Artificial Bee Colony Algorithm for Solving Green Vehicle Routing Problems with Time Windows

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Abstract. Determining the route of vehicles in logistics has a vital function for logistics companies to reduce the total cost of distribution costs. One of the exciting problems in determining vehicle routes is the green vehicle routing problem with time windows (GVRPTW). This study aims to propose the Artificial Bee Colony (ABC) algorithm to solve the GVRPTW problem. This problem's objective function is to minimize the total cost of distribution, which involves the total cost of fuel and late delivery costs. The ABC algorithm is applied to a case study of an Indonesian distribution company. Thirty customers and one distribution center were considered in this study. The results show that the ABC algorithm can minimize the total cost of distribution. In addition, the proposed algorithm produces a competitive total distribution cost compared to the nearest neighbor procedure.

Keywords: GVRPTW, Green, Routing, Algorithm, Bee Colony

1. Introduction
Distribution is the activity of moving goods from suppliers to consumers in the supply chain [1]. Determination of the proper route can improve distribution performance in the supply chain [2]. This route determination problem is called the Vehicle Routing Problem (VRP) [3]. Currently, global warming and climate change in the supply chain encourage researchers to care for this problem [4]. VRP problems that consider environmental aspects are called the Green Vehicle Routing Problem (GVRP). One variant of GVRP is GVRP with time windows (GVRPTW). This problem considers environmental aspects and customer service time-limited by opening and closing time (time windows) [5]. The GVRP problem has attracted researchers' interest to care about environmental aspects [6] [7]. One of the goals of GVRPTW is to minimize fuel consumption. This problem is caused by the issue of the depletion of fuel reserves in the world.

Researchers have proposed several VRP with Time Windows (VRPTW) studies. Ursani, Essam, Cornforth and Stocker [8] proposed a genetic algorithm to solve this problem. Nowadays, the metaheuristic procedure is a popular procedure to solve the VRPTW problem [9]. Several other algorithms to solve VRPTW include Tabu search [10], Chaos-Particle Swarm Optimization [11], Ant Colony Optimization [12], Sequential Insertion[13], Cuckoo Search [14], Improve genetic algorithm [15] [16], and Soccer Games Optimization [17]. From some literature on VRPTW issues, researchers generally focus on economic aspects. However, only a few GVRPTW studies have been published. Some of these studies include Zulvia, Kuo and Nugroho [5], Macrina, Pugliese, Guerrierio and Laporte [18], and Yu, Wang, Wang and Huang [19].

Based on the description of previous research, several studies on GVRPTW problems have been published. However, no studies utilize the Artificial Bee Colony (ABC) algorithm for solving
GVRPTW. This study attempts to use the ABC algorithm to solve the GVRPTW problem. In the GVRPTW problem, this study focuses on minimizing the total cost, which involves the fuel consumption cost and late delivery costs. This article is expected to enrich research on GVRPTW problems by proposing a new ABC algorithm procedure. This study develops the ABC algorithm proposed by Mernik, Liu, Karaboga and Črepinšek [20].

2. Methods

2.1 Assumptions, notations, and problem descriptions

The assumptions of the GVRPTW problems in this study are as follows: (1) The route starts and ends in the same distribution center (depot). (2) one distribution center considered. (3) The speed of the vehicle depends on node i to node j. (4) Demand for products is fixed. (5) the price of fuel, late penalty fees, and fixed distribution costs are fixed. (6) Service time for each customer is deterministic.

The notation used in the GVRPTW problem is presented as follows:

\( i,j \): denotes the node (customer)
\( n \): number of customers
\( m \): number of vehicles
\( d_{ij} \): distance from node i to node j
\( Fc \): The price of fuel per liter
\( Cl \): late fee per unit time
\( LPK \): fuel consumption per kilometer (liter/kilometer)
\( T_k \): load times for vehicles k
\( T_{ik} \): service start time of node (customer) i by vehicle k
\( S_{ik} \): service time of node (customer) i by vehicle k
\( v_{ij} \): speed of the vehicle from node i to node j
\( b_i \): closed time at node i
\( a_i \): opened time at node i
\( X_{ijk} \): binary number (0,1) representing the journey from i to j consumer by k th vehicle
\( q_i \): demand from the i-th consumer.
\( Q_k \): Vehicle capacity k

To describe the GVRPTW problem, this study developed a mathematical model as follows:

Objective Function

\[
\text{min } Z = \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} X_{ijk} \cdot Fc \cdot LPK + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} \left( \max(0, ((T_{ik} + T_{ik} + S_{ik} + \frac{d_{ij}}{v_{ij}}) - b_j)) \right) \cdot Cl \cdot X_{ijk}
\]  

