

Solving Heterogeneous Fleet Capacitated Vehicle Routing Problem with Soft Time Windows Using Cooperative Hybrid Firefly Algorithm

Defri Ananda, Rahmad Alfandi, Eri Wirdianto*

Department of Industrial Engineering, Faculty of Engineering, Universitas Andalas

*Corresponding author, e-mail: e.wirdianto@gmail.com

Abstract—The Vehicle Routing Problem with Time Windows (VRPTW) is a widely studied logistics optimization problem, and its complexity increases when heterogeneous fleets are considered. This study proposes the application of the Cooperative Hybrid Firefly Algorithm (CHFA), an extension of the Firefly Algorithm, to solve the Heterogeneous Vehicle Routing Problem with Soft Time Windows (HVRPSTW). The mathematical model was implemented in Python, tested on benchmark datasets, and adapted to a fleet consisting of three vehicle types with different capacities to serve 100 customers. The proposed CHFA achieved feasible routing solutions with a total transportation cost of IDR 17.58 million and a computation time of only 30 seconds. These results demonstrate that CHFA can provide fast and efficient solutions for complex routing problems, making it highly applicable in logistics operations that demand quick decision-making and cost efficiency.

Keywords: Firefly Algorithm, Heterogeneous Fleet, and Time Windows.

This article is licensed under the [CC-BY-SA](#) license.

1. Introduction

Vehicle Routing Problem (VRP) is one of the most important and widely studied combinatorial optimization problems, which is relevant to transportation logistics such as postal, parcel, and distribution services. Its objective is to obtain the lowest-cost set of routes [1]. The Capacitated Vehicle Routing Problem (CVRP) is a problem of transporting goods from a depot to all customers through the shortest route regarding vehicle capacity constraints [2]. The Vehicle Routing Problems with Time Windows (VRPTW) is a widely recognized problem in the field of logistics, involving the optimization of delivery routes for a fleet of vehicles, while considering specific time windows for each delivery. VRPTW is a notable variant within the broader context of vehicle routing problems. However, finding an optimal solution for VRPTW is a non-deterministic polynomial-hard problem, and the complexity of the problem increases significantly with the size of the input data [3]. Different types and capacities of the vehicle make VRPTW more complex, it called the Heterogeneous Vehicle Routing Problem with Time Windows (HVRPTW).

Previous researchers have attempted to solve the problem of VRP by using exact, heuristic, meta-heuristic, and hybrid methods. [4] reduce the computational complexity of CVRP with a clustering-based heuristic algorithm to solve large-scale problems. [5] using Quantum Annealing, a metaheuristic algorithm to solve an optimization problem called a Quadratic Unconstrained Binary Optimization (QUBO) problem. CVRP has to be formulated as a QUBO problem by unifying a model that can be used for representing a wide range of combinatorial optimization problems. Quantum Annealing can speed up computation time compared to classical algorithms. [6] using a new meta-heuristic called the Firefly Algorithm (FA) to solve CVRP. There is no one algorithm to satisfy all problems, a hybrid algorithm is an alternative to improve the performance of the algorithm. [7] combine 2-opt local search and the firefly algorithm to solve CVRP and call it as Cooperative Hybrid Firefly Algorithm (CHFA). [8] combine the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Giant Tour Best Cost Crossover (GTBCX) operator to solve CVRP for smart cities.

