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A Modified Camel Algorithm for Optimizing Green Vehicle Routing Problem with Time Windows

Dana Marsetiya Utama[1]*, Wa Ode Nadhilah Safitri[1], Annisa Kesy Garside[1]

Abstract: In recent years, the issue of fuel depletion has become a significant problem in the world. The logistics sector is one of the sectors with an increase in fuel consumption. Therefore, route optimization is one of the attempts to solve the problem of minimization fuel consumption. In addition, this problem generally also has time windows. This study aimed to solve the Green Vehicle Routing Problem with Time Windows (GVRPTW) using the Camel Algorithm (CA). The objective function in this problem was to minimize the total cost of distribution, which involves the cost of fuel consumption and the cost of late delivery. The CA parameter experiment was conducted to determine the effect of the parameter on distribution cost and the computation time. In addition, this study also compared the CA algorithm's performance with the Local search algorithm, Particle Swarm Optimization, and Ant Colony Optimization. Results of this study indicated that the use of Camel population parameters and the total journey step affected the quality of the solution. Furthermore, the research results showed that the proposed algorithm had provided a better total distribution cost than the comparison algorithm.

Keywords: Vehicle routing problem with time windows, fuel consumption, green vehicle routing problem, camel algorithm.

Introduction

In recent years, the logistics sector has played an essential role in various aspects such as industry, economy, and the environment [1, 2]. In the economic aspect, route determination is used to find optimal solutions to reduce logistics distribution costs and fulfill customer demands [3, 4]. This problem is famously called the Vehicle Routing Problem (VRP) [5]. In some cases, customers have operating and service times (open and close) that encourage companies to meet their demands on time windows. This problem is known as the Vehicle Routing Problem with Time Windows (VRPTW) [6]. Some VRPTW problems are that product demand is sent past the time window, which causes the company to be given a penalty for late delivery costs [7]. On-time delivery can affect loyalty and customer satisfaction, increasing company profitability [8]. Therefore, the delivery must be made quickly [9, 10] since it also impacts on reducing fuel and increases delivery times [11]. According to Moghdani *et al.* [12], reducing fuel consumption problems in VRP is classified as Green Vehicle Routing Problem (GVRP) since it concerns the depletion of fuel reserves. The literature review results have conducted by Lin *et al.* [13], and Moghdani, Salimifard [12] show that research on VRP and GVRP continues to increase every year.

[1] Faculty of Engineering, Department of Industrial Engineering, University of Muhammadiyah Malang, Jl..Raya Tlogomas 246 Malang, Jawa Timur, Indonesia. Email:dana@umm.ac.id

* Corresponding author

Researchers have investigated several GVRP studies that focus on minimizing fuel consumption. Xiao *et al.* [13] showed that fuel consumption significantly affects total transportation costs on the Capacitated VRP (CVRP) problems. Psychas *et al.* [15] investigated the minimization of travel time and fuel consumption. Furthermore, Zhang *et al.* [16] solved the problem of CVRP under three-dimensional loading constraints that assume that fuel consumption is proportional to the vehicle's total weight. Niu *et al.* [17] studied the problem of minimizing fuel consumption in the urban network by proposing A hybrid tabu search algorithm. Besides, Rao *et al.* [18] investigated the fuel minimization problem by considering the road gradient. In the GVRP problem, several studies have been published to solve this issue by offering a new algorithm effectively. Zulvia *et al.* [19] proposed a gradient evolution algorithm procedure for multi-objective optimization. Their research aimed to optimize the operational cost, deterioration cost, carbon emissions, and customer satisfaction. Macrina *et al.* [20] proposed an iterative local search heuristic algorithm to minimize vehicle energy. Yu *et al.* [21] offered a branch and bound procedure to minimize costs for the heterogeneous fleet green vehicle routing problem with time windows. Some of the other proposed metaheuristic procedures include Evolutionary Algorithm [22], Artificial Bee Algorithm [23, 24], PSO [25], ACO [26], as well as for Simulated Annealing [13, 27].

According to generalized combinatorial optimization problems, the GVRP is categorized as a Non-Polynomial-hard optimization problem [28, 29]. It cannot be solved in polynomial time [30], and several VRP, VRPTW, and GVRP studies have used Exact, heuristic, and metaheuristic approaches to solve the problem [12, 13, 31, 32]. However, the exact method often performs poorly compared to other procedures [33]. This procedure takes a very long time to find the optimal, feasible solution for small instances. Moreover, this procedure is not proper to find a solution in medium and large instances. The popularity of this procedure is due to heuristic and metaheuristic procedures having good flexibility in solving complex problems [33, 34]. Researchers have proposed several procedures in the VRPTW problem to minimize penalties time and minimize travel distance. Several proposed procedures were presented to minimize penalties time, such as Genetic Algorithm [35] and Improved Genetic Algorithm [36]. Several procedures have also been implemented to minimize travel distance, such as the hybrid Particle Swarm Optimization (PSO) [37], Ant Colony Optimization (ACO) [38], Memetic Algorithm [39], and Evolutionary Scatter Search PSO [40].

Based on previous studies, one of the attractive VRPTW models was proposed by Hu *et al.* [37]. Unfortunately, the proposed VRPTW model only considers delivery and late penalties costs that ignore fuel consumption costs. Based on this deficiency, this study tries to develop the model proposed by Hu *et al.* [37] by considering the fuel consumption cost. We called this problem a Green Vehicle Routing Problem with Time Windows (GVRPTW) because this problem considers the fuel consumption cost. Based on the description above and the literature review Moghdani *et al.* [12], this problem rare attention from researchers. In addition, one of the new interesting new algorithms to investigate is Camel Algorithm (CA). The CA is a new algorithm proposed by Ali *et al.* [41] that imitates a camel's journey in the desert. This algorithm has been successfully applied in several fields, such as estimating solar photovoltaic modules [42] and optimizing speed controller structure [43]. Some of these studies apply the CA algorithm to solve continuous problems. Unfortunately, there is no CA research to solve discrete space problems like combinatorial optimization. Therefore, this study tried to minimize the total distribution costs in GVRPTW involving fuel and late delivery costs using Camel Algorithm (CA). In this study, the CA is modified to solve GVRPTW, classified as a combinatorial problem. This study's motivations are described as follows: (1) Research to minimize the total distribution costs involving fuel and late delivery costs, which researchers rarely investigate; and (2) There has been no research on VRPTW problems that utilize the CA algorithm.

