Optimizing LPG distribution: A hybrid particle swarm optimization and genetic algorithm for efficient vehicle routing and cost minimization

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ARTICLE INFO

Article history
Received November 6, 2024
Revised June 29, 2025
Accepted July 2, 2025
Available online August 14, 2025

Keywords
Vehicle routing problem
HPSOGA algorithm
Vehicle allocation
Route optimization
Transport costs

ABSTRACT

This paper aims to develop an optimized solution for the Vehicle Routing Problem (VRP), tailored explicitly for Liquid Petroleum Gas (LPG) distribution, with a focus on minimizing transportation costs and enhancing delivery reliability. The critical role of LPG as an essential public infrastructure commodity, widely utilized for cooking and heating, makes its efficient and reliable distribution a significant logistical challenge due to the strict adherence to delivery time windows, heterogeneous fleets, multi-trip scenarios, and intricate loading and unloading requirements. To address these complexities, this study proposes a novel hybrid Particle Swarm Optimization and Genetic Algorithm (HPSOGA) that uniquely integrates multi-trip routing, time windows, and heterogeneous vehicle fleet management into a single optimization framework. The dual-phase optimization strategy leverages the exploratory capability of PSO and the solution-refining power of GA, resulting in high-quality, feasible solutions. Validation against real-world data involving VRP instances with 88 and 40 stations demonstrates the model's practical impact, achieving reductions of up to 4.56% in transportation costs compared to existing operational routes. This research makes a significant contribution to interdisciplinary domains, including logistics optimization, sustainability, and energy distribution, by offering a robust and scalable model that comprehensively addresses complex, real-world VRP constraints.

1. Introduction

Logistics and supply chain management are essential drivers of progress toward the Sustainable Development Goals (SDGs), particularly those targeting sustainable industry, innovation, and responsible consumption. In modern economies, logistics enables the efficient movement of goods from suppliers to consumers, where effective management reduces operational costs, enhances customer satisfaction, and supports competitive advantage [1]. A central challenge in logistics is the Vehicle Routing Problem (VRP), a classic optimization problem that seeks to determine the most efficient routes for a fleet of vehicles to serve customers at minimal transportation cost [2]–[4]. While the VRP has been widely studied, its practical complexity has evolved significantly, prompting researchers to propose various VRP variants that incorporate real-world constraints such as time windows, heterogeneous vehicle fleets, multi-trip schedules, capacity limitations, and loading/unloading operations (LU) [5]–[10]. These constraints are particularly relevant in critical sectors, such as energy logistics, where uninterrupted and efficient delivery plays a vital societal and economic role.

This paper addresses a specific and complex variant of the VRP encountered in the distribution of Liquid Petroleum Gas (LPG), which is a vital energy source used for cooking and heating in many regions, particularly in developing countries. The Indonesian Ministry of Energy and Mineral Resources, for instance, reported in 2023 that nearly 87 percent of households rely on LPG for cooking, following a successful nationwide transition from kerosene to LPG that began in 2007. This underscores the strategic importance of ensuring efficient LPG distribution, which presents significant logistical challenges due to strict delivery time constraints, a heterogeneous fleet of vehicles, complex loading and unloading operations, and the necessity for multi-trip route planning

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Recent developments in VRP research have increasingly focused on addressing real-world complexities such as time windows, heterogeneous fleets, multi-trip routes, capacity constraints, and loading and unloading operations. However, as summarized in Table 1, many of these studies tend to address only one or two of these constraints in isolation, without fully integrating them into a comprehensive model. This limits their practical relevance, especially in complex logistics scenarios such as LPG distribution [14]–[18].

For example, Xu *et al.* [14] and Wu *et al.* [15] concentrated on vehicle and route planning using Particle Swarm Optimization (PSO)-based algorithms, but their experiments were limited to benchmark Solomon datasets and did not consider multi-trip routing or loading and unloading activities. Ghannadpour & Zarrabi [16] incorporated time window and fleet heterogeneity constraints, yet their model did not account for loading operations. Nguyen *et al.* [17] and Wei *et al.* [18] addressed several constraints, including time windows, capacity, multi-trip routes, and loading processes, but their studies were limited to specific industries such as milk and cold-chain logistics, with minimal validation using real operational data.

Rios & Xavier [19] extended the VRP to include stochastic multi-depot scenarios with pickup and delivery features; however, their formulation excluded time windows and lacked a unified integration of routing constraints. Similarly, Pak & Mun [20] proposed a time-dependent VRP that includes heterogeneous vehicles and multi-trip features, yet their work focused only on small to medium-sized city contexts and faced limitations in terms of scalability and practical application.

More recent studies by Hayati *et al.* [21] and Zhang & Li [22] have begun addressing specialized routing challenges, such as carbon emission reduction and epidemic-related disruptions. However, these approaches often rely on simulation data and still fall short of integrating all major operational constraints into a single model.

In response to the limitations identified in previous studies, this research proposes a comprehensive VRP model that simultaneously incorporates five critical operational constraints: heterogeneous fleet composition, capacity limitations, time windows, multi-trip routing, and loading and unloading activities. These constraints are closely interconnected in LPG distribution systems, where logistics operations demand high levels of precision and efficiency. To address the complexity of this multi-constrained problem, we adopt a hybrid metaheuristic approach that combines the global search capability of PSO with the local refinement strengths of GA. This hybrid strategy is designed to enhance solution quality while maintaining computational efficiency. The novelty of the hybridization lies in the structured integration of PSO and GA in a sequential optimization pipeline. PSO is utilized to generate a globally promising set of initial solutions, which GA then refines through tailored crossover and mutation operations to explore local neighborhoods more effectively.

Unlike previous works that combine metaheuristics loosely or use them in parallel with limited interaction, this study introduces a tightly coupled architecture where the output of PSO directly seeds the GA population. This design enhances convergence speed and solution diversity while preserving feasibility under complex real-world constraints. Furthermore, the model is validated using real operational data from an LPG distribution company in Yogyakarta, Indonesia, providing strong empirical support for the practical relevance and applicability of the proposed solution.

Furthermore, the proposed model and hybrid PSO-GA algorithm demonstrate strong generalization potential across various critical logistics sectors that share similar operational constraints. These include oil and fuel distribution systems that require regulated delivery schedules and route efficiency, water tanker dispatching in underserved or disaster-prone regions that involve multi-trip and capacity-limited routing, and medical supply chains for temperature-sensitive or emergency items where time windows, safe handling, and vehicle specialization are essential. These domains reflect the same structural complexity found in LPG distribution, making the proposed model a valuable decision-support tool beyond academic settings, with practical relevance for public welfare, infrastructure reliability, and interdisciplinary planning. In summary, this study offers three principal contributions:

- The development of a novel, mathematically rigorous VRP model tailored to LPG distribution.
- The implementation of a hybrid PSO-GA capable of solving complex, high-dimensional, multi-constrained VRP instances.
- Real-world validation using operational data from the Indonesian LPG sector, establishing a practical bridge between theoretical development and applied logistics optimization.

The remainder of this paper is structured as follows: Section 2 describes the problem formulation, mathematical model, and outlines the hybrid PSO-GA algorithm. Section 3 presents the computational experiments and analysis. Finally, Section 4 concludes the study with key insights and directions for future research.

2. Method

2.1. Problem Descriptions

LPG distribution presents a highly complex VRP that involves balancing multiple, interdependent logistical challenges to ensure reliable and equitable access to energy, particularly for households in both urban and rural areas (see Fig. 1). Efficient allocation of vehicles from a central depot to numerous customer stations is required, each with distinct delivery volumes and strict time windows. These operational demands are further complicated by the use of a heterogeneous fleet, where differences in vehicle capacity, operational cost, and route compatibility introduce challenges in assignment decisions and often result in underutilization, especially in less-than-truckload (LTL) scenarios.

In addition, the process of loading and unloading LPG involves safety-critical handling procedures and significant time investments, especially for bulk deliveries. Failure to meet delivery time windows can disrupt household fuel availability, disproportionately affecting vulnerable populations and remote communities that rely heavily on timely LPG delivery for cooking and heating. These constraints are particularly important in disaster-prone or geographically isolated areas, where supply interruptions can pose serious risks to health and welfare, making route planning not just an operational issue but also a matter of social equity.