[9] adopt the Flower Pollination Algorithm (FPA) to solve VRPTW. Flower Pollination Algorithm (FPA) is an algorithm which inspired by nature, especially flower plant pollination. This algorithm is adjusted with the exact flower pollination, that is pollination concept which consists of two types, they are global pollination and local pollination. [10] using the Bee Algorithm, an algorithm that adapts the way of life of bees and their intelligence in finding a food source for solving CVRP and VRPTW. [11] develop an Improved Ant Colony Algorithm based on Tabu Search (IACATS) to solve the low-carbon and freshness degrees vehicle routing problem with time windows. [1] try to address VRPTW with the objectives of reducing the number of vehicles and minimizing the time wasted during the delivery process caused by early arrival. A Hybrid Multi-Objective Evolutionary Algorithm with fast sampling strategy-based Global search and route sequence difference-based Local search (HMOEA-GL) is proposed [1]. [2] present a novel ACO-based optimization method for VRPTW by using customer selection in order to decrease or solve the inefficiency of the customer selection in the ACO process. [12] introduces a cutting-edge Hybrid Genetic Algorithm-Solomon Insertion Heuristic (HGA-SIH) solution, reinforced by the powerful Solomon Insertion constructive heuristic to solve the VRPTW as a non-deterministic polynomial (NP)-hard problem.

The Heterogeneous Vehicle Routing Problem with Time Windows (HVRPTW) is interesting to study as its complexity varies with different types and capacities of vehicles. [13] develop the Ant Colony System (ACS) algorithm for the Heterogeneous Vehicle Routing Problem with Soft Time Window (HVRPSTW) mathematical model in determining transportation routes that can minimize costs. [14] introduces the heterogeneous vehicle routing problem with time windows and a limited number of resources (HVRPTW-LR). Solutions are improved by a hybrid variable neighborhood descent metaheuristic based on a Tabu Search algorithm for the exploration of the neighborhood and a holding list [14].

In this paper, the Cooperative Hybrid Firefly Algorithm (CHFA) by [7] is applied to solve the HVRPSTW. To the best of our knowledge, there is no study that applies such a model CHFA to solve HVRPSTW. CHFA will be used to solve HVRPSTW with 3 types of vehicles with different capacities to meet the demand of 100 customers.

2. Method

Heterogeneous Vehicle Routing Problem with Soft Time Window (HVRPSTW) is an extension of Vehicle Routing Problem (VRP) that combines the Heterogeneous Vehicle Routing Problem (HVRP) with the Vehicle Routing Problem with Soft Time Window (VRPSTW). HVRP extends VRP by considering varying vehicle capacities as well as fixed and variable costs, aiming to determine the appropriate vehicle usage according to the route and customer demand, thereby minimizing transportation costs [15]. VRPSTW, on the other hand, is an extension of VRPTW that allows vehicles to arrive past the time limit but with a penalty fee. Formulation of HVRPSTW is as follows [13].

Notation:

X_{ijk}	: Selected route from location i to location j with delivery vehicle k
C_{ijk}	: Vehicle costs from location i to location j with vehicle k
D_i	: Demand for delivery requests at location i
S_i	: Unloading time at location i
Q_k	: Maximum vehicle capacity k
BB_k	: Gasoline costs for vehicles k
L_k	: Average vehicle speed k
E_k	: Usage time limit
CP_k	: Vehicle penalty costs k
WW_k	: Fixed cost for vehicle k
BP_k	: Parking Fee
BT	: Labor Cost
EP_{ik}	: Length of early penalty time at location i with vehicle k

DP_{ik} : Length of penalty delay time at location i with vehicle k
 G_{jk} : The time vehicle k arrives at the depot
 R_{ij} : Distance between location i to location j
 T_{ijk} : Travel time from location i to location j using vehicle k
 A_{ik} : Time vehicle k arrives at location i
 U_{ij} : Auxiliary variables for sub tour elimination

Objective function:

$$\text{minimize } Z = \text{travel cost} + \text{penalty fees} + \text{labor cost} + \text{fixed cost} + \text{parking fee} \quad (1)$$

