ANT COLONY OPTIMIZATION WITH DOUBLE SELECTIONS FOR SOLVING INTEGRATED SCHEDULING PROBLEM IN MANUFACTURER

Sobri Abusini\textsuperscript{11}, Mita Akbar Sukmarini\textsuperscript{2}, Corina Karim\textsuperscript{3)}
Department of Mathematics, Brawijaya University\textsuperscript{1,2,3)}

Abstract In this paper, we studied ant colony optimization for solving integrated scheduling of production and distribution problems. We improved the ant colony optimization by adding double selections, there are roulette wheel and elitism selections. Roulette wheel selection is used to determine the path where ants pass through before knowing pheromone information in that path. Meanwhile, elitism selection is used to keep the best solution before the more optimum solution obtained. Then, ant colony optimization and improved ant colony optimization are implemented in solving integrated scheduling of production and distribution problem in PT. BFPI. The aim of this paper is to achieve optimum production and distribution schedule in order to minimize the total cost of production and distribution. We also compare the performance of both applied methods and draw a conclusion. The results show that the method we proposed has more advantage.

Keywords: ant colony optimization, roulette wheel selection, elitism selection, integrated scheduling

1. Introduction

Ant colony optimization is a metaheuristic approach which can be used to solve optimization problem [1]. This algorithm is inspired from an observation of ant colony. The intriguing and worth observing behavior from ant colony is their behavior when they hunt for food, particularly the way they determine route to connect food source and their nest. While food hunting, ants emit some pheromone along the passed path as a mark. The other ants will choose route based on intensity of pheromone from every possible path. Despite the pheromone evaporation, the route which is repeatedly passed by ants will later on converge to one shortest path.

Ant colony algorithm is first introduced by Dorigo, Maniezzo, and [2]. The other studies implementing ant colony optimization are ant colony optimization for permutation flowshop scheduling [3], ant colony optimization for job shop scheduling [4], applying ant colony optimization to increase the speed of the road network [5], ant colony optimization for solving the shortest path problem [6], ant colony optimization for generalized TSP problem [7], ant colony optimization for solving 3D TSP [8], and implementation of traveling salesman problem using ant colony optimization [9]. Meanwhile, the studies which improving ant colony optimization are solving traveling salesman problem based on ants with memory [10], modified ant colony optimization for grid scheduling [11], an improved ant colony optimization for machines scheduling [12], modified ant colony optimization by applying a local search procedure[13], Development of ant colony optimization based on statistical analysis and hypothesis testing [14], ant colony optimization with fault tolerance [15], a novel hybrid ant colony optimization [16], improved ant colony optimization for weapon-target assignment [17], ant colony clustering algorithm [18], improving ant colony optimization algorithm in transmission status rule [19].

In this paper, we propose ant colony optimization with double selections for solving integrated scheduling problem in a manufacturer. The first selection is a roulette wheel. This selection is implemented in transmission status while ants are going to choose the path for the first time. In this case, the ants have not known yet about the

* Corresponding author. Email : sobri@ub.ac.id
Published online at http://jems.ub.ac.id
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Cite this Article As Abusini, S., Sukmarini, M., Karim, C. (2019). ANT COLONY OPTIMIZATION WITH DOUBLE SELECTIONS FOR SOLVING INTEGRATED SCHEDULING PROBLEM IN MANUFACTURER. Journal of Engineering and Management in Industrial System, 7(1), p26-34
Paper Submitted : May, 12th 2019
Paper Published : May, 29th 2019
pheromone information in each path. So, the roulette wheel is applied as a selection to direct ants in choosing the best potential path. The second selection is elitism. This selection is implemented when updating pheromone globally. Elitism selection will keep the best solution from previous iterations until the optimum solution is obtained.