Based on the description of the research motivations above, this study proposes a modified CA algorithm to solve GVRPTW. The objective function of this research is to minimize the total distribution costs involving fuel consumption and late delivery costs. This research-based is on case study on distribution companies in Indonesia. Hence, The main contribution of this research is to provide the latest theoretical development by proposing a new CA algorithm for the GVRP solution, especially GVRPTW. The second contribution is to provide real solutions to companies in decision-making about GVRPTW problems. To the best of our knowledge, no study has implemented CA procedures to solve the GVRPTW problem to minimize the total distribution costs involving fuel consumption and late delivery costs. Therefore, this research is expected to impact GVRPTW problem-solving significantly.

Methods

Assumptions, Notations, and Problem Descriptions

This section describes the assumptions, notations, and problem descriptions of the GVRPTW problem. The GVRPTW problem studied assumptions are: (1) The vehicle has a speed dependent from node to node and varies. (2) The vehicle departs and ends at the depot (distribution center) that defined as node 0. (3) Demand for each customer is fixed. (4) The model being developed has one depot. (5) Late penalty delivery costs, fuel prices, and fixed delivery costs are fixed. (6) The product weight is insignificant, so the load does not affect fuel consumption. (6) Each customer has a definite service time.

Notations used in the GVRPTW problem is presented as follows:

Parameter index
i, j : index for node (customer)

Variable
K : total vehicle
L : total customer
d_{ij} : distance from node i to node j
LCT : late delivery cost per unit time (IDR per hour)
Cf : fuel prices (IDR)
LPK : rate of fuel consumption per kilometer (liter)
L_k : load time on vehicle k
s_j : arrival time of the vehicle for customer j
s_i : arrival time of the vehicle for customer i
w_i : waiting time of the vehicle for customer i
Ve_{ij} : vehicle speed from node i to node j
ST_{ik} : service time of node (customer) i by vehicle k
ET_j : opening time at node j

LT_j : closing time at node j
q_k : capacity vehicle k
g_i : demand from the customer i
TDC : total distribution cost

Decision variable
x_{ijk} : a binary variable that shows the journey from th consumer to j-th consumer by k-th vehicle
y_{ki} : a binary variable that shows vehicle k serve customer i

The GVRPTW problem is studied to minimize the total distribution cost that involves fuel consumption costs and late delivery costs. This GVRPTW problem is classified as soft time windows. It is based on the consumer receiving the delivery even though it is not following the time windows. However, the consumer provides a late penalty fee. The mathematical model for the VRPTW problem in this study is developed based on Hu *et al.* [37]. It is presented as follows:

Objective function

$$min\ TDC = \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{K} Cf.LPK.d_{ij}.x_{ijk} + \sum_{j=1}^{L}\left(max(0,(s_j - LT_j))\right).LCT \quad (1)$$

Subject to

$$\sum_{i=0}^{L} g_i.y_{ki} \le q_k\ ,\ \forall\ k = 1,\dots,K \quad (2)$$

$$\sum_{k=1}^{K} y_{ki} = 1\ ,\ i = 1,\dots,L \quad (3)$$

$$\sum_{k=1}^{K} y_{k0} = K \quad (4)$$

$$\sum_{i=0}^{L} x_{ijk} = y_{kj}\ , j = 0,1,\dots L\ ; \forall\ k = 1,\dots,K \quad (5)$$

$$\sum_{j=0}^{L} x_{ijk} = y_{ki}\ , i = 0,1,\dots L\ ; \forall\ k = 1,\dots,K \quad (6)$$

$$L_k + (s_i + w_i + ST_{ik} + \frac{d_{ij}}{Ve_{ij}}).x_{ijk} = s_j,$$
$$i = 0,1,2,\dots L;\ j = 0,1,2,\dots L;\ \forall\ k = 1,\dots,K \quad (7)$$

$$w_i = max(0,(ET_j - s)),\quad i = 0,1,\dots L \quad (8)$$

$$x_{ijk} \in [0,1],$$
$$i = 0,1,2,\dots L;\ j = 0,1,2,\dots L;\ \forall\ k = 1,\dots,K \quad (9)$$

$$y_{ki} \in [0,1], i = 0,1,2,\dots L;\ \forall\ k = 1,\dots,K \quad (10)$$

The objective function of this problem is to minimize the total distribution cost (TDC) formulated in Equation (1). It has two parts described: the first part describes the fuel consumption costs, and the second part presents the late delivery costs. Constraint (2) states that the cumulative demand of all customers on a route cannot exceed the vehicle's capacity. Constraints (3) and (4) state that each customer must be provided with a delivery service. Each customer's service can only be completed by a specific vehicle, as defined by Constraint (5) and (6): Equations (7) and (8) define the time window constraints. Finally, constraints (9) and (10) state that the decision variable x_{ijk} and y_{ki} are a binary number.

Proposed Camel Algorithm Procedure

This section discusses the proposed CA algorithm for solving GVRPTW problems. This study modified the CA algorithm proposed by Ali *et al.* [41]. The previous CA algorithms were used to solve continuous problems. Therefore, the CA algorithm needs to be modified to be used to solve combinatorial problems in GVRPTW. This study proposes three (3) main stages of a CA algorithm to solve GVRPTW. The complete CA stages are as follows: (1) initialization of camel location; (2) application of the Large Rank Value procedure to convert camel positions to the travel sequence; and (3) An update of the camel position. The pseudo-code of the proposed CA procedure can be presented in Algorithm 1. Details of the three main steps of the CA algorithm to solve GVRPTW are described in the following sub-section.