Table 1. Comparison of the current study with previous literature

Authors	VRP Characteristics					Decision Variables	Case study	Solution approach	Performance metric
	Hetero	*Cap*	*TW*	*MT*	*LU*				
Xu *et al.* [14]	√	√			√	Route planning	Solomon dataset	Particle Swarm Optimization	Minimize travel distance and costs
Wu *et al.* [15]	√	√				Route planning	Solomon dataset	Neighborhood comprehensive learning particle swarm optimization	Minimize the number of vehicles and total distances
Ghannadpour and Zarrabi [16]	√	√	√			Route planning; Vehicle selection	Not specified	NSGA II	Maximize satisfaction rates
								Cplex	Minimize distance traveled, energy consumption, and number of rental vehicles
Nguyen *et al.* [17]	√	√	√	√	√	Route planning	Milk distribution company	Adaptive large neighborhood search	Minimize total travel time
Wei *et al.* [18]	√	√	√			Route planning	Solomon dataset	Large Neighborhood Search with Modified Rat Swarm Optimization	Minimize distance traveled, energy consumption, and vehicle utilization
Rios & Xavier [19]		√	√			Route planning	Hadad *et al.* [31]'s dataset	Tabu search, Variable Neighborhood Search, Iterated Local Search	Minimize total travel costs
Pak & Mun [20]	√	√	√	√		Route planning	Urban distribution	Variable neighborhood search	Minimize fuel consumptions.
Hayati *et al.* [21]	√	√	√	√	√	Vehicle allocation to routes	Perishable product delivery	Genetic algorithm	Minimize total travel costs, emissions, maximize quality
Zhang & Li [22]					√	Route planning	Cold-chain drug distribution & Solomon dataset	Tabu search	Minimize travel time

Table 1. *(cont.)*

Authors	VRP Characteristics					Decision Variables	Case study	Solution approach	Performance metric
	Hetero	*Cap*	*TW*	*MT*	*LU*				
Zhou *et al.* [32]		√	√			Routing and scheduling	Freight service of steel enterprise in Changsha–Zhuzhou–Xiangtan metropolitan area, China	Variable Neighborhood Search with Partial Model	Minimize total cost of energy consumption, travel distance, and number of evs
Liu *et al.* [33]		√			√	Customer allocation Route planning	Salhi & Nagy [34]'s dataset	Variable Neighbourhood Search Algorithm with novel perturbation mechanism	Minimize total travel costs
Wang *et al.* [35]	√	√		√		Vehicle trips Trip allocation to vehicles	Chinese petroleum transportation company	Adaptive large neighborhood search	Minimize total travel time
Agrawal *et al.* [36]	√	√	√			Route planning	Liu and Jiuping [37]'s dataset	Genetic algorithm	Minimize operational costs
Menares *et al.* [38]		√	√			Route planning	Santiago, Chile highway network	Non-dominated solution genetic algorithm-II	Minimize operational costs and delivery failure rates
Ahmed and Yousefikhoshbakht [39]	√	√		√		Route planning	Not specified	Tabu search	Minimize total travel costs
Lehmann and Winkenbach [40]	√	√	√			Route planning	Urban distribution	Adaptive large neighborhood search	Minimize total travel costs
This paper	√	√	√	√	√	Vehicle allocation to routes	LPG distribution company	Hybrid Particle Swarm Optimization & Genetic algorithm	Minimize travel costs

Hetero: Heterogeneous fleet; Cap: Capacity of vehicle; TW: time windows; MT: multi-trip; LU: Loading and Unloading.

Despite the growing sophistication in VRP research, few models attempt to handle the combination of heterogeneous fleets, time windows, capacity constraints, multi-trip routing, and loading/unloading requirements in a single, unified optimization framework. This is due to the increased computational complexity and the difficulty in maintaining solution feasibility when multiple constraints interact dynamically. However, this level of complexity is not exclusive to LPG logistics. Similar multi-constraint challenges are also present in other sectors, such as cold-chain distribution, urban water supply, and medical goods transportation, where service timeliness and load integrity are equally critical.

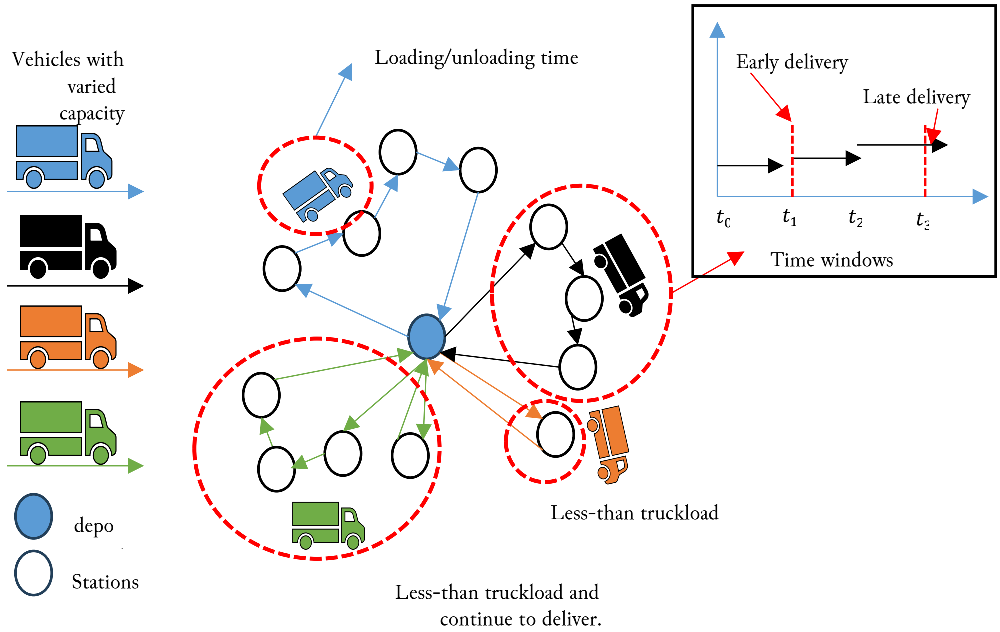


Fig. 1. Illustration of the VRP problems

Therefore, this study aims to develop an optimized routing model that minimizes total transportation cost while satisfying all LPG-specific constraints and ensuring equitable, uninterrupted access to energy across diverse delivery environments.

2.2. Notations and Assumptions

VRP is a classic combinatorial optimization problem that requires a strategic approach to modeling for practical solutions. To accurately model a VRP, it is essential to establish clear notations and assumptions that define the problem's parameters and underlying assumptions.

Notations		Descriptions
Sets and Indices		
N	:	$0,1,2,3,\dots,n$: set of stations and depot (including depot 0 and stations 1 to n).
V	:	$0,1,2,3,\dots,v$: set of vehicles.
R	:	$0,1,2,3,\dots,r$: set of routes assigned to vehicle (multi-trip consideration)
Parameters		
Q_i	:	Demand of station $i \in N$.
C^v	:	Capacity of a single vehicle $v \in V$.
d_{ij}	:	Distance of station $i \in N$ to station $j \in N$.
S^v	:	Average speed of single vehicle v.
e_i, l_i	:	Time window for station i, with earliest e_i and latest l_i, delivery times.
LO	:	Loading time per 10 units gallon.
UL	:	Unloading time per 10 units gallon.

P_{early}	:	Penalty cost per unit time for early arrivals.
P_{late}	:	Penalty cost per unit time for late arrivals.
c_{km}	:	Cost per kilometer traveled.
$A_i^{v,r}$	:	Arrival time of vehicle v at station i on route r
$T_{route}^{v,r}$	:	Total time required for vehicle v to complete route r.
Decision Variables		
z_{ij}^{v}	:	Binary variable, equal to 1 if vehicle v is assigned to route r from i to j, 0 otherwise.