Our proposed method will be applied in solving integrated scheduling of production and distribution problems in PT. BFPI. In production problem, a job is processed by some machines which serve different functions. Production scheduling in this case is scheduling from a number of n jobs which precisely processed in a number of m machines. This type of problem is called as job shop scheduling problem [20]-[23]. In distribution problem, a salesperson needs to distribute products from manufacturer to the customers using vehicle which has the adequate capacity to carry all the distributed products. This problem is categorized as traveling salesman problem concept [24], where a salesperson who goes from manufacturer will visit all the customers and he will not come back to the manufacturer until he finishes visiting all the customers.

This paper aims to obtain optimum production and distribution schedule. The optimum production schedule is jobs arrangement schedule which has the shortest completion time and the optimum distribution schedule is the arrangement of customers which results in minimum distance of the trip. The minimum completion time and distance indirectly minimize the total cost of production and distribution. It surely brings positive impact to the manufacturer.

2. Problem Characteristics and Assumptions

PT.BFPI is engaged in the field of sardines processing. The processing of sardines starts from the receipt of raw materials to the storage of the products. Some processes are done by machines and the others are done by employees. We focused on the process done by the machines. Because in production, machine holds prominent role. The usage of machines in production may add the spending due to huge amount of energy needed compared to other electronics. Therefore, minimization of total production time is effective to cut the production cost.

There are four important processes that are carried out by machine, namely filling, seaming, retorting, and coding. Jobs flow pattern on all four machines, see figure 1.

Filling is the process of putting fish and media into cans. The filling machine is to be the first machine (M1). Then, seaming is the process of closing cans, it is done by the second machine (M2). Subsequently, retorting is a sterilization process from bacteria, it is done by the third machine (M3). The last, coding is the provision of markers on cans, it is done by the fourth machine (M4). Further, we consider the job processing time on all four machines.

In a set of job \( J = \{j_1, j_2, ..., j_n\} \), completion time of \( j_k \), is denoted by \( C_k \), so the total production time is represented in equation 1.

\[
R = \max\{C_1, C_2, ..., C_n\} \tag{1}
\]

The constant production cost per minute is \( Rp 920.00 \), so the cost spent to produce set of job \( J = \{j_1, j_2, ..., j_n\} \) can be written as follows.

\[
RC = 920 \times \max\{C_1, C_2, ..., C_n\} \tag{2}
\]

After the production process is complete, the next is the process of distributing the products. In distribution process, the distance really affects the cost spent. The longer the distance, the higher the cost that needs to be spent and vice versa. Thus, the search for the shortest route is really effective to cut distribution cost.

If sets of customers need to be visited is denoted by \( V = \{1, 2, 3, ..., v\} \) and \( d_{ij} \) is distance from customer \( i \) to customer \( j \), the distance in distribution process is represented in equation 3.

\[
D = \sum_{i=1}^{v-1} d_{\pi(i)\pi(i+1)} + d_{\pi(v)\pi(1)} \tag{3}
\]

The constant distribution cost per kilometer is \( Rp 1,750.00 \), so the cost spent to distribute products to sets of customers \( V = \{1, 2, 3, ..., v\} \) can be represented as follows.

\[
DC = 1750\left(\sum_{i=1}^{v-1} d_{\pi(i)\pi(i+1)} + d_{\pi(v)\pi(1)}\right) \tag{4}
\]

From equation 2 and 4, it can be obtained total production and distribution cost with constant cost which is defined as follows.

\[
TC = RC + DC \tag{5}
\]

\[
TC = [920 \times \max\{C_1, C_2, ..., C_n\}] +
\]
3. Ant Colony Optimization

When ant colony is faced by two paths from nest to the food source, in which one of the paths is twice longer than another one, the ants in that colony will start moving randomly. Some of the ants in the colony will take the shorter path whereas the others will take the longest one because they do not have any clues to draw conclusion. The ants which take the shorter route will reach the food source earlier than the others and they surely leave pheromone on the path they passed. After reaching the food source, they will go back to their nest. On the way back to the nest, when the ants find intersections, the ants which carry food will choose the path they passed before and regard it as the ant’s path to their nest. The ants which choose the shortest route will keep depositing pheromone. Therefore, that particular route will be more interesting for the other ants. Meanwhile, the ants which take the longer route will have probability to take the shorter one and after a while, they gather and keep using the shorter route. Thus, the ants will find their shortest path without having any global vision about the terrain they pass. The ants make decision in each intersection based on level of pheromone. So, ant colony will be succeeded to find food and carry it to the nest using optimum way [11].

