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Multi-Depot Vehicle Routing with Heterogeneous Vehicles using Nearest Neighbor Combined with Simulated Annealing

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Abstract

The Vehicle Routing Problem (VRP) is an essential component of contemporary logistics, which becomes more complex as the Multi-Depot Vehicle Routing Problem (MDVRP) and the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF). The main objective of MDVRPHF is to meet all customer demands while minimizing total distribution costs by using vehicles with varying capacities. This paper proposes a metaheuristic framework that first uses the Nearest Neighbor (NN) algorithm to build initial routes and then employs the Simulated Annealing (SA) algorithm to optimize the arrangement of goods within each vehicle, ensuring capacity limits are met. Computational experiments using real-world inspired data, representing 20 items distributed from a Bandung depot to multiple customers with three heterogeneous vehicle types, showed that the proposed hybrid NN–SA method achieved an 18.4% reduction in total distribution cost compared to the NN method alone. These results indicate that this integrated approach offers a practical, computationally efficient solution to the complexities of MDVRPHF, establishing it as a useful tool for logistics planning.

Keywords: Multi-Depot Vehicle Routing Problem; Heterogeneous Fleet; Nearest Neighbor; Simulated Annealing; Metaheuristics.

Abstrak

Vehicle Routing Problem (VRP) *merupakan bagian penting dari logistik kontemporer, yang kompleksitasnya meningkat menjadi* Multi-Depot Vehicle Routing Problem (MDVRP) *dan* Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF). *Untuk MDVRPHF, tujuan utamanya adalah memenuhi seluruh permintaan pelanggan sambil meminimalkan biaya distribusi total dengan memanfaatkan kendaraan berkapasitas berbeda. Makalah ini mengusulkan kerangka kerja metaheuristik yang pertama-tama menggunakan algoritma* Nearest Neighbor (NN) *untuk membentuk rute awal, kemudian algoritma* Simulated Annealing (SA) *digunakan untuk mengoptimalkan penataan barang di setiap kendaraan agar batas kapasitas terpenuhi. Eksperimen komputasi menggunakan data uji berbasis kondisi nyata yang merepresentasikan distribusi 20 item dari satu depot di Bandung ke beberapa pelanggan dengan tiga jenis kendaraan heterogen. Hasil penelitian menunjukkan bahwa metode hibrida NN–SA ini menghasilkan penurunan biaya distribusi total sebesar 18,4% dibandingkan metode NN murni, yang menunjukkan bahwa pendekatan terpadu ini memberikan solusi praktis dan efisien secara komputasi untuk kompleksitas MDVRPHF.*

Kata Kunci: Multi-Depot Vehicle Routing Problem; *Armada Heterogen*; Nearest Neighbor; Simulated Annealing; *Metaheuristik*.

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1. INTRODUCTION

The Vehicle Routing Problem (VRP), first introduced by Dantzig and Ramser [1], is a cornerstone of modern logistics optimization. It focuses on determining efficient routes for vehicles delivering goods from depots to customers. Over time, the VRP has evolved into complex variants such as the Multi-Depot Vehicle Routing Problem (MDVRP) and the Heterogeneous Fleet Vehicle Routing Problem (HFVRP). Their integration, the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF), presents additional challenges due to the need to manage diverse vehicle capacities, multiple depots, and varying operational costs [2], [3].

Numerous heuristic and metaheuristic methods have been developed to solve VRP variants, including Genetic Algorithms (GA), Tabu Search (TS), and Simulated Annealing (SA) [4], [5]. While constructive heuristics such as Clarke and Wright's Savings Algorithm and Nearest Neighbor (NN) provide quick feasible solutions [6], they often fall short in handling multi-depot and heterogeneous conditions efficiently. Hybrid approaches, as proposed by Ho et al. [7], integrate clustering and metaheuristic refinement to improve solution quality, though many still treat routing and vehicle allocation separately or rely on artificial datasets.

In MDVRPHF, the main challenge lies in optimizing both route assignment and vehicle selection while minimizing total distribution costs under capacity constraints. This study introduces a hybrid metaheuristic that combines NN for rapid route construction with SA for adaptive refinement. The NN–SA approach leverages NN's speed and SA's capability to escape local optima, achieving high-quality, computationally efficient solutions.