Subject to:

\[\sum_{i=1}^{n} \sum_{k=1}^{m} X_{ijk} = 1, j = 2, \ldots, n\]  

(2)

\[\sum_{j=1}^{n} \sum_{k=1}^{m} X_{ijk} = 1, i = 2, \ldots, n\]  

(3)

\[\sum_{i=1}^{n} X_{i0k} - \sum_{i=1}^{n} X_{ipk} = 0, p = 1,2, \ldots, n, k = 1,2, \ldots m\]  

(4)

\[\sum_{i=1}^{n} q_i \sum_{k=1}^{m} X_{ijk} \leq Q_k, k = 1,2, \ldots, m\]  

(5)

\[T_{ik} \geq a_i, \ i = 1,2, \ldots n, k = 1,2, \ldots m\]  

(6)

\[\sum_{i=1}^{n} X_{i1k} = 1, k = 1,2, \ldots m\]  

(7)

\[X_{ijk} \in [0,1], i = 1,2, \ldots n, j = 1,2, \ldots, n, k = 1,2, \ldots m\]  

(8)
Equation (1) states the objective function of the GVRPTW problem to minimize the total cost. Part one presents the cost of fuel, and part two describes late fees. Constraints (2) and (3) formulate that each customer node is served by one vehicle. Constraint (4) illustrates that the vehicle arriving at a customer (node) must also be sure to leave the customer. Constraint (5) formulates the total number of consumer demands in a vehicle that does not exceed the vehicle's capacity serving that route. Constraint (6) is ensuring that vehicle \( k \) visits node \( i \) after node \( I \) opening time. Constraint (7) guarantees that the vehicle departs from the depot and returns to the depot. Constraint (8) shows that the \( X_{ijk} \) variable is a binary number.

2.2 Artificial Bee Colony Algorithm

This section describes the stages of the proposed Artificial Bee Colony (ABC) procedure to solve the GVRPTW problem. ABC is an optimization algorithm that mimics bees' behavior to start a food search [21]. The ABC algorithm is divided into three main parts: Employed bee, Onlooker bee, and Scout bee. Each group of bees has a different role in finding food sources. The role of Employed Bee exploits food sources. Bee onlooker waits in the hive to share information about the food source that Employed bee exploits. Scout Bee plays the role of finding new food sources randomly. The food position source was converted into a route order based on the large rank value principles [6, 7]. The stages of the ABC algorithm for solving the GVRPTW problem are as follows [21]:

a) Step 1 is parameter Initiation. The parameters used in the ABC algorithm are the maximum evaluation and number of food sources (SN).

b) Step 2 is the initialization phase. At this stage, each food source \( Z_{rs} \) is initialized some population where \( r = 1,2,\ldots,SN \) and \( s = 1,2,\ldots,D \). \( D \) shows the number of customers. The initialization of food sources is presented in equation (1).

c) \[ Z^s_z = Z^s_{min} + \text{rand}(0,1)(Z_{max} - Z^s_{min}) \]  

(9)

d) Step 3 is to calculate the nectar at each food source.

e) Step 4. The Employee Bee phase is looking for new food sources with better fitness (nectar) values. The function for finding food sources randomly is presented in equation (10). Where \( \emptyset_{rs} \) is a random value between \([-1,1]\]. The new food sources were further evaluated using formula (11).

Where Dimana \( \text{maks} (f(\hat{e}_b)) \) shows the largest objective function value, \( \text{min} (f(\hat{e}_b)) \) is the smallest objective function value, and \( f(\hat{e}_b) \) is the objective function value on the bee employee.

f) \[ v_{rs} = z_{rs} + \emptyset_{rs}(z_{rs} - z_{ts}) \]  

g) \[ f_{it} = \text{maks}(f(\hat{e}_b)) + \text{min}(f(\hat{e}_b)) - f(\hat{e}_b) \]  

(11)

h) Step 5 is calculating the probability of each employed bee. The calculation of probability \( (pr) \) is presented in equation (12).

i) \[ pr = \frac{f_{ir}}{F} \]  

(12)

j) Step 6 is the Onlooker bee Phase. For each onlooker bee, the onlooker's selection of solutions is carried out by generating a random number value between (0.1). A random number close to pr was chosen as the onlooker solution.

k) Step 7 is the bee Scout Phase. After employed bees and Onlooker bee search bees, the algorithm checks the depleted food source for immediate abandonment in a bee colony cycle. The food sources left by the bees are replaced with new food sources, which are presented in equation (9).

l) Step 8 is determining the best solution. The three phases are repeated until the maximum evaluation limit. Each evaluation is compared to the results. The food sources are best chosen as the solution.