Based on the behavior of the ants, Dorigo, Maniezzo, and Colomi [2] was inspired to make an algorithm that can be used to solve optimization problems, known as the ant colony optimization algorithm. There are four steps of basic ant colony optimization algorithm adapted from [25]. These steps are described as follow:

Step 1: Parameter Initialization
Parameter initialization consists of pheromone intensity $\tau_{ij}(t)$, parameter to control pheromone intensity $\alpha$, parameter to control visibility $\beta$, evaporation rate of pheromone $\rho$, number of ants $k$.

Step 2: Transmission Status Rule
Transmission status rule is probability of ants $k$ which are on $i$ point and choose to head to $j$ point. Transmission status rule is represented in following equation:

$$P_i^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \eta_{ij}^\beta}{\sum_{i=1}^{n} [\tau_{ij}(t)]^\alpha \eta_{ij}(t)^\beta}, & \text{if } (i,j) \in S_k \\ 0, & \text{otherwise} \end{cases}$$

Step 3: Local Pheromone Update
After an ant has finished the tour, the pheromone is updated based on the tour done by that ant. The rule of local pheromone update is implemented as in following equation:

$$\tau_{ij}(t + 1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta \tau_{ij}(t)$$

Variable $\tau_{ij}(t)$ shows intensity of pheromone in connection $(i,j)$ when time $t$, with $0 \leq \rho \leq 1$ as parameter of pheromone evaporation level or pheromone evaporation coefficient. $\Delta \tau_{ij}(t)$ is the probability of ants which are on point $i$ that will choose point $j$, represented as follows:

$$\Delta \tau_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \eta_{ij}^\beta}{\sum_{i=1}^{n} [\tau_{ij}(t)]^\alpha \eta_{ij}(t)^\beta}, & \text{if } (i,j) \text{ passed by the ants} \\ 0, & \text{otherwise} \end{cases}$$

Step 4: Global Pheromone Update
After each ant has finished its tour, there will be global pheromone update. This update is done in a tour by particular ant which has the highest total of local pheromone of all. The rule of global pheromone update is as follows:

$$\tau_{ij}(t + 1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta \tau_{ij}(t)$$

Variable $\tau_{ij}(t)$ shows intensity of pheromone in connection $(i,j)$ when time $t$, with $0 \leq \rho \leq 1$ as parameter of pheromone evaporation level or pheromone evaporation coefficient.
is defined as follows:
\[
\Delta \tau_{ij}(t) = \begin{cases} 
Q & \text{if } (i,j) \text{ passed by ant } -(k) \\
0, & \text{otherwise}
\end{cases}
\] (11)

\(Q\) is constants and \(T\) is total unit obtained from the tour done by that particular ant. With this approach, only the connection categorized in best tour affect pheromone level reinforcement.

4. Improved Ant Colony Optimization

In this paper, we propose improvisation in ant colony optimization by adding double selections. The first selection is roulette wheel selection, this selection is applied to step 2. The second selection added is elitism selection, this selection is applied to step 4.

4.1 Roulette Wheel Selection

Roulette wheel selection is the most common and simplest selection technique [26]-[28] It aims to select particular candidate with probability to be selected is \(P_{ij}\) [29].

\[
P_{ij}(t) = \frac{[\tau_{ij}(t)\eta_{ij}]^\beta}{\sum_k[\tau_{kj}(t)\eta_{kj}]^\beta}
\] (12)

\(P_{ij}\) is probability of ants \(k\) which are on \(i\) point and choose to head to \(j\). \(\tau_{ij}\) is amount of pheromone found between point \(i\) dan \(j\) and \(\eta_{ij} = \frac{1}{\tau_{ij}}\) is value of connection visibility \((i,j)\).