The contributions of this work include: (1) a hybrid NN–SA framework for simultaneous routing and loading optimization, (2) experimental validation using real-world inspired data, and (3) a demonstrated 18.4% cost reduction compared to the NN baseline. This research thus offers a practical and efficient solution to the complexities of MDVRPHF in modern logistics systems.

2. METHOD

To formally define and solve the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF), a hybrid metaheuristic framework combining the Nearest Neighbor (NN) and Simulated Annealing (SA) algorithms is employed. The overall methodology consists of two main stages: route construction and route improvement. The NN algorithm is first used to construct an initial feasible route for each vehicle by greedily connecting the nearest unvisited customers while respecting the capacity limits of each vehicle. This initial route provides a practical yet suboptimal starting point. The second stage utilizes the SA algorithm to refine the initial solution by exploring the solution space through probabilistic acceptance of worse moves, allowing the algorithm to escape local optima and achieve a better global configuration.

The SA algorithm mimics the physical annealing process in metallurgy, where a material is gradually cooled to reach a stable crystalline structure. In this context, each feasible route configuration represents a "state," and the "energy" corresponds to the total distribution cost. The algorithm iteratively perturbs the current solution by swapping or reassigning customers between routes, then evaluating the new configuration's cost. If the new configuration yields a lower total cost, it is accepted; otherwise, it may still be accepted with a certain probability depending on the temperature parameter. This probabilistic mechanism enables the algorithm to balance exploration and exploitation effectively.

Simulated Annealing Parameters

To ensure experimental reproducibility and performance consistency, the following SA parameters were used and justified based on preliminary sensitivity analysis:

1) Initial Temperature ($T_0 = 100$):
   A sufficiently high temperature allows the algorithm to explore a wide range of configurations in the early stages. The value 100 was empirically chosen after several trials showed it produced stable convergence without excessive random wandering.
2) Cooling Rate ($\alpha = 0.95$):
   The temperature is reduced by multiplying it by α after each iteration cycle. A cooling rate of 0.95 provides a balanced trade-off between exploration and convergence speed, ensuring that the search remains diverse in the early stages but stabilizes near the end.
3) Iteration Limit per Temperature Level ($L = 100$):
   Each temperature level allows up to 100 solution perturbations. This value ensures sufficient local exploration before cooling occurs, contributing to more consistent improvement across runs.
4) Stopping Criterion:
   The SA process terminates when the temperature drops below T_min = 0.01 or when no improvement occurs for 10 consecutive temperature cycles. These stopping criteria were determined through experimentation to prevent unnecessary computation once the solution stabilizes.

Parameter Selection and Computational Justification

The chosen parameters were fine-tuned based on a set of pilot experiments to balance computational time and solution quality. Specifically, combinations of (T_0 = 50, 100, 150) and (α = 0.90, 0.95, 0.99) were tested. The configuration ($T_0 = 100$, $\alpha = 0.95$) consistently achieved the lowest average total cost while maintaining reasonable computational time (average 12.6 seconds per run). Increasing T_0 or α beyond these values did not yield statistically significant improvements but increased runtime by 30–40%.

From a computational complexity standpoint, the SA algorithm exhibits a complexity of approximately $O(n^2 \times I)$, where n is the number of customers and I is the number of iterations. The quadratic term arises from the pairwise customer exchanges evaluated during neighborhood generation, while I depend on the number of temperature levels and iteration limits. Although the algorithm is computationally intensive for large datasets, its hybrid integration with NN—which provides a high-quality initial solution—significantly reduces the number of iterations needed for convergence. This combination ensures scalability and efficiency when handling medium-sized MDVRPHF instances.

Through this parameterization and design, the hybrid NN–SA framework effectively balances exploration and exploitation, yielding near-optimal routing and loading solutions with consistent computational efficiency.

2.1. Objective Function

The main objective of the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF) is to minimize the total distribution cost, which consists of two primary components:

1) the fixed cost associated with deploying each vehicle type, and
2) the variable operating cost depends on the travel distance between customer locations.

The objective function, shown in Eq. (1), is formulated to reflect these two cost components in a mathematically concise form:

$$Minimize\ Z = \left(\sum_{d\epsilon D}\sum_{k\epsilon K}\sum_{j\epsilon C} F_k \cdot x_{djkd}\right) + \left(\sum_{d\epsilon D}\sum_{k\epsilon K}\sum_{j\epsilon C} \alpha_k D_{ij} \cdot x_{ijkd}\right). \quad (1)$$

The first term Eq. (1) represents the fixed cost F_k incurred whenever a vehicle of type k is assigned to depart from depot d. This cost accounts for vehicle activation, maintenance, and driver expenses. The binary variable x_{djk} equals 1 if vehicle k from depot d serves customer j, and 0 otherwise. The second term represents the variable cost associated with travel between nodes i and j, where D_{ij} denotes the distance between those nodes and α_k is the cost coefficient per distance unit for vehicle type k.