Assumptions:

- The number of vehicles available is fixed and known in advance.
- Each vehicle has a known fixed capacity that does not change over time.
- Each vehicle has a constant average speed.
- The demand at each station (or node) is known and constant. There are no variations or uncertainties in demand.
- The distances between all pairs of nodes are known and remain constant.
- The travel time between nodes is determined by distance and the average speed of the vehicle and is not affected by external factors such as traffic.
- Each node has a specific time window within which deliveries must be made. These time windows are known in advance and do not change.
- Vehicles may continue their run at a node even if they arrive before the time window opens, incurring a penalty cost, provided there is exceptional communication between the driver and the store owner.
- Routes must be planned such that each node is visited exactly once and all demands are met

2.3. Mathematical Model

The objective function in this VRP model aims to minimize the total distribution cost of LPG by accounting for heterogeneous vehicles with varying capacities, multi-trip allocations, and loading and unloading times, while also adhering to time windows and penalties for schedule violations. It can be mathematically expressed as follows:

$$\text{Min } Z = \sum_{v\in V}\sum_{r\in R}\sum_{i\in N}\sum_{j\in N} c_{\text{km}} \cdot d_{ij} \cdot z_{ij}^{vr} + \sum_{v\in V}\sum_{r\in R}\sum_{i\in N, i\neq 0}\left(P_{\text{early}} \cdot \max(0, e_i - A_i^{vr}) + P_{\text{late}} \cdot \max(0, A_i^{vr} - l_i)\right) + \sum_{v\in V}\sum_{r\in R} P_{\text{late}}^{(0)} \cdot \max(0, A_0^{vr} - l_0) \quad (1)$$

Eq. (1) defines the objective function, which aims to minimize the total distribution cost (Z) for LPG delivery. This objective is comprised of three primary components. The first component represents the total transportation cost, calculated by summing the distance-based costs incurred when vehicle v in trip r travels from node i to node j. Here, z_{ij}^{vr} is a binary decision variable indicating the travel path, d_{ij} denotes the distance between nodes, and c_{km}reflects the per-kilometer cost associated with vehicle type k. The second component imposes penalties for time window violations at customer nodes (excluding the depot). It accounts for early arrivals ($A_i^{vr} < e_i$) and late arrivals ($A_i^{vr} > l_i$ at node i, where A_i^{vr} is the actual arrival time of vehicle v during trip r, and $[e_i, l_i]$ defines the allowed time window. The associated penalties are scaled by P_{early} and P_{late}, respectively. The third component is a penalty for late returns to the depot (node 0), applied when a vehicle returns later than the designated closing time l_0. This is represented by A_0^{vr} and penalized by $P_{\text{late}}^{(0)}$. Together, these components ensure that the model strikes a balance between cost efficiency and strict adherence to delivery schedules and depot return requirements, thereby supporting timely and reliable LPG distribution operations. Thus, these penalties can be mathematically expressed as follows:

$$P_{\text{early}} = \sum_{i\in N, i\neq 0} \begin{cases} P_{\text{early}} \left[\max(0, e_i - A_i^{v,r})\right] & If\ (e_i - A_i^{v,r}) \geq 1\ hour \\ 0 & If\ (e_i - A_i^{v,r}) < 1\ hour \end{cases} \quad (2)$$

$$P_{\text{late}} = \sum_{i\in N, i\neq 0} \begin{cases} P_{\text{late}} \left[\max\left(0, A_i^{v,r} - l_i\right)\right] & If\ \left(A_i^{v,r} - l_i\right) \geq 1\ hour \\ 0 & If\ \left(A_i^{v,r} - l_i\right) < 1\ hour \end{cases} \tag{3}$$

$$P_{late}^{(0)} = \sum_{i\in N, i\neq 0} \begin{cases} P_{\text{depot}} \left[\max\left(0, e_i - A_i^{v,r}\right)\right] & If\ \left(e_i - A_i^{v,r}\right) \geq 1\ hour \\ 0 & If\ \left(e_i - A_i^{v,r}\right) < 1\ hour \end{cases} \tag{4}$$

Additionally, other constraints related to Eq. (1) can be considered as follows:
Assignment constraints

$$\sum_{v\in V} \sum_{r\in R} \sum_{j\in N} z_{ij}^{vr} = 1, \quad \forall i \in N,\ i \neq 0 \tag{5}$$

This ensures that each node (except the depot) is visited exactly once.
Capacity constraints

$$\sum_{i\in N} Q_i \cdot \sum_{j\in N} z_{ij}^{vr} \leq C^v, \quad \forall v \in V, \forall r \in R \tag{6}$$

This ensures that the demand served by a vehicle on each of its trips does not exceed its capacity.
Time windows constraints:

$$e_i \leq A_i^{vr} \leq l_i, \quad \forall i \in N, \forall v \in V, \forall r \in R \tag{7}$$

This ensures that the vehicle arrives at each node within the specified time window.
Travel time constraints:

$$A_j^{vr} \geq A_i^{vr} + \frac{d_{ij}}{s^v} \cdot z_{ij}^{vr} + \Upsilon\Lambda_i, \quad \forall i,j \in N, \forall v \in V, \forall r \in R \tag{8}$$

This constraint ensures that the travel time between nodes, plus any unloading time at node i, is properly accounted for.
Loading time at depot (for multiple trips):

$$LO_r^v = LO \cdot \frac{\sum_{i\in N} Q_i \cdot z_{0i}^{vr}}{10}, \quad \forall v \in V, \forall r \in R \tag{9}$$

This ensures that the loading time at the depot is calculated based on the total demand loaded onto the vehicle before each trip.
Unloading time at nodes:

$$UL_i^v = UL \cdot \frac{Q_i}{10}, \quad \forall i \in N, \forall v \in V \tag{10}$$

This calculates the time required for unloading at each node.

Total Time Constraint (including Multiple Trips)

$$T_{route}^v = \sum_{r\in R} \left(LO_r^v + \sum_{(i,j)\in N} \left(\frac{d_{ij}}{s^v} \cdot z_{ij}^{vr} \right) + \sum_{i\in N} UL_i^v \right), \quad \forall v \in V \tag{11}$$

This ensures that the total time taken for each route, including travel, loading, and unloading time, is properly calculated for each trip.

Multiple Trips Constraints:

$$\sum_{r\in R} \sum_{i\in N} Q_i \cdot z_{i0}^{vr} \leq C^v \times \sum_{r\in R} \sum_{i\in N} z_{i0}^{vr}, \quad \forall v \in V \tag{12}$$

This ensures that vehicles can return to the depot, reload, and serve additional nodes without exceeding their capacity.

Vehicle Routing Constraints:

$$\sum_{j \in N} z_{0j}^{vr} = 1, \quad \sum_{i \in N} z_{i0}^{vr} = 1, \quad \forall v \in V, \forall r \in R \tag{13}$$

This ensures that each vehicle begins and ends its route at the depot

2.4. Solution Approach

The proposed Hybrid Particle Swarm Optimization and Genetic Algorithm (HPSOGA) framework introduces a structured integration between PSO and GA, designed explicitly for solving multi-constrained VRP [23], [24]. PSO is employed to explore the global solution space and generate a high-quality initial population, leveraging its strength in rapid convergence. This population is then passed to GA, which applies adaptive crossover and mutation operators to enhance local exploitation and maintain diversity [25]–[29]. The novelty of this hybridization lies in the dynamic interdependence between both algorithms: PSO does not operate in isolation but directly influences the initialization and adjustment process within GA. This synergistic design enables the hybrid model to effectively balance exploration and exploitation while ensuring solution feasibility under complex constraints such as time windows, multi-trip routing, vehicle heterogeneity, and loading/unloading procedures. The overall method of the HPSOGA for solving VRP is presented in Fig. 2.