Initialization of the Camel Location

In the camel initialization position stage, the CA algorithm parameters are selected to solve the GVRPTW problem. The parameters used are total camel caravan (N), journey steps ($iter$), maximum temperature, minimum temperature, and visibility value. In this study, the dimension (d) of the camel's position is based on the number of GVRPTW problem nodes. The initial position of the camel is generated randomly from several camel caravans and some nodes (D). The upper and lower limits camel's value is determined to establish the camel's location. Determination of the initialization of the camel location is presented in Equation (11). Xd^i formulates the location for camel i in vector d, where $i = 1,2,\dots,N$, and $d = 1,2,\dots,D$. $Xmax$ present the upper limit of the camel caravan position. $Xmin$ is the lower limit of the camel caravan position. $Rand$ is a random number with uniform distribution with a range of values between 0 and 1.

$$\mathrm{Xd^i} = (\mathrm{Xmax} - \mathrm{Xmin})\mathrm{Rand} + \mathrm{Xmin} \quad (11)$$

$$population = \begin{bmatrix} 1{,}21 & 3{,}92 & 1{,}71 & 2{,}18 \\ 6{,}51 & 3{,}54 & 3{,}24 & 6{,}16 \\ 8{,}57 & 2{,}99 & 7{,}56 & 7{,}94 \end{bmatrix} \text{(a)}$$

$$population = \begin{bmatrix} 2{,}18 & 3{,}92 & 1{,}18 & 1{,}18 \\ 6{,}51 & 3{,}54 & 6{,}16 & 6{,}16 \\ 8{,}57 & 8{,}57 & 7{,}56 & 7{,}94 \end{bmatrix} \text{(b)}$$

Figure 1. Position of each camel in the population (a) Accepted camel population; (b) Rejected camel population

Figure 1 presents the vector position camel in the population for four customer nodes and three camel caravans. The position of each camel caravan in the population vector position is generated based on Equation (9). At this stage, the camel i is ensured that there is no repetition for each d. An illustration of the camel population is presented in Figure 1. In Figure 1a, the camel population can be accepted if each camel has not the same value in one (1) population.

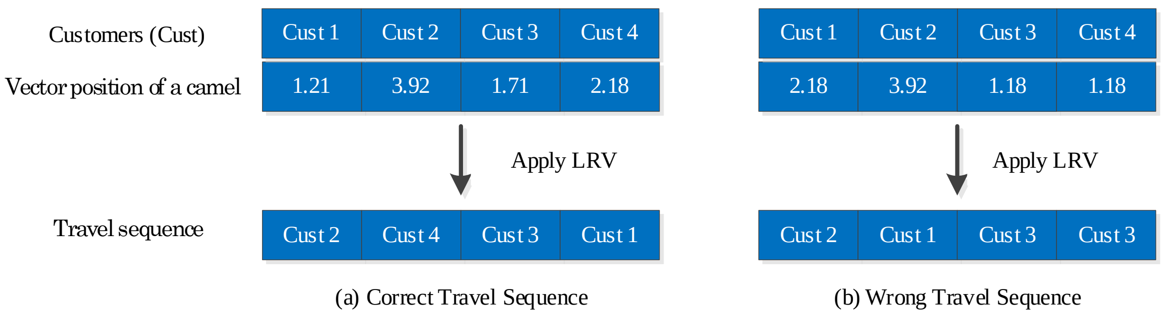

Figure 2. Implementation of LRV

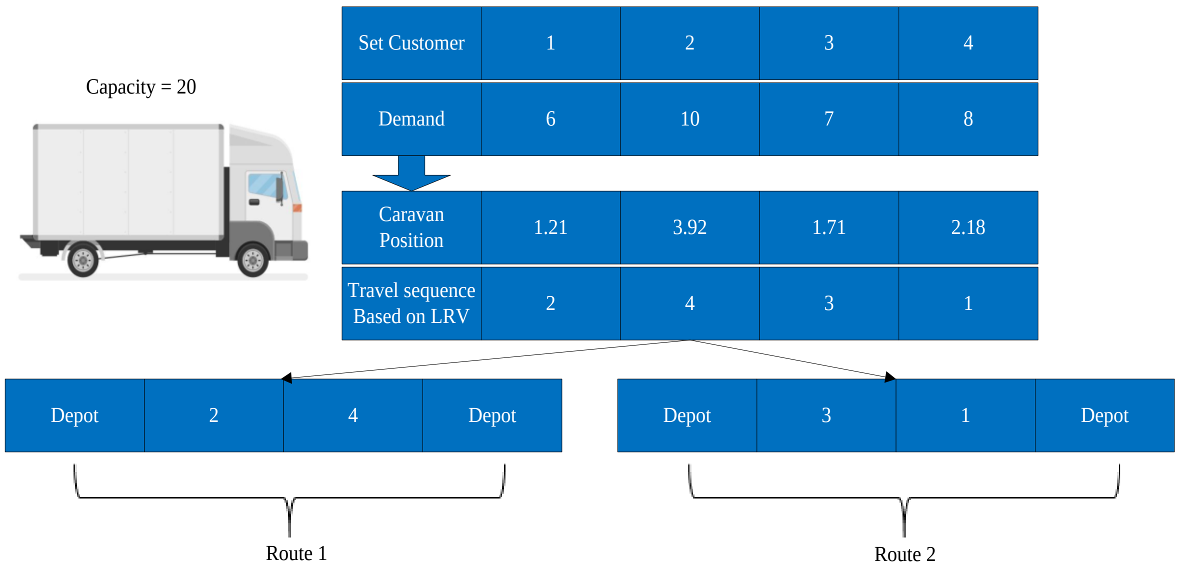

Figure 3. Illustration of determining the route of each camel

The camel population in Figure 1b is unacceptable because each camel has the same value in one (1) population. Repeating values on position camels should be avoided to facilitate the conversion of camel positions to travel sequences. The same value in the position vector of a camel caravan can hamper conversion camel position to travel order. The procedure for converting camel positions to travel sequences is presented in the next section.

Implementation of Large Rank Value

This study proposed the Large Rank Value (LRV) procedure to transform the position of each camel into travel sequences. LRV is a straightforward procedure for converting a position vector into a combinatorial problem [44, 45,46,47,47,49]. As previously described, GVRPTW is a combinatorial problem. Therefore, the continuous numbers on the camel positions need to be converted into a travel sequence. The principle of LRV is to order the d positions of each camel from largest to smallest. This principle is famous because it effectively converts a continuous number to a travel sequence [31, 32, 50].