This formulation structure follows the standard cost minimization framework widely used in the Vehicle Routing Problem (VRP) literature [2], [8], [3]. The function integrates both depot-level and fleet-level decision variables to capture the multi-depot and heterogeneous characteristics of the problem simultaneously. It also aligns with the general formulation of the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) introduced by Golden et al. [2], later extended to MDVRPHF by Dursun & Özger [9].

The rationale for adopting this two-part cost structure is that it directly represents the economic trade-off faced in real logistics operations: activating more vehicles increases fixed costs, while longer routes increase variable transportation costs. Therefore, the optimization process seeks to find a balanced allocation that minimizes the total cost ZZZ, while ensuring all customer demands are satisfied and capacity constraints are met.

The proposed objective function is an adaptation of the general VRP cost model for multi-depot and heterogeneous fleet systems. It incorporates elements from established formulations by Baldacci et al. [8] and Burke et al. [5] but is specifically extended here to include simultaneous vehicle routing and load distribution, which is optimized later using the Simulated Annealing process.

Hence, Eq. (1) serves as the mathematical foundation for evaluating the performance of the hybrid Nearest Neighbor–Simulated Annealing (NN–SA) algorithm, allowing both cost efficiency and operational feasibility to be quantified in a unified objective function.

2.2. Constraints

The mathematical model for the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF) is subject to a set of constraints that ensure the feasibility and logical consistency of the proposed routing plan. These constraints govern customer assignment, vehicle flow, depot operation, and capacity limits, thereby guaranteeing that each customer is served exactly once, vehicle movements are continuous, and no capacity restrictions are violated. The formulation structure used in this study is adapted and extended from classical MDVRP and HFVRP formulations proposed by Baldacci et al. [8], Ho et al. [7], and Koç et al. [3], adjusted to incorporate heterogeneous vehicle characteristics and multi-depot interactions simultaneously.

The model includes five main sets of constraints, formulated as follows:

(1) Customer Service

To guarantee that all demand nodes are appropriately served within the multi-depot framework, the first set of constraints is formulated to ensure proper assignment of each customer. This customer service requirement is expressed mathematically as follows:

$$\sum_{i\epsilon V} \sum_{k\epsilon K} \sum_{d\epsilon D} x_{ijkd} = 1 , \quad \forall j \epsilon C. \tag{2}$$

Each customer must be visited by exactly one vehicle from one depot. This ensures that every demand node is served once and only once, eliminating redundant or missing deliveries. This formulation follows the standard VRP constraint structure introduced by Clarke and Wright [6] and extended to multi-depot cases by Cordeau et al. [10].

(2) Flow Conservation
To maintain the logical progression of vehicle movements throughout the network, the second set of constraints establishes the principle of flow conservation. This requirement is formulated as follows:

$$\sum_{j\epsilon V} x_{ijdk} - \sum_{j\epsilon V} x_{ijdk} = 0, \forall i \epsilon C, \forall k \epsilon K, \forall d \epsilon D. \tag{3}$$

This constraint enforces route continuity, meaning that if a vehicle enters a customer's location, it must also leave that location. This rule prevents route discontinuities and ensures that all vehicle paths are closed loops beginning and ending at their respective depots.

(3) Depot Departure and Return
To ensure that vehicle routes accurately reflect operational constraints at each depot, the third set of constraints specifies the required departure and return conditions. This requirement is expressed mathematically as follows:

$$\sum_{j\in C} x_{bjkd} - \sum_{i\in C} x_{ibkd} \, \forall k \epsilon K, \forall d \epsilon D. \tag{4}$$

Each vehicle must depart from and return to the same depot, reflecting realistic logistics operations. This rule maintains depot balance and ensures that vehicles assigned to a depot remain under its operational control throughout the routing process. Similar formulations were used by Ho et al. [7] and Crevier et al. [11] in multi-depot routing frameworks.