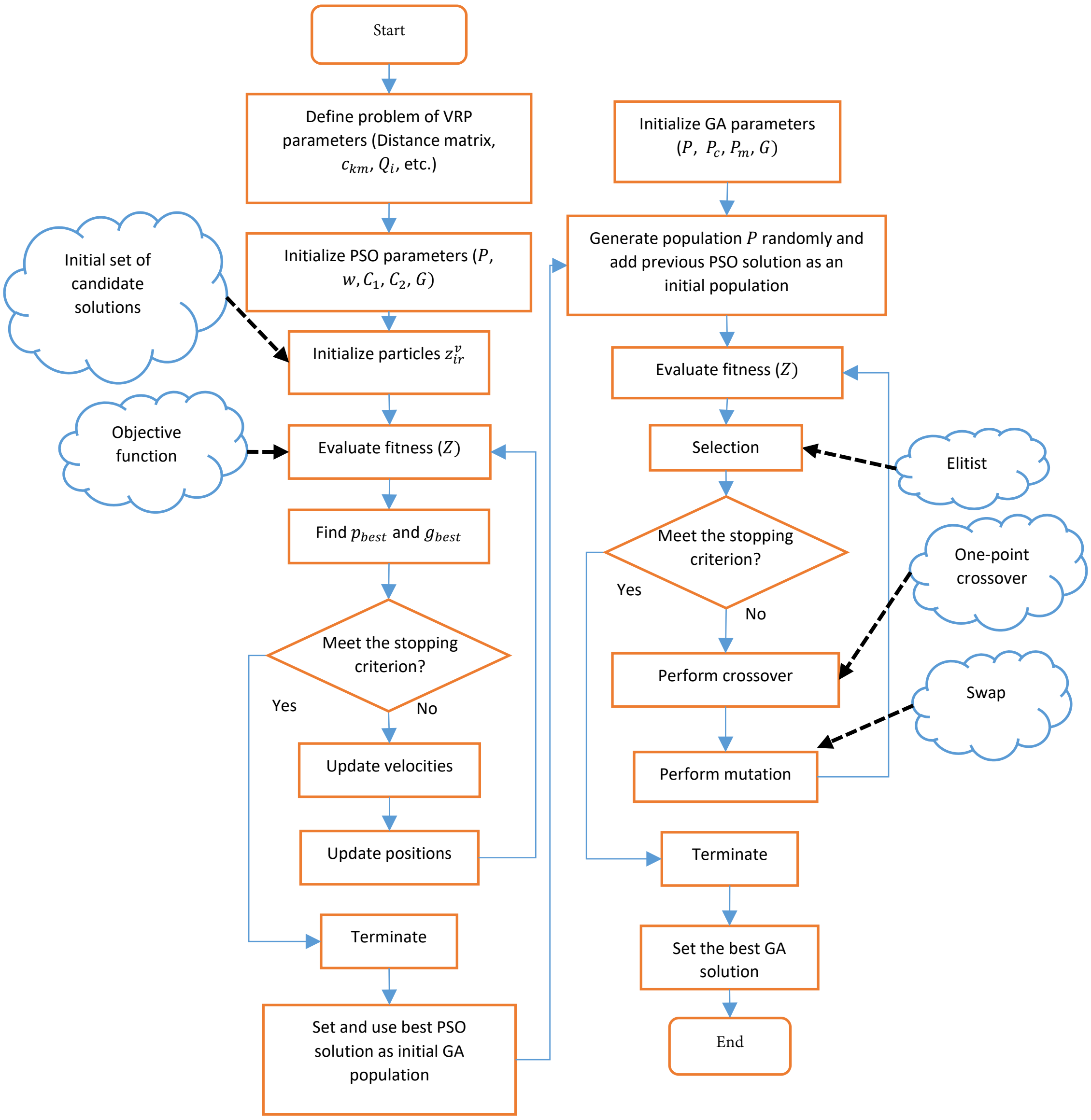


Fig. 2. The procedure of solving VRP based on HPSOGA

The overall procedure of the proposed HPSOGA method (Fig. 2), which sequentially combines PSO and GA optimization stages, is summarized in the unified pseudocode presented in Algorithm 1.

Algorithm 1. Pseudocode of the proposed HPSOGA

```
Begin
  Step 1: Initialization
    Initialize particle positions and velocities (PSO Population)
    Evaluate fitness (Objective function)
  Step 2: PSO Stage
    For generation = 1 to Max_PSO_Generations:
      Update velocities and positions of particles
      Evaluate new fitness values
      Update personal best and global best solutions
    End For
  Step 3: Transfer the best solution from PSO to GA
    Select the global best solution from PSO as the initial population for GA
  Step 4: GA Stage
    For generation = 1 to Max_GA_Generations:
      Perform selection operation on GA population
      Perform crossover operation to generate offspring
      Perform mutation operation for exploration
      Evaluate fitness values of offspring
      Update population with better solutions
    End For
  Step 5: Finalize
    Select the best overall solution from GA as the final optimized solution
End
```

Based on Algorithm 1, the HPSOGA follows a dual-phase approach, which operates as follows:

1) Define VRP Parameters: Set up problem parameters, including distance matrix, demand, transportation costs, vehicle capacities, and other relevant data

2) PSO initialization

   Initialize PSO parameters (Swarm size P_{swarm}, inertia weight w, cognitive C_1 and social coefficients C_2, and maximum iterations G). Generate an initial particle population, each representing a potential solution with vehicle-to-route assignments $z_{ij}^{v,r}$. The particle in the context of $z_{ij}^{v,r}$ can be visualized in Fig. 3. Based on Fig. 3, the search space's dimensionality is determined by the number of binary variables $z_{ij}^{v,r}$. For example, if there are N stations and V vehicles, the total number of binary decision variables is $N \times N \times V$. Thus, the search space is defined by all possible combinations of these binary variables.

$$Z_{i,j}^{1,r} = \begin{pmatrix} z_{11}^1 & z_{12}^1 & z_{13}^1 & z_{14}^1 & z_{15}^1 \\ z_{21}^1 & z_{22}^1 & z_{23}^1 & z_{24}^1 & z_{25}^1 \\ z_{31}^1 & z_{32}^1 & z_{33}^1 & z_{34}^1 & z_{35}^1 \\ z_{41}^1 & z_{42}^1 & z_{43}^1 & z_{44}^1 & z_{45}^1 \\ z_{51}^1 & z_{52}^1 & z_{53}^1 & z_{54}^1 & z_{55}^1 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Route planning = $\{Depot\ (0) > Station\ 2 > Station\ 3 > Depot\ (0)\}$

Fig. 3. A representation of a particle for vehicle 1 ($\boldsymbol{Z_{i,j}^{1,r}}$)

3) PSO execution

   - **Evaluate Fitness:** Measure the total transport cost for each particle using Eq. (1).

- Find p_{best} and g_{best}. Each particle's best position p_{best} and the global best position g_{best} across all particles are determined.
- Check stopping criterion. The algorithm checks whether the stopping criterion (e.g., reaching a maximum number of iterations) has been met. In this study, the algorithm is terminated after 500 iterations. If the stopping criterion is not met, the particles' velocities and positions are updated.
- Velocity and position update. Adjust particle velocities and update positions based on p_{best} and g_{best} to improve solution quality iteratively. For each particle, update the velocity matrix $\left(u_{ij}^{vr}\right)$ using PSO formula:

$$u_{ij}^{vr}(t+1) = w \cdot u_{ij}^{vr}(t) + c_1 \cdot r_1 \cdot \left(p_{ij,\text{best}}^{vr} - z_{ij}^{vr}(t)\right) + c_2 \cdot r_2 \cdot \left(g_{ij,\text{best}}^{vr} - z_{ij}^{vr}(t)\right) \tag{14}$$

where $u_{ij}^{vr}(t+1)$ is the updated velocity of the particle i at time step $t+1$. w is the inertia weight, which controls the influence of the previous velocity. $u_{ij}^{vr}(t)$ is the current velocity of particle i at time step t. c_1 and c_2 are acceleration coefficients that represent the cognitive (individual) and social (group) components, respectively. r_1 and r_2 are random numbers uniformly distributed between 0 and 1. $p_{ij,\text{best}}^{vr}$ is the best-known position of the particle i (personal best). $g_{i,j,best}^{v}$ is the best-known position of the entire swarm (global best $z_{ij}^{vr}(t)$ is the current position of the particle i at time step t. Meanwhile, update each particle's position based on the newly computed velocity.