Cost:

$$\text{travel cost} = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} X_{ijk} * R_{ij} * BB_k \quad (2)$$

$$\text{penalty fees} = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} X_{ijk} * (DP_{jk} + EP_{jk}) * CP_k \quad (3)$$

$$\text{labor costs} = \sum_{i \in N, i \leq 1} \sum_{j \in N, j \geq 1} \sum_{k \in K} X_{ijk} * BT \quad (4)$$

$$\text{fixed cost} = \sum_{i \in N, i \leq 1} \sum_{j \in N, j \geq 1} \sum_{k \in K} X_{ijk} * WW_k \quad (5)$$

$$\text{parking fee} = \sum_{i \in N, i \neq 1} \sum_{j \in N} \sum_{k \in K} X_{ijk} * TBP_{ik} * BP_k \quad (6)$$

Constraints:

1. Limitation for the maximum number of vehicles that can serve one location.

$$\sum_{i \in N} \sum_{k \in K} X_{ijk} = 1 \quad (7)$$

2. Limitation for the maximum number of vehicles that can serve one location.

$$\sum_{j \in N} \sum_{k \in K} X_{ijk} = 1 \quad (8)$$

3. Route continuity limiter

$$\sum_{i \in N, i \neq p} X_{ipk} - \sum_{j \in N, j \neq p} X_{pjk} = 0 \quad (9)$$

4. Sub route elimination delimiter

$$U_{ik} - U_{jk} + N * X_{ijk} \leq N - 1 \quad (10)$$

5. Limiting the number of vehicle loads.

$$\sum_{i \in N, i \neq 1} \sum_{j \in N} X_{ijk} * D_i \leq Q_k \quad (11)$$

6. Binary number delimiter

$$X_{iik} = 0 \quad (12)$$

7. Binary number delimiter

$$X_{ij} = \{0, 1\} \quad (13)$$

8. Travel time limiter

$$T_{ijk} = \frac{R_{ij}}{L_k} \quad (14)$$

9. The time limit arrives

$$A_{jk} \geq B_{ik} + T_{ijk} - M(1 - X_{ijk}) \quad (15)$$

10. Vehicle departure time limiter

$$A_{jk} \leq B_{ik} + T_{ijk} + M(1 - X_{ijk}) \quad (16)$$

11. Time limit for vehicle use

$$E_k \geq G_{jk} \quad (17)$$

12. Time limit for vehicle use

$$G_{jk} \geq B_{ik} + T_{ijk} + M(X_{ijk} - 1) \quad (18)$$

13. Departure time limit.

$$A_{ik} \geq B_{ik} + S_i \quad (19)$$

14. Multi-trip elimination limiter

$$\sum_{i \in N} X_{ijk} \leq 1 \quad (20)$$

The Heterogeneous Vehicle Routing Problem with Soft Time Windows (HVRPSTW) is formulated to minimize the total distribution cost, which consists of travel cost, penalty cost for early or late arrivals, labor cost, fixed cost, and parking cost. The decision variable X_{ijk} indicates whether vehicle k travels from customer i to j . Constraints are imposed to ensure that each customer is visited exactly once, vehicle capacities are not exceeded, and all routes start and end at the depot. The time window requirement $[a_i, b_i]$ is also considered, where early or late arrivals are allowed but penalized, thus differentiating the model from the classical VRPTW with hard time windows.

The cooperative hybrid firefly algorithm (CHFA) by [7] is applied to solve the HVRPSTW formulated above. CHFA has multiple populations that exchange solutions (fireflies) through occasional. Several hybrid firefly algorithms are randomly initialized. Each of the HFAs creates and evolves its population independently. They only communicate and exchange solutions between them when the communication interval is triggered.

Figure 1 shows a virtual representation of the CHFA model with three hybrid firefly algorithms (HFAs). Each HFA has its parameters, and they run independently. At every communication interval, HFAs communicate with each other by exchanging some solutions according to a predefined communication strategy. The communication topology is fully connected (each HFA can communicate with any other HFA in the model).