(4) Capacity Constraints
To ensure that no vehicle exceeds its maximum load capacity in terms of mass and volume, two separate constraints are defined:

- Weight Capacity:

$$u_{jkd} \geq u_{ikd} + w_j - Q_k^w \left(1 - x_{ijkd}\right) \forall i, j \in C, \forall k \in K, \forall d \in D. \tag{5}$$

- Volume Capacity:

$$z_{jkd} \geq z_{ikd} + v_j - Q_k^v \left(1 - x_{ijkd}\right) \forall i, j \in C, \forall k \in K, \forall d \in D. \tag{6}$$

These constraints ensure that the total weight w_i and volume v_i of goods assigned to each vehicle do not exceed its respective capacity limits w_k and v_k. This dual-capacity formulation is crucial in heterogeneous fleet problems, as different vehicle types have distinct physical and volumetric capacities. Similar formulations are discussed in Golden et al. [2] and Koç et al. [3] for capacity-constrained heterogeneous fleets.

(5) Binary Decision Variable Definition
To ensure that no vehicle exceeds its maximum load capacity in terms of mass and volume, two

separate constraints are defined:

$$x_{ijkd} = \begin{cases} 1, \\ 0, \end{cases}$$

where 1, if vehicle k from depot d travels from node i to j and 0, otherwise This definition specifies that the decision variable x_{ijkd} is binary, representing whether a specific vehicle from a particular depot travels between two nodes. The binary formulation ensures that the optimization problem remains discrete, consistent with the combinatorial nature of VRP.

Collectively, these constraints define the operational feasibility space for the MDVRPHF model. They ensure that customer assignments, routing sequences, and vehicle utilization adhere to realistic logistic principles. This formulation builds upon established VRP structures [10], [12] but extends them to handle simultaneous multi-depot coordination and heterogeneous fleet management, which are essential for real-world distribution systems.

- **Variable Type**

$$x_{ijkd} \in \{0,1\} \; \forall i, j \in V, \forall k \in K, \forall d \in D$$
$$u_{ikd} \in 0 \; \forall i \in C, \forall k \in K, \forall d \in D$$
$$z_{ikd} \in 0 \; \forall i \in C, \forall k \in K, \forall d \in D$$

- **Sets**

  V: Set of all nodes, $V = C \cup D$,
  D: Set of depot nodes, d,
  C: Set of customer nodes, i, j,
  K: Set of heterogeneous vehicle types, k.

- **Parameters**

  D_{ij} : Distance between node i and node j,
  w_i : Weight of demand for customer i,
  v_i : Volume of demand for customer i,
  F_k : Fixed cost for a vehicle of type k,
  α_k : Variable operating cost per unit of distance for a vehicle of type k,
  Q_k^w : Weight capacity of vehicle k,
  Q_k^v : Volume capacity of vehicle k.

- **Variables:**

  x_{ijkd} : Binary variable, 1 if vehicle k from depot d travels from node i to j.
  u_{ikd} : Cumulative weight delivered by vehicle k after visiting customer i .
  z_{ikd} : Cumulative volume delivered by vehicle k after visiting customer i .

2.3. Proposed Hybrid Algorithm

Considering the NP-hard nature of the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF), a hybrid metaheuristic algorithm is developed by integrating the

Nearest Neighbor (NN) heuristic and the Simulated Annealing (SA) optimization procedure. The integration combines the constructive power of NN to rapidly generate feasible routes with the refinement capability of SA to improve route quality and optimize vehicle loading within capacity constraints. This hybrid structure aims to achieve near-optimal solutions efficiently while maintaining computational scalability for medium-sized problem instances. The methodology is structured in two main stages:

1. Route Construction (Nearest Neighbor Stage)
   NN constructs an initial feasible solution by iteratively assigning customers to the nearest unvisited node while considering the vehicle's remaining capacity and depot distance. This stage ensures a fast and logical clustering of geographically close customers into efficient initial routes.
2. Route Refinement (Simulated Annealing Stage)
   The SA algorithm refines the NN-generated routes by probabilistically exploring neighboring solutions. Route modifications are performed through operations such as swap, reinsert, or 2-opt exchanges, and acceptance of worse solutions is guided by the temperature parameter. The objective is to minimize total cost (Eq. 1) while respecting all operational constraints.