$$z_{ij}^{vr}(t+1) = z_{ij}^{vr}(t) + u_{ij}^{vr}(t+1) \tag{15}$$

4) Transition to GA: Use the best solution from PSO as an initial candidate for GA to further refine vehicle-to-route assignments
5) GA Initialization
   - GA parameters such as population size P_{GA} crossover probability P_c, mutation probability P_m, and the number of generations G are initialized.
   - Generate the initial GA population by incorporating the best solution from PSO as a starting point. The GA population consists of individual solutions, represented as chromosomes, where each chromosome defines a specific allocation of vehicles to routes for the VRP, denoted as $z_{ij}^{v,r}$. An example of this chromosome structure is shown in Fig. 4

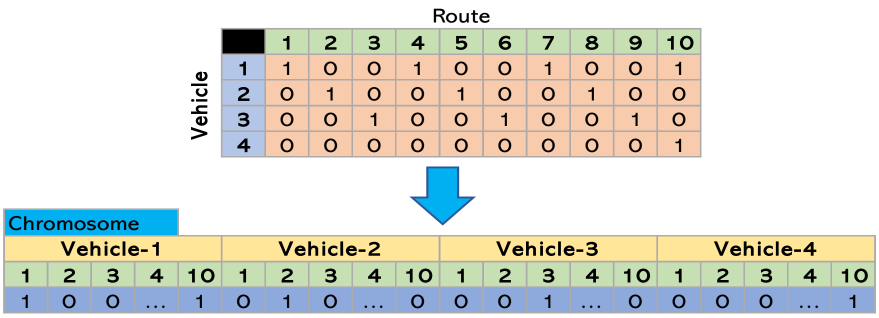


Fig. 4. A representation of chromosome structure within the context of the VRP

6) GA Execution
   - Evaluate fitness: Assess the cost function for each chromosome using Eq. (1).
   - Selection: Use an elitist strategy to retain the best solutions for reproduction.

- Stopping criterion. The algorithm checks whether the GA's stopping criterion has been met. If not, it proceeds to perform crossover and mutation. This study sets the number of generations to 500.
- Crossover. Perform one-point crossover on selected parents to generate offspring, enhancing genetic diversity. The crossover rate (Pc) determines how frequently this occurs; a higher rate increases diversity by blending parent traits, while a lower rate retains more parent characteristics. Fig. 5 illustrates a one-point crossover.

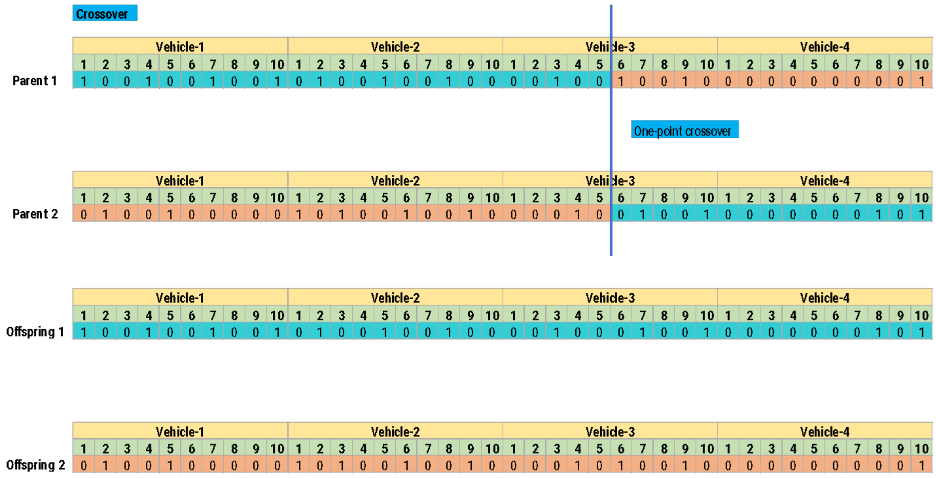


Fig. 5. Example of one-point crossover

- Mutation. Apply swap mutation to introduce variation within solutions. The mutation rate (controls its frequency: a higher rate enhances diversity and exploration, while a lower rate retains existing traits. Fig. 6 illustrates the swap method.

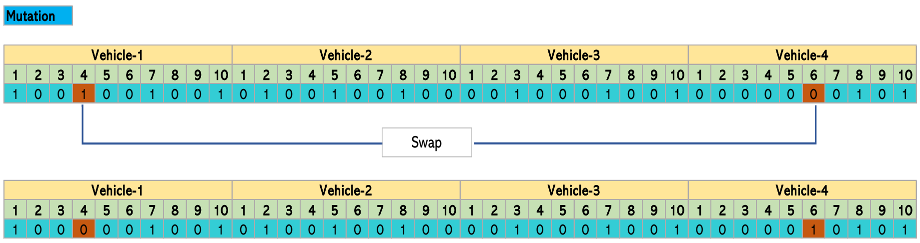


Fig. 6. Example of swap mutation

7) Final solution: The best solution from the GA phase represents the optimal routing configuration, minimizing transportation costs while satisfying the VRP constraints for LPG distribution

3. Results and Discussion

To address the VRP in LPG distribution, the mathematical model is encoded in Microsoft Excel and solved using a HPSOGA approach facilitated by the XL Optimizer (https://xloptimizer.com/) and Genehunter (https://www.wardsystems.com/genehunter.asp) add-ins. XL Optimizer is employed for implementing PSO to generate strong initial solutions, while Genehunter applies GA for further exploration and refinement. This combined use of add-ins improves the efficiency and effectiveness of route planning. To assess the performance of this approach, several numerical experiments were conducted on a PC with processor Intel (R) Core ™ i5 10500H CPU @ 2.5 GHz and 8 GB RAM under Windows 10 Professional.

3.1. Test Instances and Parameter Setting of the Proposed Algorithm

This paper addresses a complex problem that incorporates real-world constraints rarely covered in existing literature, making direct comparisons challenging due to the lack of prior research and benchmark datasets. To evaluate the algorithm's effectiveness, experiments were conducted using data from an actual LPG distribution case in Yogyakarta. This dataset, detailed in a distance matrix covering 89 locations (one depot and 88 stations) is linked here (https://bit.ly/4cN3WfV), includes essential information for route planning, such as distances, demand, real route, and time windows. Additional operational parameters, such as vehicle capacity and transportation costs, are provided in Table 2, ensuring the VRP model's solutions are practical for real-world distribution scenarios.

Table 2. Data related to delivery operations

Vehicle type, V	C^v (Units)	S^v (Km/hr)	c_{km} (Rupiah/Km)	P_{early} & P_{late} (Rupiah/hr)	P^0_{late} (Rupiah/hr)	LO (second)	UL (second)
1	560	50	1410	5000	10000	39.29	32.56
2	560	50					
3	360	55					
4	250	65					

In the process of solving the proposed VRP model, this research carefully determined the HPSOGA parameters to ensure effective experimentation and solution quality. For PSO, parameters were set as follows: $P_{swarm} = 50$, inertia weight $w = 0.9$, acceleration coefficients $C_1 = 2$, $C_2 = 2$, and $G = 500$. These values were selected based on preliminary trials showing that smaller swarms (e.g., 20–30) converged faster but often produced suboptimal solutions due to limited exploration, while larger swarms (e.g., >70) increased computation time without significant improvement, making 50 a balanced choice. Initial PSO particles were generated randomly within the feasible solution space, respecting capacity and time-window constraints; this randomized initialization strategy is known to preserve diversity and prevent early convergence in metaheuristic search.