An illustration of the application of LRV is shown in Figure 2. In Figure 2a, the position vector of a camel caravan does not have the same value. Therefore, the travel sequence is generated correctly. However, in Figure 2b, the position vector of a camel caravan has the same value. Hence, the travel sequence conversion is incorrect. In this illustration, four customers are visited by vehicles. A camel will have a position vector of several customers (in this illustration, it is four customers). This vector position will update each iteration according to the camel position update. For example, in Figure 2 (a), the position vectors for customer 1 to customer 4 are 1.21, 3.92, 1.71, and 2.18. By applying LRV, the travel sequence for this camel is customers 2, 4, 3, and 1. Therefore, the same value must avoid the value of the position vector of a camel. Therefore, it affects the conversion sequences. In Figure 2 (b), the vector position on customer 3 has the same value, namely 1.18. It will be a problem when LRV is applied because customers 3 and 4 have the same order. The travel order becomes customer 2, 1, and 3. Therefore, the value of the camel position vector must be avoided with the same value. Furthermore, the results of LRV are used to determine the number

Algorithm 1. Camel Optimization algorithm pseudo-codes.
Begin
Step 1: Initialization: Set parameters CA such as Tmin, Tmax, Number camel caravan size, the visibility threshold, and Initialize the location of each camel from Eq. (9).
Step 2: Convert the location of each camel using LRV; determine the fitness value of each camel using equation 1; Determine the current best location and fitness in the initial solution.
Step 3: While ($iter < number\ of\ jurney\ step$) **do**
For i=1: Number Camel Caravan size
Compute the temperature of camel ($Td^{i,iter}$) using Equation (10).
Compute the endurance of camel ($Ed^{i,iter}$) using equation (11)
If $v^{i,iter}$ (random number between 0 to 1) < visibility threshold **then**
Update the camel position using equation (12)
Else
Update the camel position using equation (9)
End If
End for
Convert location camel to travel sequence using LRV and determine the total distribution cost in each camel.
If fitness the new locations is better than the older one
The new best is the global best and save the best solution (fitness and location)
End If
Assign new visibility for each camel
Step 4: End While
Step 5: Output the best solution
End

of routes. It needs to be done because the vehicle has the capacity limit.

Moreover, demand fulfillment cannot be fulfilled in one trip. The route determination illustration of each camel is shown in Figure 3. In this illustration, there are customers with varying demands. LRV is applied to convert the caravan position to a travel visit based on the camel caravan position. The results show that the travel sequence for this camel is customers 2, 4, 3, and 1. However, because the vehicle has a capacity limit, four customers are not delivered in the same vehicle. Therefore, based on capacity considerations, there are two routes or vehicles to solve this problem. This procedure is used in the initialization stage and updates the position in each iteration. The route produced by each camel is used as input for fitness calculations. The calculation of the fitness value for each camel is based on Equation (1).

Camel Position Update

This section describes the procedure for updating the position of each camel. As described by Ali *et al.* [41], camel travel is affected by the ambient temperature. Therefore, the ambient temperature affects the camel's resistance to travel. On a trip to a certain location, the camel undergoes temperature changes, giving rise to a different level of camel resistance for each camel. Therefore, the camel position update is influenced by the maximum ambient temperature ($Tmax$), the minimum ambient temperature ($Tmin$), and the visibility value (v). Therefore, the camel temperature on each camel and iteration have different values. The formula for determining the temperature of the camel in each iteration is presented in Equation (12). $Td^{i,iter}$ indicate the temperature of camel i in each iteration $iter$. $iter$ = 1, 2, 3... is total journey steps. $Rand$ is a random number with uniform distribution with a range of values between 0 and 1.

$$\mathrm{Td^{i,iter}} = (\mathrm{Tmax} - \mathrm{Tmin})\mathrm{Rand} + \mathrm{Tmin} \quad (12)$$

Different temperatures in each location affect the resistance (E) of the camel. Therefore, the camel endurance at each iteration is modeled in Equation (13). $Ed^{i,iter}$ shows the endurance of camel i from iteration $iter$, where $iter$ = 1,2,3...total journey steps.

$$\mathrm{Ed^{i,iter}} = 1 - \frac{(\mathrm{Td^{i,iter}} - \mathrm{Tmin})}{(\mathrm{Tmax} - \mathrm{Tmin})} \quad (13)$$

In search of grass areas, camels' sight in the desert is often blocked by sand dunes. Therefore, some camels cannot update the route to the areas of grass that other camels found. Two scenarios are proposed for updating the camel's location. In scenario 1, when the visibility of camel i in an iteration is greater than the visibility threshold (v), the camel position updating uses Equation (14). The visibility value of camel i in an iteration is denoted as $v^{i,iter}$ which is generated from random numbers 0 to 1. Xd^{best} is the best location for all previous iterations.

$$Xd^{i,iter} = Xd^{i,iter-1} + Ed^{i,iter}\,(Xd^{best} - Xd^{i,iter-1}) \quad (14)$$

Table 1. Customer distance matrix data (kilometers).

Node	DC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
DC	0	1.1	5.4	1.6	2.8	4.9	2.2	2.4	4.3	4	4.1	3.2	3.7	1.6	5.7	5.7	4.5	3.1	5.2	2.1
1	1.1	0	5.4	2.6	3.3	3.8	1.1	3.2	4.7	4.4	3.1	3.5	4.5	1.4	3.6	6	3.5	2	4.1	6.1
2	5.4	5.4	0	3.1	3.4	2.6	5.5	3	3.8	2.8	3.5	2.7	4.2	5.9	4.1	3.1	3	6.5	2.4	3.1
3	1.6	2.6	3.1	0	1.5	4.1	3.5	1.2	3.1	3	5.5	1.7	1.4	3.9	1.4	4.6	4.5	4.5	3.8	4.6
4	2.8	3.3	3.4	1.5	0	4.2	4.6	1	2	2.8	6.6	1.1	1.3	4.9	1.9	4.4	4.5	5.5	3.9	4.4
5	4.9	3.8	2.6	4.1	4.2	0	4.5	4.1	4.9	3.9	1	3.7	5.3	3.5	5.1	5.7	0.4	2.8	0.3	5.8
6	2.2	3	5.5	3.5	4.6	4.5	0	5.4	5	4.7	2.8	3.8	4.8	1.2	6.3	6.3	3.2	1.8	3.8	3
7	2.4	3.2	3	1.2	1	4.1	5.4	0	2.1	2.4	4.8	0.9	1.4	4.6	1.6	4.4	4.3	5.2	3.6	4.1
8	4.3	4.7	3.8	3.1	2	4.9	5	2.1	0	2.5	6	1.3	1.5	6.2	3.5	3	5.4	6.8	4.8	3.3
9	4	4.4	2.8	3	2.8	3.9	4.7	2.4	2.5	0	4.5	2.4	3.7	5.6	3.9	1.6	3.9	6.2	3.3	1.6
10	4.1	3.1	3.5	5.5	6.6	1.5	2.8	4.8	6	4.5	0	4.6	6.2	2.8	6.8	6.6	0.7	2.1	1.2	6.7
11	3.2	3.5	2.7	1.7	2.1	3.7	3.8	0.9	1.3	2.4	4.6	0	1.4	4.8	2.1	3.6	4.1	5.4	3.5	3.9
12	3.7	4.5	4.2	1.4	1.3	5.3	4.8	1.4	1	3.7	6.2	1.4	0	5.8	2.8	3.5	5.4	6.4	4.8	3.9
13	1.6	1.4	5.9	3.9	4.9	3.5	1.8	4.6	6.2	5.6	2.8	4.8	5.8	0	7.3	7.3	2.9	1.5	3.6	3.7
14	2.1	3.6	4.1	1.4	1.9	5.1	6.3	1.6	3.5	3.9	6.8	2.1	2.8	7.3	0	2.3	5.6	6.9	5	4.5
15	5.7	6	3.1	4.6	4.4	5.7	6.3	4.4	3	1.6	6.6	3.6	3.5	7.3	1	0	5	6.9	4.4	2.1
16	4.5	3.5	3	4.5	4.5	0.7	3.2	4.3	5.4	3.9	0.7	4.1	5.4	2.9	5.6	5	0	5.8	0.7	3.7
17	3.1	2	6.5	4.5	5.5	2.8	1.8	5.2	6.8	6.2	2.1	5.4	6.4	3	6.9	6.9	5.8	0	3	4.7
18	5.2	4.1	2.4	3.8	3.9	0.7	3.8	3.6	4.8	3.3	1.2	3.5	4.8	3.6	5	4.4	0.8	3	0	3
19	5.7	6.1	3.1	4.6	4.4	5.8	3	4.1	3.3	1.6	6.7	3.9	3.9	3.7	4.5	2.2	3.7	4.7	3	0