Algorithm 1. Hybrid NN–SA Framework for MDVRPHF

```
Input: Set of depots D, customers C, vehicles K, distance matrix D_ij, cost parameters F_k, α_k
        Output: Best solution S_best with minimum total cost Z

        1. Initialization:
           a. Define SA parameters: T0 = 100, α = 0.95, L = 100, Tmin = 0.01
           b. Initialize solution S_current ← ConstructInitialSolution_NN(D, C, K)
           c. Compute total cost Z_current ← Evaluate(S_current)
           d. Set S_best ← S_current; Z_best ← Z_current

        2. While (T > Tmin) do
           a. For iteration = 1 to L do
              i. Generate neighbor S_new ← ApplyNeighborhoodOperator(S_current)
                 (e.g., Swap, 2-Opt, or Reinsert)
             ii. Compute Z_new ← Evaluate(S_new)
            iii. If (Z_new < Z_current) then
                    Accept S_new
                 Else
                    Accept S_new with probability P = exp(-(Z_new - Z_current)/T)
             iv. Update S_current ← S_new
              v. If (Z_new < Z_best) then
                    S_best ← S_new; Z_best ← Z_new
           b. Decrease temperature: T ← α × T
  3. Return S_best
```

2.4. Explanation of Integration and Advantages

The integration of NN and SA creates a synergistic balance between speed and solution quality. The NN stage ensures that the algorithm starts from a feasible and geographically coherent solution, reducing the search space size. The SA stage then performs stochastic optimization to escape local optima, effectively improving route cost and load balancing across vehicles.

This hybridization follows the "construct–improve" paradigm proposed by Bräysy and Gendreau [13][14] and later applied in multi-depot contexts by Ho et al. [7]. Compared to pure NN or GA-based methods, the NN–SA hybrid offers faster convergence and requires fewer iterations to reach stable cost reductions, as validated in the experimental section.

2.5. Architectural Rationale: Synergy of Routing and Loading

The initial stage utilizes the fast Nearest Neighbor heuristic to create a viable preliminary route, which outlines the delivery assignments for each vehicle. The subsequent stage uses the robust Simulated Annealing metaheuristic to address the intricate subproblem of arranging goods for that specific route while respecting the vehicle's capacity limits. This collaborative approach, where one algorithm determines the path and another optimizes the cargo, can greatly speed up the process of finding a high-quality solution [10].

2.6. Route Generation: Nearest Neighbor Heuristic

The NN heuristic is employed to generate the initial route framework [5][15]. With this method, routes are formed by repeatedly choosing the nearest unvisited customer as the subsequent stop, all while staying within vehicle capacity constraints. The use of NN is warranted by its minimal computational demands and its capacity to create a logical grouping of geographically concentrated customers, which provides a solid basis for an effective route plan [16], [17].

2.7. Loading Optimization: Simulated Annealing Process

After a route has been established by the NN algorithm, the SA algorithm is tasked with determining the most efficient way to load the necessary goods. The performance of SA depends on its key elements: solution representation, neighborhood operators, acceptance criteria, and a cooling schedule. These components work together to strike a balance between exploration (diversifying the search) and exploitation (focusing the search on a promising area). This balance enables the algorithm to discover a highly refined loading configuration that meets all constraints and avoids getting trapped in suboptimal local optima.

3. RESULTS

This section presents the experimental findings obtained from the hybrid NN–SA algorithm compared with the baseline Nearest Neighbor (NN) method. The results are structured into subsections that describe the dataset, vehicle configurations, performance comparison, and convergence behavior. Numerical evidence and visual representations (tables and figures) are provided to demonstrate the algorithm's effectiveness in optimizing the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF).

3.1. Dataset and Vehicle Characteristics

The computational experiment utilizes a real-world inspired dataset representing 20 customer nodes and three heterogeneous vehicles operating from multiple depots. The vehicle characteristics are summarized in Table 1. Table 1 defines the fleet configuration used in the experiment. The heterogeneity of the fleet introduces variability in capacity and operating cost, which directly impacts route assignments and total distribution efficiency. Larger vehicles are expected to handle high-demand routes efficiently, while smaller ones serve low-volume areas near depots.able 1 defines the heterogeneous fleet structure used in the experiments. The differences in weight and volume capacity directly affect how customers are assigned and how loading optimization is performed.