For GA, parameter settings included $P_{GA} = 175$, $P_c = 0.95$, $P_m = 0.01$, and $G = 500$. The initial GA population was seeded with the best PSO solution supplemented by additional randomly generated feasible individuals. This hybrid seeding strategy, which combines strong heuristic solutions with random variability, has been shown to enhance both convergence speed and population diversity in GA research [30]. Tests with lower crossover rates (e.g., 0.7) reduced convergence speed and diversity, whereas higher mutation rates (>0.05) led to unstable behavior. Overall, this configuration balances exploration, exploitation, and stability across the hybrid framework. By integrating global search via PSO with local refinement by GA, HPSOGA effectively navigates complex VRP landscapes and consistently improves solution quality

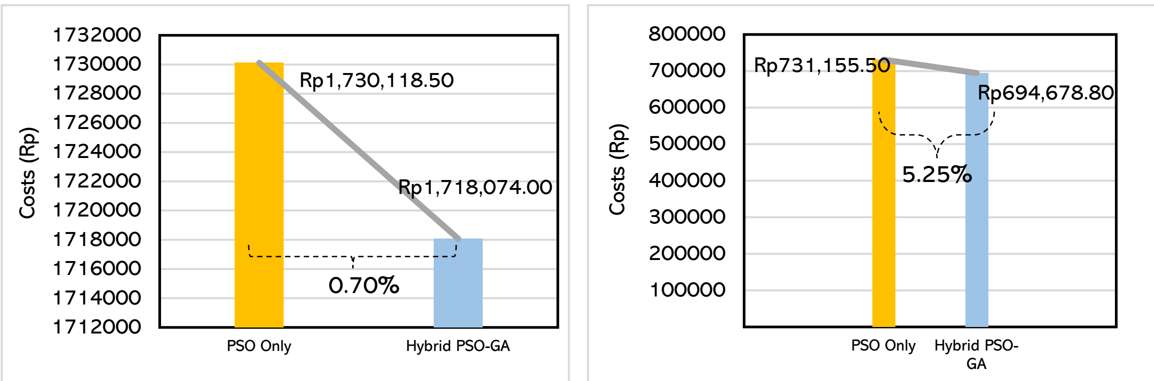
3.2. Experimental Analysis of HPSOGA for Solving VRP on 88 and 40 nodes

Numerical experiments using real data sets were conducted to evaluate the efficiency of the proposed HPSOGA in solving the VRP model for two problem sizes: 88 nodes and 40 nodes. These two scales were chosen to examine the algorithm's robustness and scalability. As the number of nodes and vehicles increases, the number of possible route combinations grows rapidly, making the solution space much larger and more complex. In the 88-node problem, the search space becomes more difficult to explore due to the combination of delivery time windows, vehicle capacity limits, and multi-trip routing, which together reduce the number of feasible solutions. Compared to the 40-node case, the 88-node problem requires more intensive search strategies to avoid being trapped in local optima. This highlights the benefit of combining PSO for global exploration and GA for further refinement. Each experiment was repeated five times using the same PSO parameters to ensure consistent and reliable results. The best transportation cost achieved was Rp1,730,118.50 for the 88-node case and Rp731,155.50 for the 40-node case, as shown in Table 3, confirming the effectiveness of the proposed approach in minimizing total cost.

Table 3. Performance costs of PSO for VRP model across five experimental runs under 88 nodes and 40 nodes

Problem Size	**Run Test**	**PSO ($P_{swarm} = 50, w = 0.9, C_1 = 2, C_2 = 2$, and $G = 500$)**		**GA ($P_{GA} = 175, P_c = 0.95, P_m = 0.01$, and $G = 500$)**	
		Cost Transport (Rp)	*Time (s)*	*Cost Transport (Rp)*	*Time (s)*
88 nodes	1	1,763,112.50	1523	1,730,118.50	3401
	2	1,847,560.50	1518	**1,718,074.00**	3650
	3	1,819,382.50	1616	1,730,118.50	3401
	4	1,775,038.00	1603	1,730,118.50	3401
	5	**1,730,118.50**	1605	1,730,118.50	3401
Average		1,787,042.4	1573	1,727,709.6	3450
40 nodes		775,147.50	1313	724,993.80	3214
		813,217.50	1302	**694,678.80**	3150
		778,785.30	1302	709,300.50	3200
		731,155.50	1305	709,864.50	3314
		817,549.30	1300	710,569.50	3199
Average		783,171.02	1304	709,881.42	3215

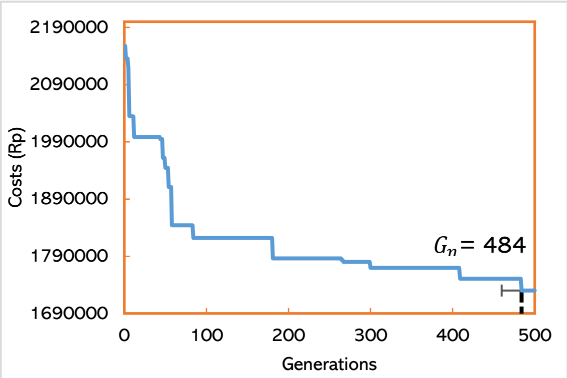
The PSO-generated solution with the lowest cost was subsequently refined using GA, aiming to further minimize overall transportation costs. This two-stage process represents the core structure of the HPSOGA approach. In this study, PSO also serves as a comparative baseline to assess the added value of hybridization. As shown in Table 3 and Fig. 7, the GA-based refinement led to significant improvements over the standalone PSO results. For the 88-node problem (Fig. 7 (a)), the cost was reduced from Rp1,730,118.50 to Rp1,718,074.00, reflecting a 0.70% reduction. For the 40-node problem (Fig. 7 (b)), a more substantial improvement was observed, with costs dropping from Rp731,155.50 to Rp694,678.80 (a 5.25% reduction). These results confirm that HPSOGA consistently outperforms standalone PSO, especially in smaller-scale problems where the solution space is less rugged and more amenable to fine-tuned optimization. Although the standalone GA was not applied separately in this study, its performance in the hybrid structure demonstrates its strength in exploiting promising regions identified by PSO. Overall, the hybrid approach offers a clear advantage in solution quality, accompanied by acceptable increases in computational cost.



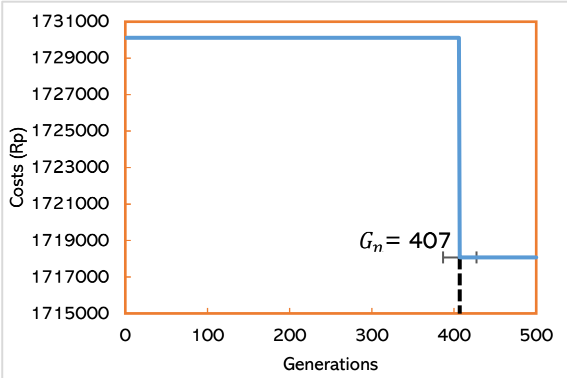
(a) 88 nodes (b) 40 nodes

Fig. 7. Cost improvements for 88-node and 40-node VRP models after hybrid optimization with GA

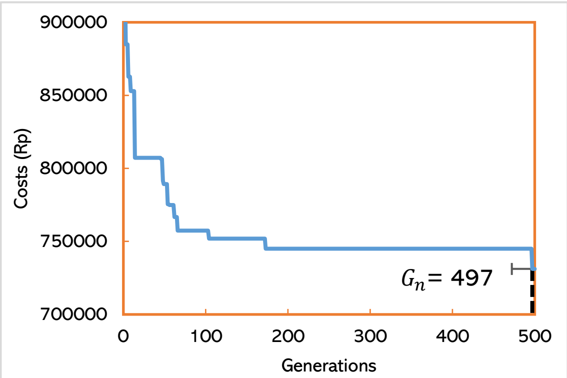
Fig. 8(a) shows the cost minimization process for the 88-node problem using PSO, reaching the lowest cost at the 484th generation in 1605 seconds, demonstrating PSO's gradual convergence. In comparison, Fig. 8(b) displays GA's performance for the same problem, achieving minimum cost at the 407th generation with a runtime of 3650 seconds, indicating GA's detailed exploration and further cost refinement. For the 40-node problem, PSO (Fig. 8 (c)) found the minimum cost at the 497th generation in 1305 seconds, while GA (Fig. 8 (d)) reached it at the 444th generation in 3150 seconds. This balance between PSO's broad exploration and GA's focused refinement highlights HPSOGA's effectiveness.