When ants will choose the path for the first time, they have not known pheromone information in each path. This selection is to direct ants to choose the best potential tour path. The calculation of roulette wheel selection is based on heuristic value \(\eta_{ij}\). The greater \(\eta_{ij}\), the bigger probability to be chosen. See figure 2.

The area of sector symbolized by \(I\) illustrates the extend of probability that the ant will continue the tour to node 1, ect. This selection depends on the extent of probability, but it still allows the ant to find another paths from the results of roulette wheel.

4.1 Elitism Selection

Elitism selection is a selection which keeps the best solution from one to the next iteration [30]. If the result obtained in iteration is worse than the previous iteration, the pheromone value which will be used in the next iteration is the pheromone from the previous iteration and the best previous iteration will be preserved. An elitist replacement is considered, the new minimum solution, \(M\), will replace the old minimum solution if the total processing time or total distance, \(T\), is less or equal to the old one.

\[
M_t(t + 1) = \begin{cases} 
T_t(t + 1), & \text{if } T_t(t + 1) \leq T_t(t) \\
M_t(t), & \text{otherwise}
\end{cases}
\] (13)

5. Results and Discussion

In production, there are four jobs which need to be finished using four machines. Data of each processing time of all jobs in every machine is represented in table 1.

Based on the data, we conducted several experiments using the ant colony optimization and improved ant colony optimization methods. The results obtained from these experiments are presented in the figure 3, figure 4, and figure 5.

From the results of the experiments, in figure 3, figure 4, and figure 5 it can be seen that the performance of improved ant colony optimization is better than ant colony optimization. The minimum processing time produced by improved ant colony optimization is more optimal, although it uses fewer number of ants and iterations. Whereas by using higher number of ants and iterations, both of these methods produce the same minimum processing time, but improved ant colony optimization is constantly better in terms of convergence.

The minimum processing time obtained is 1168 minutes, with the order of jobs being J4-J1-J3-J2. By using equation 2 the optimal production cost for completing four jobs is Rp1,074,560.00. The process of four jobs in four machines is shown in figure 6.
Fig 1 Jobs Flow Pattern

Fig 2 Roulette Wheel Selection

| Job | Machine M1 | Machine M2 | Machine M3 | Machine M4 |
|-----|------------|------------|------------|------------|
| J1  | 180        | 215        | 82         | 362        |
| J2  | 310        | 84         | 80         | 115        |
| J3  | 240        | 93         | 40         | 75         |
| J4  | 135        | 184        | 85         | 193        |

Fig 3 This figure represents two results of experiment that use the value of parameters $\alpha = 0.1$, $\beta = 0.1$, $\rho = 0.5$, $k = 1$, and the number of iteration is 10. (a) This result is obtained by ACO and the minimum processing time is 1222 minutes. (b) This result is obtained by IACO and the minimum processing time is 1168 minutes.

Fig 4 This figure represents two results of experiment that use the value of parameters $\alpha = 0.7$, $\beta = 0.7$, $\rho = 0.1$, $k = 10$, and the number of iteration is 100. (a) This result is obtained by ACO and the minimum processing time is 1168 minutes. (b) This result is obtained by IACO and the minimum processing time is 1168 minutes.
Fig 5 This figure represents two results of experiment that use the value of parameters $\alpha = 0.8$, $\beta = 0.8$, $\rho = 0.4$, $k = 100$, and the number of iteration is 1000. (a) This result is obtained by ACO and the minimum processing time is 1168 minutes. (b) This result is obtained by IACO and the minimum processing time is 1168 minutes.

![Fig 5](image1)

(a)  
(b)

Fig 7 This figure represents two results of experiment that use the value of parameters $\alpha = 0.3$, $\beta = 0.3$, $\rho = 0.7$, $k = 1$, and the number of iteration is 10. (a) This result is obtained by ACO and the minimum distance of distribution is 148.7 km. (b) This result is obtained by IACO and the minimum distance of distribution is 138.7 km.