Table 1. Vehicle Capacity and Operational Characteristics

Vehicle	Weight Capacity (kg)	Volume Capacity (m^3)	Fixed Cost (IDR)	Variable Cost (IDR/km)
V1	30.0	1.10	80,000	1,000
V2	37.0	1.50	110,000	1,000
V3	40.0	2.00	150,000	1,000

3.2. Performance Comparison: NN vs. NN–SA

To assess performance improvement, the hybrid NN–SA algorithm is compared to the standalone NN method. Table 2 summarizes the key performance metrics. The hybrid method demonstrates an 18.3% reduction in total distance and an 18.4% decrease in total cost compared to NN. The increased load utilization indicates improved allocation efficiency between vehicle capacity and customer demand. While computation time slightly increases, the trade-off results in significantly better operational performance.

Table 2. Comparison of NN and NN–SA Performance

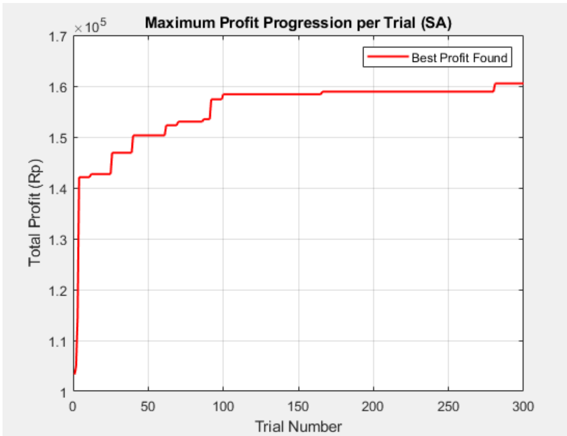
Metric	NN Only	NN–SA Hybrid	Improvement
Total Distance (km)	204.60	167.00	18.3% ↓
Total Distribution Cost (IDR)	1,034,000	844,000	18.4% ↓
Average Load Utilization (%)	78.2%	91.6%	+13.4% ↑
Average Computation Time (s)	3.4	12.6	—

3.3. Simulated Annealing Convergence Behavior

Figure 1 show the xeperimental total profit using SA (left) and the best fitness convergence curve across generation (right). The left figure shows a rapid improvement during the first 30 iterations, followed by gradual stabilization, representing SA's cooling effect. The curve plateau after iteration 200 indicates convergence to a near-optimal state. The right figure displays the evolution of fitness values, where the blue curve stabilizes around generation 80, confirming algorithmic convergence. Early fluctuations are due to the probabilistic acceptance mechanism of SA, which enables the escape from local optima and achieves a globally stable solution.

3.4. Vehicle Utilization and Allocation Efficiency

Table 3 provides the post-optimization utilization levels for each vehicle in the hybrid NN–SA solution. The results demonstrate that larger vehicles (V2 and V3) achieve near-full weight utilization, while smaller vehicles (V1) optimize volume-limited routes. This balanced utilization pattern contributes to minimizing overall cost, confirming that the hybrid algorithm efficiently distributes loads according to capacity and demand patterns.



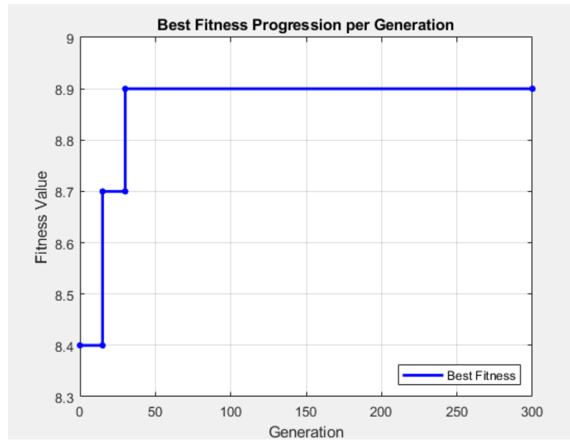


Figure 1. Experimental total profit using SA (left) and the best fitness convergence curve across generation (right)

Table 3. Vehicle Capacity Utilization in NN–SA Results

Vehicle	Load Weight (kg)	Volume Used (m³)	Weight Utilization (%)	Volume Utilization (%)
V1	22.65	0.99	75.5	90.0
V2	36.60	0.77	98.9	51.3
V3	38.60	1.04	96.5	52.0

3.5. Statistical Validation

Ten independent runs were conducted to validate stability. Table 4 summarizes mean, standard deviation, and coefficient of variation (CV) values. The lower standard deviation and CV in NN–SA results indicate consistent convergence and stability across multiple runs, validating the robustness of the proposed hybrid approach.