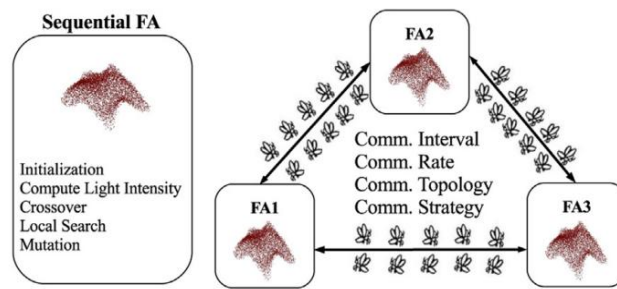


Figure 1. Cooperative hybrid firefly algorithm model

(Source: [7])

The following parameters are used to control the communication between the HFAs:

1. Number of HFAs (n): determines semi-isolated HFAs' number in the CHFA model.
2. The Communication Interval (CI): determines the number of iterations to start communication between HFAs.
3. The Communication Rate (CR): defines as the percentage of solutions selected for exchange among the HFAs.
4. The Communication Topology: the HFAs interconnection is typically referred to as the communication topology.
5. The Communication Policy: specifies the manner of selecting solutions, for exchange, from source HFA, and substituting them in the destination HFA.

The CHFA procedure begins by initializing multiple hybrid firefly algorithms (HFAs), each evolving independently with its own population of candidate solutions. At every iteration, solutions are evaluated against the HVRPSTW objective function, and the brightness or quality of each solution is measured accordingly. Fireflies with inferior performance are then guided toward brighter ones, simulating the natural attraction behavior while ensuring that promising routes are more likely to be explored. To refine the search, local operators such as 2-opt and mutation are applied to adjust customer sequences and improve route feasibility. In addition, crossover is occasionally performed to recombine high-quality routes, generating new solutions that inherit desirable characteristics from their parents. Periodic communication between HFAs enables the transfer of selected solutions, which not only diversifies the overall search space but also reduces the risk of populations becoming trapped in local optima. Through this combination of movement, local refinement, and inter-population exchange, the algorithm achieves a balance between global exploration of new regions and local exploitation of promising areas, ultimately improving solution robustness and convergence speed.

The pseudocode in Algorithms 1–4 illustrates the implementation of this cooperative framework in detail. Algorithm 1 presents the main hybrid firefly algorithm cycle, where initialization, evaluation, and iterative improvement of solutions occur, supported by crossover and mutation to maintain diversity. Algorithm 2 focuses on the mutation operator, which introduces controlled randomness into existing solutions to explore alternative routes and prevent premature stagnation. Algorithm 3 describes the communication mechanism that periodically identifies weak solutions in one HFA and replaces them with stronger solutions imported from another, ensuring that knowledge gained in one subpopulation benefits the entire system. Finally, Algorithm 4 integrates all components into the cooperative scheme, coordinating the evolution of semi-isolated HFAs that run in parallel but share information at defined intervals until the termination criterion is satisfied. This layered structure allows CHFA not only to search broadly but also to retain high-quality solutions across the evolutionary process, making it particularly well suited for complex distribution problems such as HVRPSTW.

Algorithm 1: Pseudo-code of hybrid FA

```

1 begin
2   Initialize algorithm parameters (population size (P-S), maximum number of iterations (MI),
   crossover rate (C-R), and mutation rate (M-R);
3   Initialize firefly population with their positions (solutions)
    $X = (x_1, x_2, \dots, x_{p-s})$ ;
4   Evaluate the objective function of each position  $F(x_i)$ ;
5   Calculate the light intensity at each position  $(x_i)$ ;
6   Sort the population and determine the best position  $x^*$ ;
7    $t=0$  : /*t is the iteration number */
8   while stopping criteria are not met do
9     for  $i=1$  to P-S do
10      for  $j=1$  to  $i$  do
11        if  $Light\_intensity_i > Light\_intensity_j$  then
12          if  $rand < C-R$  then
13            Apply PMX procedure between  $(x_i)$  and  $x^*$  according to C-R;
14          end
15          Apply improved 2-Opt local search for  $(x_i)$ ;
16          Apply one mutation_procedure for  $(x_i)$  according to M-R;
17          Evaluate the objective function of each new position  $F(x_i)$ ;
18        end
19      end
20    end
21    Assign the light_intensity at each new position  $(x_i)$ ;
22    Sort the population and determine the best position  $x^*$ ;
23     $t=t+1$ ;
24  end
25  Return global best solution  $x^*$ ;
26 end