Table 2. Vehicle speed matrix data.

Node	DC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
DC	0	37	39	30	36	33	32	32	36	40	35	35	39	40	37	35	39	34	39	30
1	37	0	39	39	37	30	30	31	36	35	35	35	32	31	35	36	39	40	30	30
2	39	39	0	36	30	30	39	40	34	32	38	36	35	37	35	40	32	38	31	33
3	30	39	36	0	30	30	39	30	34	32	38	36	35	37	35	40	32	38	31	33
4	36	37	30	30	0	30	35	30	37	32	37	30	40	31	35	32	37	32	38	34
5	33	30	30	30	30	0	33	39	38	32	30	36	37	33	35	34	30	36	37	32
6	32	30	39	39	35	33	0	36	30	36	39	30	30	30	38	40	31	38	36	40
7	32	31	40	30	30	39	36	0	40	32	38	30	35	30	30	30	40	40	34	39
8	36	36	34	34	37	38	30	40	0	33	39	32	34	31	31	38	38	34	30	32
9	40	35	32	32	32	32	36	32	33	0	37	30	32	38	32	35	36	35	33	36
10	35	35	38	38	37	30	39	38	39	37	0	35	36	39	30	33	39	35	38	36
11	35	35	36	36	30	36	30	30	32	30	35	0	30	37	34	33	35	34	30	33
12	39	32	35	35	40	37	30	35	34	32	36	30	0	33	39	38	31	37	36	38
13	40	31	37	37	31	33	30	30	31	38	39	37	33	0	36	33	37	30	31	31
14	37	35	35	35	35	35	38	30	31	32	30	34	39	36	0	34	40	37	36	33
15	35	36	40	40	32	34	40	30	38	35	33	33	38	33	34	0	39	32	30	31
16	39	39	32	32	37	30	31	40	38	36	39	35	31	37	40	39	0	31	30	34
17	34	40	38	38	32	36	38	40	34	35	35	34	37	30	37	32	31	0	37	33
18	39	30	31	31	38	37	36	34	30	33	38	30	36	31	36	30	30	37	0	32
19	30	30	33	33	34	32	40	39	32	36	36	33	38	31	33	31	34	33	32	0

In the second scenario, the location update process occurred when $v^{i,iter} < v$. In this scenario, the camel randomly updated its location based on Equation (9). Each position update is converted into a sequence with the LRV principle presented in the previous subsection in every iteration. The camel's new position is evaluated with the previous solution. Suppose the camel's new location has better fitness than the previous. In that case, the camel's new location is chosen as the best solution. However, if the previous solution has better fitness results, the previous solution is the best. The process of updating this position continued until the specified number of journey steps is reached.

Results and Discussions

Data and Experiment Procedure

Data Collection

The data collection of this research was based on case studies on distribution companies in Indonesia. The company has one Distribution Center (DC), which fulfills 19 nodes (customers). The distance matrix data is presented in Table 1. Vehicle speed matrix data is presented in Table 2. The vehicle capacity to deliver was 40 units. The costs used in this study were fuel costs and late delivery costs per hour. The fuel cost (fc) was IDR 7,650 per liter. The late delivery cost (Cl) was IDR 15,000 per hour. Demand data, customer opening times, and service time for each customer are presented in Table 3. The rate of fuel consumption per kilometer (LPK) was 0.0250 kilometers per liter. The load time for each item transported was 0.0017 hours. The company had its opening times at 11:00 am.

Experiment Procedure

This study utilized two main parameters of the CA algorithm: the number of camel population (N) and the total journey step of the camel ($iter$). The selection of parameters is based on the research of Omran *et al.* [43], which states that the CA algorithm produces the best solution at the journey step of the camel ($iter$) and the Camel population of 100. Hence, we tried to investigate several population variations and journey steps to complete GVRPTW. Camel population parameters and total journey steps ($iter$) consisted of three-level parameters: the 10, 50, and 100. Other determined parameters were Visibility (v) = 0.1, Tmax = 100, and Tmin = 10. This study examined the effect of camel population parameters and total journey steps on total distribution costs.

Table 3. Customer demand data and time windows.

Node	Demand	Time Windows		Service Time
		Open	Closed	(Hour)
1	6	11.00	12.00	0.050
2	6	11.00	12.30	0.050
3	5	11.00	12.30	0.033
4	5	11.00	12.30	0.033
5	5	11.00	12.30	0.033
6	3	11.00	12.00	0.033
7	3	11.00	13.00	0.033
8	6	11.00	13.00	0.050
9	4	11.00	14.00	0.033
10	7	11.00	12.00	0.050
11	3	11.00	12.30	0.033
12	4	11.00	12.30	0.050
13	4	11.00	12.30	0.033
14	5	11.00	13.00	0.050
15	4	11.00	12.30	0.042
16	5	11.00	12.30	0.042
17	3	11.00	12.30	0.033
18	6	11.00	12.00	0.050
19	7	11.00	14.00	0.058

In addition, the influence of parameters on distribution cost structure such as fuel and late delivery costs was also investigated. In this experiment, the combination parameter was repeated three times. Hence, 27 experiments were conducted to investigate the effect of these parameters on distribution costs. The minimum total distribution cost is the optimal total distribution cost from the experiment.

