,0423	0,0346	0,0361	0	0,8130	0,0740	V_2	$V_4 \rightarrow V_2$		
k_5	V_5	0,0401	0,0330	0,0344	0,8114	0	0,0811	V_2	$V_5 \rightarrow V_2$		
<i>k</i> ₆	V 6	0,1166	0,1025	0,1060	0,3215	0,3534	0	V_4	$V_6 \rightarrow V_4$		

The next step is to continue the second journey in the same way as the previous journey in which the points that started were based on the selection of random numbers generated.

	Original			Prob	abiliy			Selected	
Ants	Point	V_1	V_2	V_3	V_4	V_5	V_6	Point	Tabu List
k_{I}	V_4	0	0,0361	0,0377	0	0,8489	0,0773	V_6	$V_1 \mathop{\rightarrow} V_4 \mathop{\rightarrow} V_6$
k_2	V_6	0,1300	0	0,1181	0,3582	0,3937	0	V_3	$V_2 \rightarrow V_6 \rightarrow V_3$
k_3	V_4	0,0439	0,0360	0	0	0,8434	0,0767	\mathbf{V}_1	$V_3 \rightarrow V_4 \rightarrow V_1$
k_4	\mathbf{V}_2	0,4927	0	0,3118	0	0,1140	0,0815	V_5	$V_4 \rightarrow V_2 \rightarrow V_5$
k_5	\mathbf{V}_2	0,4900	0	0,3100	0,1190	0	0,0810	V_3	$V_5 \rightarrow V_2 \rightarrow V_3$
k_6	V_4	0,0456	0,0374	0,0390	0	0,8780	0	V_5	$V_6 \rightarrow V_4 \rightarrow V_5$

Table 4. Second Travel of Ants

The next step is to continue the third journey in the same way as the previous journey in which the point that started were based on the selection of random numbers generated.

 Table 5. Third Travel of Ants

	Original			Prob	abiliy			Selected	
Ants	Point	V1	V_2	V 3	V_4	V 5	V_6	Point	Tabu List
k_1	V_6	0	0,1823	0,1887	0	0,6290	0	V5	$V_1 \mathop{\rightarrow} V_4 \mathop{\rightarrow} V_6 \mathop{\rightarrow} V_5$
k_2	V 3	0,7103	0	0	0,1482	0,1415	0	V_1	$V_2 \rightarrow V_6 \rightarrow V_3 \rightarrow V_1$
k 3	\mathbf{V}_1	0	0,6804	0	0	0,1916	0,1280	V_2	$V_3 \rightarrow V_4 \rightarrow V_1 \rightarrow V_2$
<i>k</i> 4	V 5	0,2576	0	0,2210	0	0	0,5214	V_1	$V_4 \rightarrow V_2 \rightarrow V_5 \rightarrow V_1$
k_5	V_3	0,7410	0	0	0,1546	0	0,1044	V_6	$V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_6$
<i>k</i> ₆	V_5	0,3731	0,3067	0,3202	0	0	0	V_3	$V_6 \rightarrow V_4 \rightarrow V_5 \rightarrow V_3$

The next step is to continue the fourth journey in the same way as the previous journey in which the point that started were based on the selection of random numbers generated.

	Original	_		Prob	abiliy			Selected	
Ants	Point	V_1	\mathbf{V}_2	V_3	V_4	V_5	V_6	Point	Tabu List
k_1	V_5	0	0,4892	0,5108	0	0	0	V_2	$V_1 \rightarrow V_4 \rightarrow V_6 \rightarrow V_5 \rightarrow V_2$
k_2	\mathbf{V}_1	0	0	0	0,5128	0,4872	0	V_5	$V_2 \rightarrow V_6 \rightarrow V_3 \rightarrow V_1 \rightarrow V_5$
k_3	\mathbf{V}_2	0	0	0	0	0,5833	0,4167	V_5	$V_3 \rightarrow V_4 \rightarrow V_1 \rightarrow V_2 \rightarrow V_5$
k_4	\mathbf{V}_1	0	0	0,8657	0	0	0,1343	V_3	$V_4 \rightarrow V_2 \rightarrow V_5 \rightarrow V_1 \rightarrow V_3$
k_5	V_6	0,2661	0	0	0,7339	0	0	V_4	$V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_6 \rightarrow V_4$
k_6	V_3	0,6572	0,3428	0	0	0	0	V_1	$V_6 \rightarrow V_4 \rightarrow V_5 \rightarrow V_3 \rightarrow V_1$

Table 6. Fourth Travel of Ants

Because there is one point left that has not been visited so that the fifth ant journey is easier to get, namely:

	Table	7.	Fifth	Travel	of	Ants
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	Original			Prob	abiliy			Selected	
Ants	Point	V_1	V_2	V_3	V_4	V_5	V_6	Point	Tabu List
k_1	\mathbf{V}_2	0	0	1	0	0	0	V ₃	$V_1 \rightarrow V_4 \rightarrow V_6 \rightarrow V_5 \rightarrow V_2 \rightarrow V_3$
k_2	V_5	0	0	0	1	0	0	V_4	$V_2 \rightarrow V_6 \rightarrow V_3 \rightarrow V_1 \rightarrow V_5 \rightarrow V_4$
k_3	V_5	0	0	0	0	0	1	V_6	$V_3 \rightarrow V_4 \rightarrow V_1 \rightarrow V_2 \rightarrow V_5 \rightarrow V_6$
k_4	V_3	0	0	0	0	0	1	V_6	$V_4 \rightarrow V_2 \rightarrow V_5 \rightarrow V_1 \rightarrow V_3 \rightarrow V_6$
k_5	V_4	1	0	0	0	0	0	V_1	$V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_6 \rightarrow V_4 \rightarrow V_1$
k_6	\mathbf{V}_1	0	1	0	0	0	0	V_2	$V_6 \rightarrow V_4 \rightarrow V_5 \rightarrow V_3 \rightarrow V_1 \rightarrow V_2$

Because all points have been stopped for the development of the initial (first) cycle solution (NC = I) and are based on the definition of the *Traveling Salesman Problem* that

if it starts from the starting point and definitely ends at the starting point as well, so that the list of trips for the entire first cycle is obtained as below:

Ants	Tabu List	Length (L_k)	$\Delta ijk = \frac{1}{L_k}$
k_1	$V_1 \rightarrow V_4 \rightarrow V_6 \rightarrow V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_1$	15,71	0,0636
k_2	$V_2 \rightarrow V_6 \rightarrow V_3 \rightarrow V_1 \rightarrow V_5 \rightarrow V_4 \rightarrow V_2$	23,51	0,0425
<i>k</i> 3	$V_3 \rightarrow V_4 \rightarrow V_1 \rightarrow V_2 \rightarrow V_5 \rightarrow V_6 \rightarrow V_3$	23,13	0,0432
k_4	$V_4 \rightarrow V_2 \rightarrow V_5 \rightarrow V_1 \rightarrow V_3 \rightarrow V_6 \rightarrow V_4$	23,52	0,0425
k_5	$V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_6 \rightarrow V_4 \rightarrow V_1 \rightarrow V_5$	23,53	0,0424
k_6	$V_6 \rightarrow V_4 \rightarrow V_5 \rightarrow V_3 \rightarrow V_1 \rightarrow V_2 \rightarrow V_6$	16,10	0,0621

Table. 8 Route of Ants Travel and Its Pheromone Count Increase

For the first cycle (*NC*=1) the best route was obtained, namely the route taken by k1 ants with a route length of 15.71 km with routes $V_1 \rightarrow V_4 \rightarrow V_6 \rightarrow V_5 \rightarrow V_2 \rightarrow V_3 \rightarrow V_1$, after information about the best route was obtained. The addition of pheromones will be carried out with the number of recently added pheromones of $\Delta_{ij,k} = 0,0636$ using the following formula:

$$\begin{split} \tau_{ij,k} \left(new \right) &= \left(1 - \rho \right) \tau_{ij,k} + \Delta_{ij,k} \\ \tau_{1.4} &= \tau_{4.1} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \\ \tau_{4.6} &= \tau_{6.4} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \\ \tau_{6.5} &= \tau_{5.6} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \\ \tau_{5.2} &= \tau_{2.5} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \\ \tau_{2.3} &= \tau_{3.2} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \\ \tau_{3.1} &= \tau_{1.3} = \left(1 - 0,10 \right) \left(0,3824 \right) + 0,0636 = 0,4077 \end{split}$$

Because the newly acquired pheromone traces are between the points obtained in the table as follows:

Pheromone	\mathbf{V}_1	V_2	V ₃	V_4	V 5	V ₆
V_1	0	0,3824	0,4077	0,4077	0,3824	0,3824
\mathbf{V}_2	0,3824	0	0,4077	0,3824	0,4077	0,3824
V 3	0,4077	0,4077	0	0,3824	0,3824	0,3824
\mathbf{V}_4	0,4077	0,3824	0,3824	0	0,3824	0,4077
V_5	0,3824	0,4077	0,3824	0,3824	0	0,4077
V_6	0,3824	0,3824	0,3824	0,4077	0,4077	0

Table 9. Pheromones Between Points

Guided by the table, in the next literacy it can be estimated that point 3 or 4 will tend to be chosen by ants at point 1 rather than point 5. The 4th or 4th point tends to be chosen by ants at point 2.

CONCLUSION

This case in this research is Travelling Salesman Problem (TSP), especially using the ant colony algorithm in finding the shortest path for the driver of PT. Socfindo Bangun Bandar for six location points can be solved using the ant colony algorithm where this algorithm adopts the workings of the ant colony to get the shortest route. So that, the best route was obtained while the first travel cycle was the PT Fertilizer Warehouse. Socfindo Bangun Bandar (V₁) to Block 55 (V₄) then Block 63 (V₆) to Block 61 (V₅) then Block 51 (V₂) to Block 52 (V₃) and back to PT Fertilizer warehouse. Socfindo Build Bandar (V₁). Ant colony algorithm in finding the route of distribution of PT. Socfindo Bangun Bandar is obtained more minimum with a distance of 15.71 km compared to the route usually taken by drivers, which is 16.10 km. The results of this research provide the results of a shorter distance change than the usual route carried out by the company. This can speed up the time it takes trucks to distribute fertilizer so that trucks can be used by workers to transport the harvested palm fruit. That way the harvested palm fruit can be transported more quickly and brought to the factory to be processed immediately.

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