```

Algorithm 2: Pseudo-code of the mutation procedure

```

1 begin
2   Input: The current solution 'position  $x_i$  and M-R;
3   Output: The solution position  $x_i$ ';
4   Generate  $rand = \text{random}(0,1)$ ;
5   if  $rand \leq M - R$  then
6     Transform  $x_i$  to Tsp-Sr y;
7     Enhance y by 2 2-h-opt;
8     Transfrom y to CVRP-SR  $x_i$ ';
9   end
10  Generate  $rand = \text{random}(0,1)$ ;
11  if  $rand \leq M - R$  then
12    Generate  $R = \text{random}(0,1)$ ;
13    if  $R \leq 0.5$  then
14      Step 1: for solution position  $x_i$ , select one route  $r1$ , randomly;
15      Step 2: select two costumers  $c1$  and  $c2$  in the route  $r1$  at random;
16      Step 3 : Swap  $x_i(ri(ci))$  and  $x_i(ri(ci))$ ;
17    end
18    else
19      Step 1: for solution position  $x_i$ , select two routes  $r1$  and  $r2$ 
20      Step 2: select two costumer  $c1$  from route  $r1$  and  $c1$  from route  $r2$  random
21      Step 3 : swap  $x_i(ri(ci))$  and  $x_i(r1(c2))$ ;
22    end
23  end
246

```

24 Return the modifiesolution postion x_i ’;
 25. **end**

Algorithm 3: Pseudo-codde of exchange solutions procedure

```

1 begin
2   input: Source_HfA, Destination_HFA, C-R;
3   for  $i=1$  to Communication_Rate do
4     X= select a random solution from Source_HFA;
5     Y= find the worst solution in Destination_HFA;
6     Let Y=X;
7   end
8 end
  
```

Algorithm 4: CVRP-CFA Algorithm

```

1 begin
2   Initial FA parameters for each HFA;
3   for  $i=1$  to  $n$  do
4     Initialize random population ( $P_i$ );
5     for  $j = 1$  to  $P-S$  do
6       objectivefunction ( $j$ ) = Evaluate( $P_i[j]$ );
7     end
8   end
9    $t=0$ ;
10  while termination vriterion nit reached do
11    for  $I = 1$  to  $n$  do
12      HFA( $P_i$ );
13    end
14    if  $t \text{ MOD } communication\_interval == 0$  then
15      for  $m=1$  to  $n$  do
16        Select some solutions to transfer based on communication rate HFA
17        Send selected solutions to another population
18        Replace a number of solutions in HFA [rand]
19      end
20      Sort each HfA and determine its position  $x^*$ ;
21    end
22     $t=t+1$ 
23  end
24  Return the best solutions among all HFAs;
25 end
  
```

3. Result and Discussion

The input of the data processing is data from the source <http://vrp.galgos.inf.puc-rio.br/index.php/en/> which is the VRPTW problem data. The data consists of demand data, depot and customer position data, the amount of available capacity, and the number of vehicles that are similar. Then the data is modified in the type of vehicle that was originally similar consisting of 25 units of vehicles that have a capacity of 200 kg into 3 types of vehicles with different capacities with details of small box vehicles with a capacity of 80 kg as many as 18 units, crank box vehicles with a capacity of 250 kg as many as 8 units, and CDD long vehicles with a capacity of 520 kg as many as 3 units with the same total capacity of 5000 kg. The data can be accessed through the following link <https://drive.google.com/file/d/1nIMF7MGD1JUg31AB-7iXrJFYwdsWB6m/view?usp=sharing>. Calculation of transportation costs is done with the help of the Visual Studio Code application with python programming language to find the optimal route in the HVRPSTW mathematical model using the firefly algorithm. The following are the results of running that has been done as shown in Table 1.