Furthermore, this study attempted to investigate the effect of CA algorithm parameters on computation time. Computation time was one of the performances needed to solve the GVRPTW problem. Therefore, a sensitivity analysis was also provided to examine changes in the variable to distribution costs. The sensitivity analysis experiment was based on the best solution selected from the parameter experiment. The experiment included the effect changes in Loading time (Lt), LKP, fuel prices, and Service time (St) on distribution costs. Seven different data variations were used in the sensitivity analysis in the experiment.

To measure the performance of the algorithm, this study compared the proposed CA algorithm with the Local Search algorithm [20], PSO [37], and ACO [38]. Ten nodes divided into 3 cases (small, medium, and large) were used as experimental. In the small case, this study used variations of nodes 10, 15, 19, and 20. Variations of nodes 30, 40, and 50 were applied to the medium case. In the large case, this study used four variations of nodes such as 60, 40, 80, and 100. Data was produced from generating random numbers from those presented in Table 1, Table 2, and Table 3.

Relative Error Percentage (REP) was used to assess performance, as shown in Equation (15). A positive REP indicated that the proposed algorithm outperformed the others. However, when compared to other algorithms, the proposed algorithm has a negative REP, indicating that it is not competitive. The Cost Ratio (CR) is also used to evaluate the algorithms' performance. The CR is calculated by dividing the proposed algorithm's cost by the cost of other algorithms (Equation 16). Finally, the comparison algorithm is tested using the Wilcoxon Test based on CR via SPSS 21. This research utilized the Matlab R2014a software run on a processor core i5, 500 Gb Hard disk, 4Gb memory on Microsoft Windows 10.

$$REP = \frac{Cost_{Other\_algorithm} - Cost_{proposed\_algorithm}}{Cost_{proposed\_algorithm}} \times 100\% \quad (15)$$

$$CR = \frac{Cost\ proposed\ algorithm}{Cost\ other\ algorithm} \quad (16)$$

Effect of CA parameters on costs

This section presents the experimental results of the CA parameter's effect on total distribution costs. The experimental results are shown in Table 4, indicating that the total distribution cost is small when the camel population and the total travel steps are large. Conversely, the total distribution cost increases when the camel population and the total journey step are smaller. It is reasonable because the number of populations and the total journey steps camels large resulted in many solutions. Three experiments in each parameter population and total journey step show that the results of each trial produce different total cost distributions. The optimal solution for solving the problem of 19 customers from the case study resulted in 13,518 IDR. It shows that in the jurney step and population of 100, the algorithm provides an optimal solution. These results are in accordance with the research by Omran *et al.* [43].

The experimental result of the CA algorithm parameters on fuel costs is presented in Table 5. Table 6 describes the result of the effect of parameters of the CA algorithm on late delivery costs. Furthermore, these show decreasing fuel costs and late delivery costs if the camel population and total journey steps are increased. These results proved that fuel and late delivery cost is influenced by the camel population and the total journey step. Therefore, the number of camel populations and the total journey step could minimize the total distribution cost. This study's results are consistent with Coelho, *et al.* [49], which explained that the algorithm parameter affects the total cost of distribution. In addition, three experiments in each parameter population and total journey step show that the results of fuel cost and late delivery costs algorithm has random characteristics in solving problems suitable for solving the GVRPTW problem.

Table 4. Effect of parameters of the CA algorithm on TDR (in IDR).

Population	Experiment	Total journey step		
		10	50	100
10	1	40,098	40,750	30,121
	2	37,822	33,093	29,909
	3	26,042	28,656	25,722
50	1	33,708	30,850	26,668
	2	22,821	29,727	20,253
	3	27,926	21,097	20,852
100	1	30,796	27,971	20,173
	2	24,175	21,592	18,284
	3	21,265	14,733	13,518

Table 5. Effect of parameters of the CA algorithm on fuel costs (in IDR).

Population	Experiment	Total journey step		
		10	50	100
10	1	9,505	11,054	9,180
	2	11,191	10,959	9,180
	3	10,784	10,155	10,442
50	1	10,787	9,715	9,237
	2	10,366	9,390	9,811
	3	9,046	9,505	9,237
100	1	11,073	10,175	10,002
	2	11,117	9,352	10,232
	3	8,988	9,128	9,887

Table 6. Effect of parameters of the CA algorithm on late delivery costs (in IDR).

Population	Experiment	Total journey step		
		10	50	100
10	1	30,593	29,696	20,941
	2	26,631	22,134	20,729
	3	15,294	18,500	15,280
50	1	22,921	21,135	17,431
	2	12,548	20,337	10,442
	3	18,880	11,706	11,615
100	1	19,723	17,796	10,171
	2	13,058	12,240	8,052
	3	12,276	5,519	3,630

Table 7. Effect of camel population and total journey step on computation time (second).

Population	Experiment	Total journey step		
		10	50	100
10	1	0.06	0.25	0.49
	2	0.06	0.26	0.49
	3	0.09	0.26	0.49
50	1	0.28	1.31	2.72
	2	0.33	1.30	2.61
	3	0.29	1.31	3.84
100	1	0.56	2.54	4.82
	2	0.52	3.75	5.23
	3	0.59	2.73	5.83

Effect of CA Parameters on Computation Time

This section describes the experimental results of population size and the total jour-ney camel parameters on computation time. The results of the experiment are shown in Table 7. It shows that the variation in the population and the total journey step camel affected the computation time of the GVRPTW. The computation time is directly proportional to the population and the total journey step camel. When the camel population and the total journey step are greater, the computation time is higher. Conversely, When the camel population and the total journey step are smaller, the computation time is lower. It is reasonable because the more camel population and the total journey step, the more variations in the solution search, which causes the computation time to increase.

Sensitivity Analysis

The results of the sensitivity analysis experiment are presented in this section. The variables tested for the sensitivity analysis included loading time (Lt), liters per kilometer (LKP), fuel costs (Cf), and service time (St). In addition, these were used to examine the effect of changing variables on costs and total distribution cost. The results of the sensitivity analysis are presented in the following section.