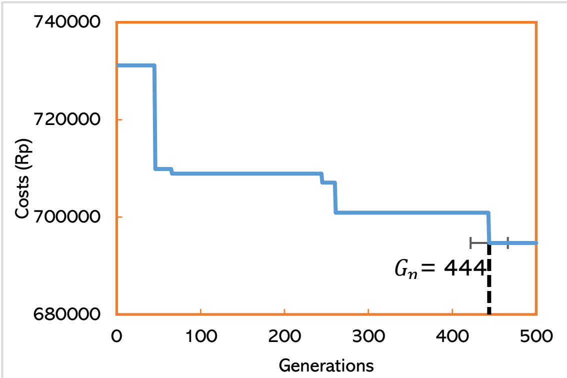
(a) PSO search process for 88 nodes



(b) GA search process for 88 nodes



(c) PSO search process for 40 nodes



(d) GA search process for 40 nodes

Fig. 8. Performance of PSO (a) and GA (b) in achieving optimal Solutions for the VRP Model

Based on the computational experiments illustrated in Fig. 8, both the standalone PSO and the proposed hybrid PSO-GA (HPSOGA) were executed with an equal number of generations, where PSO ran for 500 generations, followed by an additional 500 generations for GA. During the PSO phase, the algorithm demonstrated a rapid reduction in transportation cost in the early generations. However, as it approached the 500th generation, improvement plateaued, indicating convergence to a local optimum. To overcome this stagnation, GA was subsequently employed using the best PSO solution as its initial input. This continuation enabled broader exploration of the solution space and led to further refinements, ultimately improving solution quality beyond what standalone PSO could achieve.

Although this sequential optimization strategy yields improved performance, it inherently introduces higher computational complexity due to its dual-phase structure. The computational load increases further with larger problem instances, as the search space expands with the number of nodes. Therefore, for applications involving national-scale routing or larger datasets, additional strategies such as parallel computing or dynamic population control may be necessary to maintain computational efficiency.

Moreover, as shown in Table 4, HPSOGA successfully identifies near-optimal solutions for minimizing transportation costs across both 88-node and 40-node scenarios. In the 88-node case, the algorithm effectively allocates vehicles with varying capacities (from 250 to 560 units) across multiple trips, even assigning the smallest vehicle to the longest route. In the 40-node case, the reduced number of delivery points results in shorter distances and simpler routes. The algorithm's ability to accommodate multi-trip deliveries while balancing vehicle loads highlights its cost-efficiency and operational flexibility. These results confirm HPSOGA's strong optimization capability and scalability in addressing complex and realistic VRP scenarios.

Table 4. Allocation of vehicles to routes forming the transportation network for 88 nodes and 40 nodes

88 Nodes	44 Nodes
Vehicle 1: 308.70 km	*Vehicle 1: 158.50 km*
Trip 1: 0 → 9 → 26 → 65 → 53 → 47 → 36 → 27 → 0 Trip 2: 0 → 22 → 77 → 43 → 7 → 34 → 51 → 0 Trip 3: 0 → 50 → 4 → 81 → 25 → 11 → 0 Trip 4: 0 → 40 → 10 → 17 → 57 → 6 → 0	Trip 1: 0 → 65 → 87 → 20 → 73 → 38 → 54 → 0 Trip 2: 0 → 47 → 22 → 43 → 32 → 12 → 7 → 37 → 0
Vehicle 2: 252.20 km	*Vehicle 2: 112.58 km*
Trip 1: 0 → 56 → 64 → 85 → 73 → 38 → 54 → 0 Trip 2: 0 → 44 → 23 → 55 → 28 → 2 → 16 → 24 → 0 Trip 3: 0 → 52 → 62 → 88 → 1 → 83 → 84 → 66 → 0	Trip 1: 0 → 56 → 85 → 70 → 3 → 82 → 21 → 0 Trip 2: 0 → 36 → 15 → 60 → 42 → 86 → 75 → 23 → 0
Vehicle 3: 312.70 km	*Vehicle 3: 83.90 km*
Trip 1: 0 → 71 → 31 → 87 → 8 → 0 Trip 2: 0 → 20 → 59 → 76 → 60 → 0 Trip 3: 0 → 42 → 86 → 39 → 0 Trip 4: 0 → 72 → 58 → 33 → 48 → 0 Trip 5: 0 → 80 → 69 → 78 → 46 → 0 Trip 6: 0 → 5 → 35 → 0	Trip 1: 0 → 9 → 26 → 8 → 59 → 0 Trip 2: 0 → 76 → 27 → 0
Vehicle 4: 337.80 km	*Vehicle 4: 137.70 km*
Trip 1: 0 → 70 → 3 → 82 → 0 Trip 2: 0 → 21 → 67 → 18 → 0 Trip 3: 0 → 15 → 32 → 12 → 75 → 0 Trip 4: 0 → 37 → 19 → 68 → 0 Trip 5: 0 → 14 → 49 → 0 Trip 6: 0 → 74 → 61 → 30 → 0	Trip 1: 0 → 71 → 64 → 53 → 0 Trip 2: 0 → 31 → 67 → 18 → 0 Trip 3: 0 → 77 → 44 → 0

3.3. Experimental: Mathematical Formulation Validation

In the validation using real LPG transportation data (see https://bit.ly/4cN3WfV), HPSOGA demonstrated strong performance in handling complex VRP scenarios involving multi-trip requirements, capacitated vehicles, heterogeneous fleets, time windows, and loading/unloading constraints. As shown in Fig. 9, the algorithm effectively optimizes route allocation across various vehicle types, minimizing transportation costs.

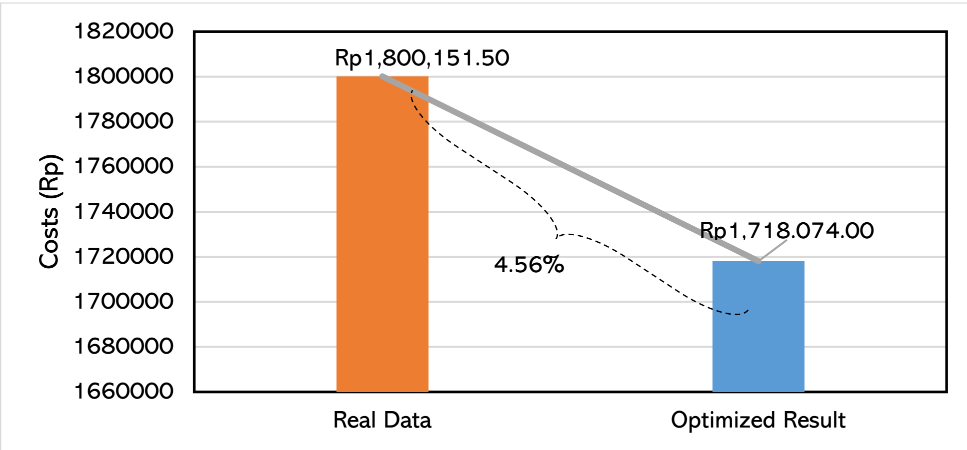
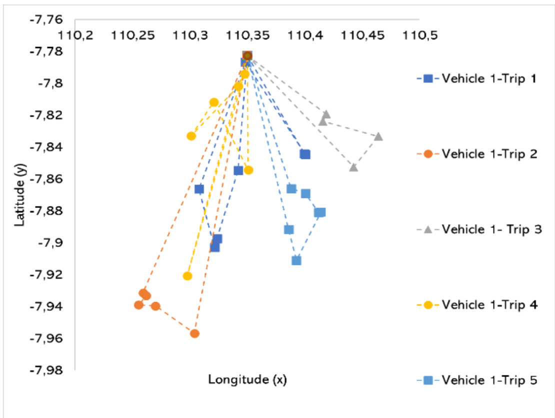
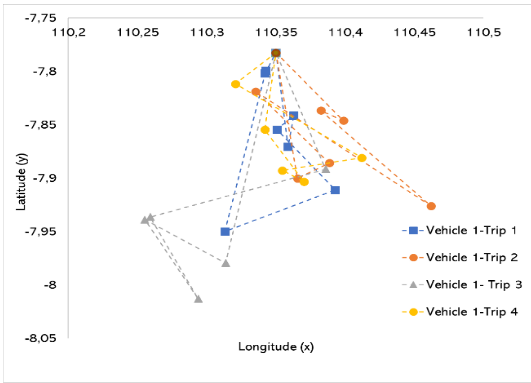


Fig. 9. Comparison of transport costs between optimized routes from the HPSOGA algorithm and original routes from actual real data

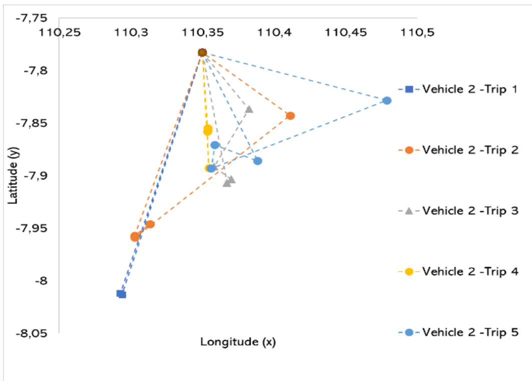
Real data reflects a transportation cost of Rp1,800,151.50, while the optimized route reduces this to Rp1,718,074.00, achieving a 4.56% savings (Rp82,077.50). This improvement results from optimized routes and efficient truck capacity utilization, streamlining operations by reducing trips and fuel consumption, thereby enhancing supply chain profitability. As depicted in Fig. 9, transportation costs are strongly influenced by route efficiency, with Fig. 10 providing a visual comparison of the transportation network between the real route and the optimized route for each vehicle.