Table 1. Route Results Obtained

Vehicle	Route	Total Transportation Cost
a	[0, 38, 44, 24, 69, 49, 86, 30, 85, 99, 68, 27, 43, 7, 0, 84, 82, 12, 98, 19, 72, 3, 41, 81, 71, 52, 62, 39, 40, 0]	IDR 3.449.032
b	[0, 51, 1, 97, 16, 22, 60, 5, 74, 11, 57, 91, 53, 45, 31, 21, 92, 93, 56, 80, 0]	IDR 2.911.993
c	[0, 37, 63, 100, 26, 76, 15, 59, 95, 20, 2, 50, 32, 23, 83, 47, 67, 0]	IDR 2.865.690
d	[0, 66, 17, 14, 79, 90, 94, 61, 54, 0]	IDR 1.425.249
e	[0, 65, 28, 42, 75, 48, 18, 8, 58, 0]	IDR 1.327.784
f	[0, 13, 88, 29, 96, 34, 9, 55, 25, 35, 0]	IDR 1.844.172
g	[0, 46, 87, 33, 36, 73, 0]	IDR 1.211.331
h	[0, 89, 64, 0]	IDR 403.816
i	[0, 6, 0]	IDR 197.600
j	[0, 10, 78, 0]	IDR 667.953
k	[0, 0]	IDR 0
l	[0, 77, 0]	IDR 540.800
m	[0, 0]	IDR 0
n	[0, 0]	IDR 0
o	[0, 4, 70, 0]	IDR 737.616
p	[0, 0]	IDR 0
q	[0, 0]	IDR 0
r	[0, 0]	IDR 0
s	[0, 0]	IDR 0
t	[0, 0]	IDR 0
u	[0, 0]	IDR 0
v	[0, 0]	IDR 0
w	[0, 0]	IDR 0
x	[0, 0]	IDR 0
y	[0, 0]	IDR 0
z	[0, 0]	IDR 0
aa	[0, 0]	IDR 0
bb	[0, 0]	IDR 0
cc	[0, 0]	IDR 0
Total		IDR 17.583.037
Total computation time		30 Seconds

The results obtained are 12 routes that can be used in the process of distributing goods and 17 unused vehicles. The total transportation cost obtained is IDR 17,583,037 with a computation time of 30 seconds. The following are the route plot results obtained from the running results carried out as shown in Figure 2.