2.3 Data and experiments

The research data was generated from case studies of distribution companies in Indonesia. One depot (distribution center) was used to serve 30 customers. Customer demand ranges in the 7-100 unit. Closing time for each customer is a minimum of 1 hour and a maximum of 8 hours. 31 (including depot) node distance and the speed between nodes were generated. The vehicle capacity was 250 units. \( Fc \) was IDR 5,150. \( Cl \) used was IDR 2,000 / hour. Loading time is 0.0056 hours per unit per vehicle. LPK = 0.111 Liters / kilometer. Service time for each customer was a minimum value range
of 0.0672 hours and a maximum value of 1.2 hours. In this study, the company used one vehicle to serve customers. The vehicle departs and returns until all customers are served.

This study used two parameters of maximum evaluation and the number of foods. Each evaluation parameter and number of foods used five different data variants. Each maximum evaluation and number of foods used five variations: 100, 200, 400, 600, and 1000. The results of the experiment recorded the total distribution costs in each experiment. This research was conducted using Matlab R2014a software on i5 core CPU Processor, 500Gb Hard disk, 4Gb memory on Microsoft Windows 10. This study compared the proposed algorithm's results with the nearest neighbor procedure, which was used as the company’s actual solution. This study also conducted a sensitivity analysis to determine the effect of changes in LKP on the total distribution costs. Six variations of data were tried for sensitivity analysis. The LKP value was changed by adding and subtracting the LKP data (0.111 liters/kilometer) from the values of ±0.0010, ±0.0020, and ±0.0030.

3. Result and Discussions

3.1 Artificial Bee Colony Experiments

The experimental results for solving the GVRPTW using the ABC algorithm are presented in Table 1. These results indicate that each variation of the ABC algorithm parameter experiment results in a varying total distribution cost. In the maximum evaluation parameter, the experimental results show a downward trend in the total distribution cost if the maximum evaluation is large. Conversely, there is a tendency for the total distribution cost to increase if the maximum evaluation is small. The same finding also occurred for the Source of Foods parameter. The greater the source of food used, the smaller the total distribution costs generated. Conversely, if the food source is getting smaller, the resulting total distribution costs will be large.

| Source of Foods | Maximum evaluation | 100  | 200  | 400  | 600  | 1000 |
|-----------------|--------------------|------|------|------|------|------|
| 100             | 62,312             | 61,625 | 58,243 | 60,597 | 58,547 |
| 200             | 61,199             | 60,020 | 57,237 | 55,991 | 57,398 |
| 400             | 60,549             | 59,948 | 59,387 | 57,824 | 56,949 |
| 600             | 60,199             | 59,107 | 58,301 | 59,055 | 59,863 |
| 1000            | 58,515             | 59,586 | 59,588 | 58,637 | 54,693 |

3.2 Algorithm Comparison

The results of the comparison between the proposed algorithm and the nearest-neighbor procedure are shown in Figure 1. The benchmark used in the comparison algorithm is the total distribution cost. The results show that the proposed algorithm produces a lower total distribution cost than the nearest-neighbor procedure. The proposed procedure can save the total distribution cost by 50.14%.

![Figure 1. Comparison of the proposed algorithm with the nearest neighbor procedure](image-url)
3.3 The effect of LKP on the total distribution costs

Sensitivity analysis is conducted to determine changes in several variable values on changes in the total value of distribution costs. The effect of the LKP value on costs (IDR) is presented in table 2. The results showed that the greater the LKP used, the greater the total distribution costs and fuel consumption costs. On the other hand, the smaller the LKP used, the smaller the total distribution costs and fuel consumption costs. For the effect of LKP on late penalty fees, LKP does not affect late delivery penalty fees.

| LKP | Total Distribution Costs | Penalty cost for late | Fuel Consumption Costs |
|-----|--------------------------|-----------------------|------------------------|
| 0.114 | 55,131                   | 38,452                | 16,680                 |
| 0.113 | 54,985                   | 38,452                | 16,533                 |
| 0.112 | 54,839                   | 38,452                | 16,387                 |
| 0.111 | 54,693                   | 38,452                | 16,241                 |
| 0.110 | 54,546                   | 38,452                | 16,094                 |
| 0.109 | 54,400                   | 38,452                | 15,948                 |
| 0.108 | 54,254                   | 38,452                | 15,802                 |

4. Conclusion

This research attempts to propose the ABC algorithm to solve the GVRPTW problem. The proposed ABC algorithm can be used to solve the GVRPTW problem. The results showed that the Source of Foods parameter and the maximum evaluation affected the resulting solution's quality. The greater the source of food and the maximum evaluation used, the smaller the total distribution costs. The proposed algorithm is compared with the nearest neighbors algorithm. This comparison is minimal to determine the performance of the proposed algorithm. Further research can be explored by comparing the sophisticated metaheuristic procedures to determine the ABC algorithm's performance.

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