Effect of loading time (Lt) on the total cost distribution

The effect of the change in Lt on the costs is presented in Table 8. Lt was changed in the range of 0.0014 to 0.002 hours. These results show that changes in loading time (Lt) influence the total cost of distribution. When the loading time is greater, the total cost of distribution is higher. Conversely, when the loading time the smaller, the total cost of distribution is lower.

Furthermore, influence the loading time (Lt) on fuel cost (Fc) and the cost of late delivery are also presented. The experiment results describe that changes in the value of Lt affected late delivery costs. However, it does not influence fuel costs. When the Lt value is higher, the late delivery cost is greater. Conversely, when the Lt value is smaller, the late costs are also smaller.

Table 8. Effect of change in Lt on costs.

Lt (hour)	fuel cost (IDR)	late delivery cost (IDR)	Total distribution cost (IDR)
0.0014	9,887	2,910	12,797
0.0015	9,887	3,150	13,037
0.0016	9,887	3,390	13,277
0.0017	9,887	3,630	13,517
0.0018	9,887	3,870	13,757
0.0019	9,887	4,110	13,997
0.0020	9,887	4,382	14,269

Table 9. Effect of changes LKP on costs.

LKP (liter)	Fuel cost (IDR)	Late delivery cost (IDR)	Total distribution cost (IDR)
0.040	15,820	3,630	19,450
0.035	13,843	3,630	17,473
0.030	11,865	3,630	15,495
0.025	9,887	3,630	13,517
0.015	7,932	3,630	11,562
0.010	5,995	3,630	9,625
0.005	3,977	3,630	7,607

Table 10. Effect of changes fuel price on costs.

Fuel price (IDR)	Fuel cost (IDR)	late delivery cost (IDR)	Total distribution cost (IDR)
7,100	9,176	3,630	12,806
7,300	9,453	3,630	13,083
7,500	9,693	3,630	13,323
7,650	9,887	3,630	13,517
7,800	10,082	3,630	13,712
8,000	10,340	3,630	13,970
8,200	10,599	3,630	14,229

Effect of Liter Per-Kilometer (LKP) on cost

The results of the sensitivity analysis of LKP on costs are shown in Table 9. In this analysis, the LKP was changed in the range of 0.005 to 0.04 liters per kilometer. The results show that LKP influences fuel cost and total distribution costs. However, LKP does not affect late delivery costs. In addition, the experimental results find that when the LKP value the smaller, the fuel cost and total distribution cost are also smaller. Conversely, when the value of the LKP is greater, the fuel cost and total distribution costs are higher.

Effect of Fuel Price (Cf) on cost

Table 10 describes the experimental results of changes Cf on costs. Sensitivity analysis on fuel price was carried out by changing the fuel price range of IDR 7,100 to IDR 8,200. The results experiment present that changes Cf influence into fuel cost and total distribution costs. However, the late delivery cost does not change. When the Cf is lower, the fuel cost and total distribution cost decrease. Conversely, when the Cf value is higher, the fuel cost and total distribution cost increase.

Effect of Service Time (St) on cost

Changes of St were conducted by adding and subtracting St in Table 3 with a range of ± 0.01 hours per unit. The results of change Service time (St) on costs are presented in Table 11. The results show that St influences total distribution costs and late delivery costs. It looks that if the value of St increases, the late delivery cost and the total distribution costs also increase.

Table 11. Effect of St Changes on Costs.

St (hour)	fuel cost (IDR)	late delivery cost (IDR)	Total distribution cost (IDR)
0.01	9,887	13,013	22,900
0.005	9,887	7,534	17,421
0.0025	9,887	5,494	15,381
0	9,887	3,630	13,517
-0.0025	9,887	2,715	12,602
-0.005	9,887	1,883	11,770
-0.01	9,887	785	10,672

Table 12. Comparison algorithms towards the total distribution costs (IDR).

Cases	Node	Local search [20]	PSO[37]	ACO [38]	CA
Small	10	**4,674***	**4,674***	**4,674***	**4,674***
	15	**6,311***	**6,311***	**6,311***	**6,311***
	19	**13,518***	**13,518***	**13,518***	**13,518***
Medium	20	10,404	**9,677***	**9,677***	**9,677***
	30	17,844	16,046	16,256	**15,836***
	40	23,313	24,404	22,281	**20,885***
	50	39,242	36,507	37,789	**32,015***
Large	60	36,433	34,961	36,051	**34,425***
	70	40,354	39,436	39,627	**37,389***
	80	51,255	48,099	46,225	**45,709***
	100	55,545	52,354	51,985	**50,254***

*asterisks and bold indicated the best solution

Conversely, if the value of St decreases, the late delivery cost and the total distribution cost also decrease.

Comparison Algorithm

This section presents a comparison of the algorithm's performance towards the total distribution cost and computation time. The algorithm comparison based on total distribution cost is shown in Table 12. It shows that, in small cases, the proposed CA algorithm has a good solution than [37] and ACO [38] algorithms. However, in medium and large cases, the CA algorithm is proven better than the Local search algorithm [20], PSO[37], and ACO [38].

Results REP values are shown in Figure 4 as a comparison between the proposed algorithm and other algorithms. The average REP value for the 11 experimental node variants for Local search algorithms [20] was 8.26 percent. In the PSO [37] and ACO [38] algorithms, the REP values are 4.42 and 3.88 percent, respectively. A positive REP value indicates that the proposed algorithm is more effective in solving the GVRPTW problem than the existing algorithm. These results indicate no average REP for the completion of the 11 experimental node variants that resulted in a negative REP value. It shows that the proposed CA algorithm is more competitive than other algorithms and significantly improves the quality of GVRPTW. The ACO algorithm [38] is the algorithm with the smallest positive REP, followed by the PSO Algorithm [37] and Local search algorithms [20].