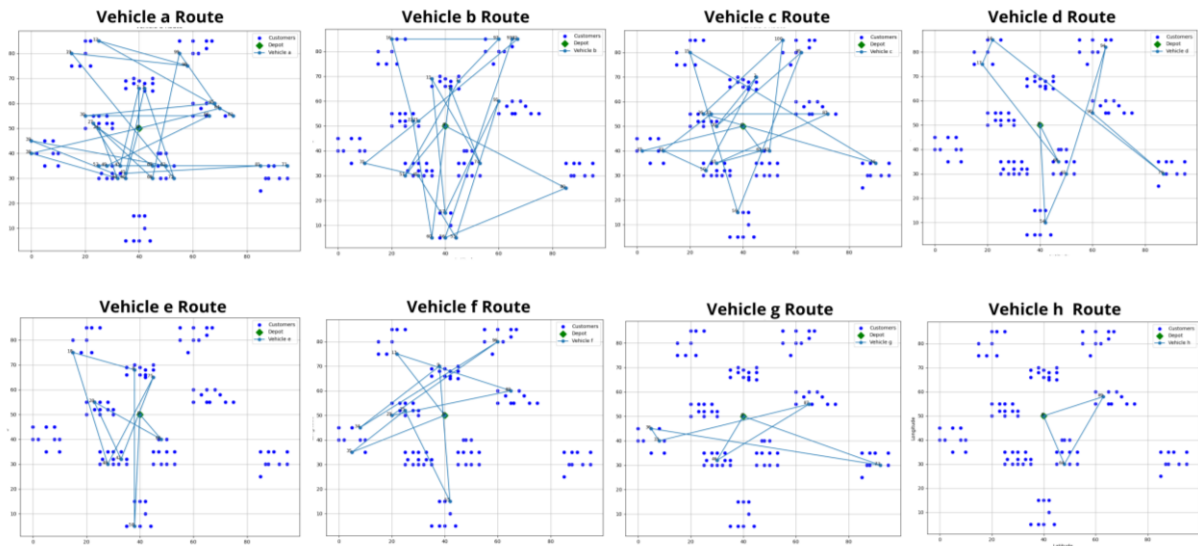


Figure 2. Plot Vehicles Route

Across the heterogeneous fleet, CHFA activates only 12 out of 29 available vehicles, indicating that the model effectively selects capacity while avoiding unnecessary fixed costs for idle units. Under soft time windows, early or late arrivals are allowed and captured by the penalty component of the objective, which keeps the solution feasible without enforcing hard rejections. In practice, the resulting plan trades off travel, labor, parking, and penalty components to reduce overall cost while satisfying demand and vehicle capacities. With an instance size of up to 100 customers, the 30-second runtime suggests near real-time responsiveness for tactical planning and same-day operational re-optimization.

The tests conducted demonstrate that the Cooperative Hybrid Firefly Algorithm (CHFA) is able to provide an effective and efficient solution in solving heterogeneous vehicle routing problems with capacity constraints and time windows. The ability of the CHFA to provide feasible solutions quickly is very suitable for field applications, especially in the logistics and transport industries that often face changing operational conditions. Fast response to fluctuating demand and sudden route adjustments are advantages that are highly required by industry practitioners. Thus, CHFA not only offers a robust theoretical solution but also provides significant practical benefits in improving operational efficiency and customer satisfaction. In addition, the limited magnitude of time-window penalties indicates that schedule deviations are controlled rather than excessive, which is consistent with the soft-time-window setting.

4. Conclusion

Based on the results, the Cooperative Hybrid Firefly Algorithm (CHFA) can effectively solve the Heterogeneous Fleet Capacitated Vehicle Routing Problem with Soft Time Windows (HVRPSTW). The algorithm generated 12 efficient routes with a total distribution cost of IDR 17.58 million and computation time of only 30 seconds, showing its capability for near real-time applications. These findings demonstrate that CHFA is not only able to minimize travel and operational costs but also adapt to heterogeneous fleets and soft time window constraints, making it highly relevant for logistics operations facing fluctuating demand and dynamic conditions. The Firefly Algorithm further shows advantages in fast convergence and flexible parameter tuning, positioning it as a strong candidate for broader VRP optimization. This study highlights practical benefits for industry applications while also opening avenues for future research, such as testing CHFA on real-world data and integrating it with other metaheuristic methods to further enhance performance. Moreover, the proposed approach provides a valuable reference for decision-makers in transportation planning, especially in scenarios requiring fast yet reliable solutions. In conclusion, the contribution of this research lies in bridging theoretical optimization models with practical logistics needs, offering both academic significance and industrial applicability.