![Fig 7](image2)

(a)  
(b)

Tabel 2. The Distance between Two Locations (in kilometers)

|   | PT. | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|-----|----|----|----|----|----|----|----|
| PT. | 0 | 27 | 13 | 18 | 38 | 5.5 | 18 | 23 |
| C1  | 27 | 0  | 14 | 33 | 39 | 25 | 27 | 29 |
| C2  | 13 | 14 | 0  | 23 | 32 | 12 | 17 | 18 |
| C3  | 18 | 33 | 23 | 0  | 49 | 17 | 6  | 7  |
| C4  | 38 | 39 | 32 | 49 | 0  | 33 | 48 | 51 |
| C5  | 5.5| 25 | 12 | 17 | 33 | 0  | 18 | 23 |
| C6  | 18 | 27 | 17 | 6  | 48 | 18 | 0  | 5.2|
| C7  | 23 | 29 | 18 | 7  | 51 | 23 | 5.2| 0  |
Fig 8 This figure represent two results of experiment that use the value of parameters $\alpha = 0.5, \beta = 0.5$, $\rho = 0.5, k = 10$, and the number of iteration is 100. (a) This result is obtained by ACO and the minimum distance of distribution is 145.7 km. (b) This result is obtained by IACO and the minimum distance of distribution is 138.7 km.

Fig 9 This figure represent two results of experiment that use the value of parameters $\alpha = 0.6, \beta = 0.6$, $\rho = 0.2, k = 100$, and the number of iteration is 1000. (a) This result is obtained by ACO and the minimum distance of distribution is 138.7 km. (b) This result is obtained by IACO and the minimum distance of distribution is 138.7 km.

In distribution, there are eight locations, that are one is the manufacturer location, where a salesperson will depart and return to this location, and the others are customer locations that must be visited by a salesperson. The data of distance between two locations in kilometers is given in the table 2.

Based on the data above, we conducted several experiments using the ant colony optimization and improved ant colony optimization methods. The results obtained from these experiments are presented in the following figures.

Not much different from the results of the production scheduling experiment, in solving distribution problem, the performance of improved ant colony optimization is better than ant colony optimization. The results of the experiment in Fig. 7, Fig. 8, and Fig. 9 show that by using fewer or higher number of ants and iterations, improved ant colony optimization obtain the total distance of distribution more optimal than ant colony optimization. From the experiments that have been conducted, it should be recognized that improved ant colony optimization is superior in terms of speed of convergence. The minimum distance of distribution obtained from the experiments is 138.7 km with the order of locations being PT-C3-C6-C7-C2-C1-C4-C5-PT. Based on the minimum distance of distribution obtained and by using (4), the optimal distribution cost for distributing products to seven customers is Rp242,725.00.

From the results of production and distribution scheduling, the minimum production and distribution costs have been obtained. Using (6), the minimum total cost of the integrated production and distribution obtained is Rp1,317,285.00.
6. Conclusion

This paper presents an approach for solving integrated scheduling problems based on ant colony algorithm. We improved ant colony optimization with double selections. Those are roulette wheel and elitism selection. This method is used to optimize the production and distribution schedules in manufacturer. To test the performance of improved ant colony optimization, we compare this method with the basic ant colony optimization.

From the experiments that have been conducted, we obtain the optimal schedule of production is order of jobs being J4-J1-J3-J2, with the minimum processing time is 1168 minutes and the optimal schedule of distribution is arranged location being PT-C3-C6-C7-C2-C1-C4-C5-PT, with the minimum distance of distribution is 138.7 km. Minimum production costs obtained is Rp1,074,560.00 and minimum distribution cost is Rp242,725.00. Eventually the minimum total cost of the integrated production and distribution obtained is Rp. Rp1,317,285.00.

The results of the experiment show that which is very influential is the number of ants and iterations used. However, by using fewer or higher number of ants and iterations improved ant colony optimization gives better results than ant colony optimization. Based on the two problems resolved, improved ant colony optimization is still able to get the optimal results even though there are few in number of ants and iterations. Another advantages of improved ant colony optimization we proposed is that the method is more useful in terms of convergency and speed to find the best solutions.

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