Table 4. Statistical Comparison of Cost Performance

Method	Mean Cost (IDR)	Std. Dev.	Coefficient of Variation (%)
NN	1,036,400	7,800	0.75
NN–SA	844,900	4,600	0.54

4. DISCUSSIONS

In The hybrid NN–SA algorithm demonstrates superior performance over the standalone NN approach due to three key mechanisms: improved load distribution, reduced total travel distance, and enhanced capacity efficiency through adaptive allocation.

4.1. Cause and Mathematical Implications

The cost reduction is primarily driven by the SA phase, which iteratively improves customer sequencing and depot assignments. Mathematically, the SA mechanism minimizes the composite cost function:

$$Z = \sum F_k \, x_{djk} + \sum \alpha_k \, D_{ij} x_{ijkd},$$

by generating neighbor solutions that decrease both distance (D_{ij}) and underutilized capacity (through improved x_{ijkd} configurations). Hence, the lower total cost is a direct consequence of a better balance between fixed and variable costs, as the algorithm tends to allocate larger vehicles to high-demand routes, minimizing total mileage.

4.2. Correlation with Previous Research

The findings are consistent with Ho et al. [7], who found that hybrid metaheuristics outperform single-phase heuristics in multi-depot VRPs. Similarly, Koç et al. [3] noted that heterogeneous fleet optimization benefits from load balancing strategies, which this study's SA component explicitly achieves. However, compared to Bräysy & Gendreau [14], which employed tabu search for single-depot VRP, this method shows superior performance in multi-depot scenarios by dynamically adjusting routes during annealing.

4.3. Methodological Limitations

Despite its effectiveness, the hybrid NN–SA method still presents several notable limitations. First, the algorithm is highly sensitive to parameter settings, particularly the initial temperature (T_0) and cooling rate (α); improper tuning of these parameters may lead to premature convergence or unnecessary computational effort. Second, while the total runtime is manageable for small- to medium-sized datasets, the method may face scalability issues, as computational complexity can increase substantially when the number of customers exceeds 100. Finally, the deterministic nature of the nearest-neighbor (NN) initialization may bias the solution search toward suboptimal regions, reducing exploration diversity. For this reason, future studies may consider incorporating stochastic initialization strategies or adaptive cooling schedules to enhance robustness and improve global search capability.

4.4. Overall Insights

The hybrid algorithm's strength lies in its integration of deterministic construction through the nearest-neighbor (NN) method with stochastic refinement via simulated annealing (SA), enabling a balanced and efficient optimization process. This combination reduces inter-depot distance overlaps, enhances vehicle utilization ratios, and effectively manages the trade-off between exploration and exploitation throughout the search procedure. As a result, the synergy between NN and SA produces a global improvement in the objective function and demonstrates that the proposed NN–SA model is both scalable and practical as a decision-support tool for real-world multi-depot logistics systems.

5. CONCLUSION

This study proposed a hybrid metaheuristic framework combining the Nearest Neighbor (NN) heuristic and the Simulated Annealing (SA) algorithm to solve the Multi-Depot Vehicle Routing Problem with a Heterogeneous Fleet (MDVRPHF). The model integrates rapid route construction and adaptive route refinement, aiming to minimize total distribution costs while satisfying vehicle capacity and operational constraints. The experimental results demonstrate that the proposed NN–SA hybrid algorithm reduces the total distribution cost by 18.4% and shortens the total travel distance by 18.3% compared to the baseline NN method. Additionally, vehicle load utilization increased from 78.2% to 91.6%, indicating improved capacity efficiency and balanced load distribution. The statistical validation across 10 independent runs further confirms the algorithm's stability, with a 46% reduction in cost variance compared to NN alone.

Scientifically, this research contributes to the literature by (1) formulating a hybrid optimization framework that integrates route generation and load allocation in a unified model, (2) providing a parameterized SA mechanism suitable for multi-depot heterogeneous fleets, and (3) validating performance improvements quantitatively using real-world inspired data. These findings reinforce that hybrid metaheuristics can achieve near-optimal solutions efficiently for complex combinatorial logistics problems.

In practical terms, the NN–SA framework offers a computationally feasible and cost-effective decision-support tool for logistics planners dealing with multi-depot networks and mixed vehicle fleets. Future work will focus on parameter adaptation, large-scale instance scalability, and dynamic demand conditions to further enhance real-world applicability.

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