References

- [1] W. Zhang, D. Yang, G. Zhang, and M. Gen, “Hybrid multiobjective evolutionary algorithm with fast sampling strategy-based global search and route sequence difference-based local search for VRPTW,” *Expert Syst. Appl.*, vol. 145, p. 113151, 2020, doi: 10.1016/j.eswa.2019.113151.
- [2] S. Kosolsombat and C. Ratanavilisagul, “Modified ant colony optimization with selecting and elimination customer and re-initialization for VRPTW,” *Bull. Electr. Eng. Informatics*, vol. 11, no. 6, pp. 3471–3482, 2022, doi: 10.11591/eei.v11i6.3943.
- [3] X. Liu, Y. Chen, and L. Y. Por, “A Systematic Literature Review of Vehicle Routing Problems with Time Windows,” pp. 1–20, 2023.
- [4] F. Alesiani, G. Ermis, and K. Gkiotsalitis, “Constrained Clustering for the Capacitated Vehicle Routing Problem (CC-CVRP),” *Appl. Artif. Intell.*, vol. 36, no. 1, 2022, doi: 10.1080/08839514.2021.1995658.
- [5] S. Feld *et al.*, “A hybrid solution method for the capacitated vehicle routing problem using a quantum annealer,” *Front. ICT*, vol. 6, no. JUN, 2019, doi: 10.3389/fict.2019.00013.
- [6] A. M. Altabeeb, A. M. Mohsen, and A. Ghallab, “An improved hybrid firefly algorithm for capacitated vehicle routing problem,” *Appl. Soft Comput. J.*, vol. 84, p. 105728, 2019, doi: 10.1016/j.asoc.2019.105728.
- [7] A. M. Altabeeb, A. M. Mohsen, L. Abualigah, and A. Ghallab, “Solving capacitated vehicle routing problem using cooperative firefly algorithm,” *Appl. Soft Comput.*, vol. 108, p. 107403, 2021, doi: 10.1016/j.asoc.2021.107403.
- [8] M. Sajid *et al.*, “Article a novel algorithm for capacitated vehicle routing problem for smart cities,” *Symmetry (Basel)*, vol. 13, no. 10, pp. 1–23, 2021, doi: 10.3390/sym13101923.
- [9] A. B. Pratiwi, I. Y. Rakhmawati, and E. Winarko, “Flower Pollination Algorithm for Vehicle Routing Problem with Time Windows (VRPTW),” *Tensor Pure Appl. Math. J.*, vol. 2, no. 2, pp. 45–52, 2021, doi: 10.30598/tensorvol2iss2pp45-52.
- [10] C. Natalia, V. Triyanti, G. Setiawan, and M. Haryanto, “Completion of Capacitated Vehicle Routing Problem (CVRP) and Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) Using Bee Algorithm Approach to Optimize Waste Picking Transportation Problem,” *J. Mod. Manuf. Syst. Technol.*, vol. 5, no. 2, pp. 69–77, 2021, doi: 10.15282/jmmst.v5i2.6855.
- [11] J. Chen, P. Gui, T. Ding, S. Na, and Y. Zhou, “Optimization of transportation routing problem for fresh food by improved ant colony algorithm based on tabu search,” *Sustain.*, vol. 11, no. 23, 2019, doi: 10.3390/su11236584.
- [12] A. Maroof, B. Ayvaz, and K. Naeem, “Logistics Optimization Using Hybrid Genetic Algorithm (HGA): A Solution to the Vehicle Routing Problem with Time Windows (VRPTW),” *IEEE Access*, vol. 12, no. March, pp. 36974–36989, 2024, doi: 10.1109/ACCESS.2024.3373699.
- [13] S. Kristina, R. Sianturi, and V. J. Wijaya, “Pengembangan Algoritma Ant Colony System Pada Heterogeneous Vehicle Routing Problem with Soft Time Window,” *J. Integr. Syst.*, vol. 3, no. 2, pp. 85–102, 2020, doi: 10.28932/jis.v3i2.2839.
- [14] J. C. Molina, J. L. Salmeron, I. Eguia, and J. Racero, “The heterogeneous vehicle routing problem with time windows and a limited number of resources,” *Eng. Appl. Artif. Intell.*, vol. 94, no. July 2018, p. 103745, 2020, doi: 10.1016/j.engappai.2020.103745.
- [15] J. T. Soman and R. J. Patil, “A scatter search method for heterogeneous fleet vehicle routing problem with release dates under lateness dependent tardiness costs,” *Expert Syst. Appl.*, vol. 150, p. 113302, 2020, doi: 10.1016/j.eswa.2020.113302.