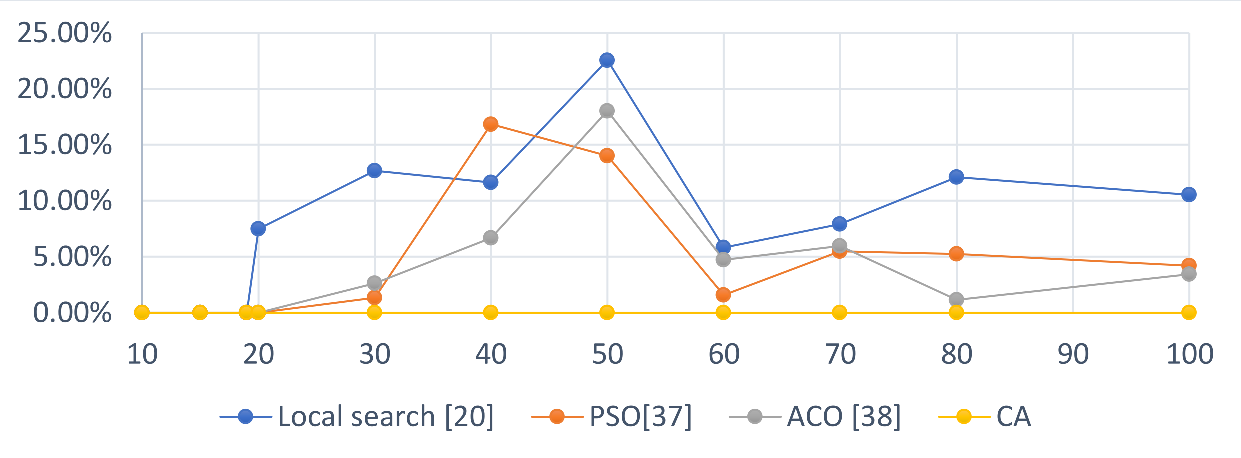

Figure 4. REP results for each algorithm

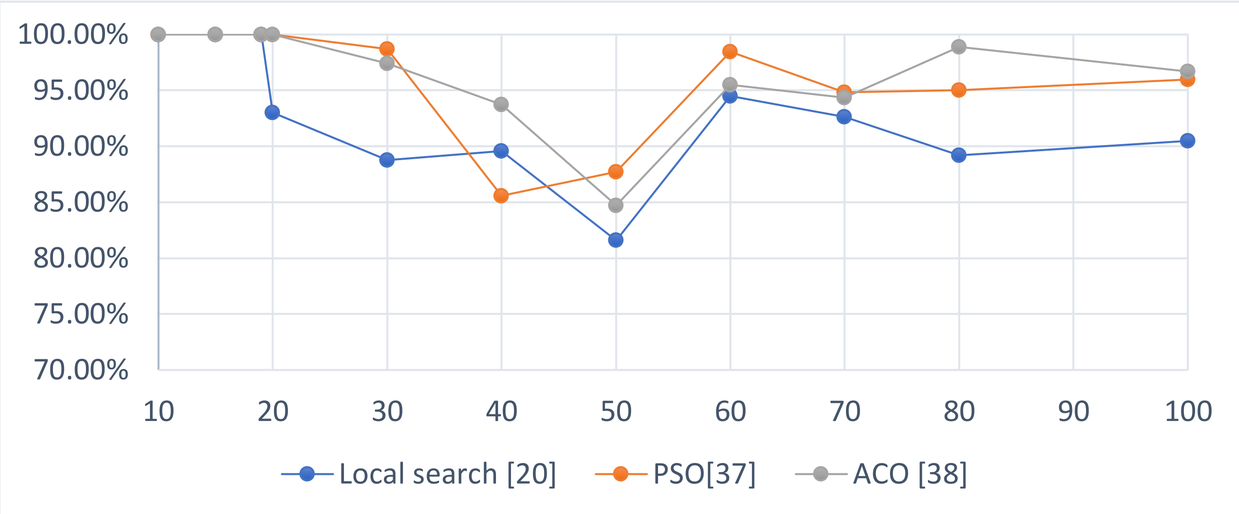

Figure 5. CR results for each algorithm

Table 13. Wilcoxon test of the CR

Test	Z	Asymp. Sig. (2-tailed)
Proposed Algorithm - Local search algorithm [20]	-2.521	0.012
Proposed Algorithm - PSO[37]	-2.366	0.018
Proposed Algorithm - ACO [38]	-2.366	0.018

Table 14. Comparison algorithms towards the computation time (Second).

Cases	Node	Local Search	PSO	ACO	CA
Small	10	4.20	1.04	2.29	1.83
	15	4.99	1.02	2.48	2.01
	19	6.02	1.68	2.68	2.43
Medium	20	6.17	1.80	2.69	2.53
	30	7.57	2.48	3.51	3.73
	40	9.33	2.32	4.81	4.57
	50	13.07	3.08	5.52	6.49
Large	60	14.14	3.45	6.97	7.39
	70	15.63	3.96	7.63	7.94
	80	21.85	4.61	10.37	9.87
	100	25.12	7.75	12.15	11.89

The performance of each algorithm is also compared based on the CR value. The proposed algorithm has better performance than other algorithms if the CR is less than 100 percent. However, the proposed Algorithm has the same good performance if the CR is 100 percent. Furthermore, if the CR is greater than 100%, another algorithm performs better than the proposed algorithm. CR results for each algorithm are shown in Figure 5. The calculation results show that the average CR values for the Local search algorithm [20], PSO[37], and ACO [38] are 92.70, 96.02, and 96.48 percent, respectively. Thus, it shows that the proposed algorithm provides a better solution than other procedures.

Statistical tests are also presented to test the performance of the proposed algorithm compared to other algorithms. This study utilizes the Wilcoxon test. This test is based on the CR value on the 11 experimental node variants. The results of the Wilcoxon statistical test are presented in table 13. It shows that statistically, the proposed algorithm produces better solutions than other algorithms.

The algorithms comparison in computation time is presented in Table 14. It shows that the number of nodes has a significant effect on computation time. Based on experiments, the PSO [37] procedure produces the fastest computation time, followed by the CA, ACO [38], and Local search algorithms [20].

Conclusion

This study proposed a Camel Algorithm (CA) to solve GVRPTW problems. This study successfully developed the CA algorithm to minimize the total distribution costs involving fuel and late delivery costs. The results show that the CA parameters variation influences the total distribution costs. This study also conducted a sensitivity analysis to examine the effect of variables on costs. To measure the algorithm performance, this study compared the proposed algorithm with some state-of-the-art algorithms. The comparison results showed that the CA algorithm was effective in solving the GVRPTW problem. Some of the limitations of this study were (1) this study ignoring the pickup and delivery loading and (2) demand which was assumed to be deterministic. Future research is expected to consider the pickup and delivery loading in solving the GVRPTW problem. Moreover, research needs to explore the uncertainty of the demand.

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