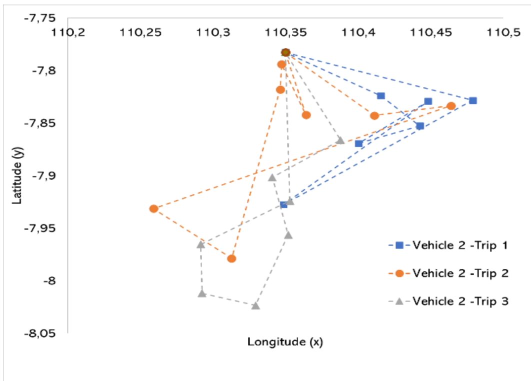
Vehicle-1 (Real route data)



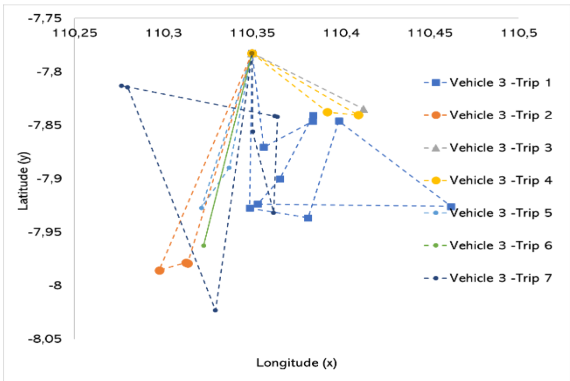
Vehicle-1 (Optimized route data)



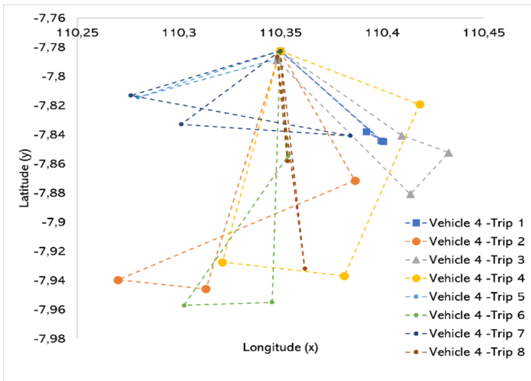
Vehicle-2 (Real route data)



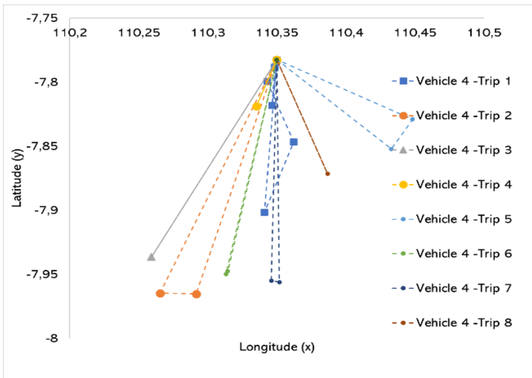
Vehicle-2 (Optimized route data)



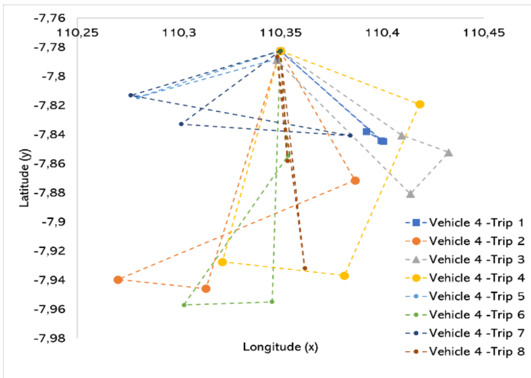
Vehicle-3 (Real route data)



Vehicle-3 (Optimized route data)



Vehicle-4 (Real route data)



Vehicle-4 (Optimized route data)

Fig. 10. Comparison of the transportation network per vehicle for real route data and optimized routes based on the HPSOGA algorithm

The optimization of vehicle route allocation, as demonstrated through the comparison between real and optimized route data, shows a marked improvement in operational efficiency and cost-effectiveness. The optimized routes successfully minimize total distance traveled and significantly reduce penalty costs by improving adherence to delivery time windows. As shown in Table 5, the real (pre-optimization) routes incurred a total of 5 penalty violations, primarily due to early or late arrivals, whereas the optimized routes reduced this number to only 1 violations, demonstrating enhanced scheduling accuracy. Additionally, the optimized solution ensures full compliance with vehicle capacity constraints. Each assigned route delivers quantities that do not exceed the capacity limits of the respective vehicles: Vehicle 1 = 560, Vehicle 2 = 560, Vehicle 3 = 360, and Vehicle 4 = 250 units. Furthermore, the routing also accounts for loading and unloading time requirements, enabling vehicles to meet service windows without excessive delays or idle time. This improved allocation of resources enhances route efficiency and ensures better utilization of the fleet.

These outcomes confirm that the optimization approach not only streamlines the overall transportation process but also produces solutions that comply with all operational constraints, including capacity, timing, and service handling. Ultimately, the resulting solution contributes to a more reliable, cost-efficient, and scalable logistics operation—particularly valuable for high-stakes distribution systems such as LPG, where route compliance and punctuality directly affect public service continuity and safety

4. Conclusion

This study presents the development and application of a Hybrid Particle Swarm Optimization and Genetic Algorithm (HPSOGA) approach to address a complex variant of the Vehicle Routing Problem (VRP) in the context of Liquid Petroleum Gas (LPG) distribution. The proposed model integrates multiple real-world constraints, including heterogeneous fleet management, specific delivery time windows, penalties for early or late arrivals, multi-trip routing, and complex loading and unloading processes. These constraints are not only operationally significant but also directly linked to public safety, household-level reliability, and social welfare, particularly in rural and disaster-prone areas.

A key novelty of this research lies in the tightly integrated hybridization of PSO and GA. Unlike conventional approaches that apply these metaheuristics sequentially or in isolation, our framework enables PSO to guide initial solution generation while GA performs adaptive refinement, achieving a more balanced and efficient search process. This coordination significantly enhances convergence speed and robustness under high-dimensional constraints.

Through extensive computational experiments on instances involving 88 and 40 delivery stations, the HPSOGA demonstrated superior performance compared to standalone methods. The hybrid algorithm improved total transportation cost efficiency by up to 4.56%, optimized vehicle capacity utilization, and minimized delivery penalties. Validation using real operational data confirmed that the model not only generates optimal or near-optimal routing solutions but also aligns well with the realities of field operations, reinforcing its practical relevance.

Beyond technical effectiveness, the model contributes meaningfully to several SDGs. By improving delivery timeliness and efficiency, it supports SDG 7 (Affordable and Clean Energy) through enhanced energy access. The cost-efficient routing also translates to lower fuel usage, contributing to SDG 13 (Climate Action) by reducing CO_2 emissions, and aligns with SDG 11 (Sustainable Cities and Communities) by decreasing vehicle activity and air pollution in urban environments. These benefits underscore the societal and environmental impact of optimized LPG distribution.

In addition to optimization performance, the model can support broader public policy and societal objectives. Its structure is compatible with national or regional LPG distribution regulations, where reliable delivery and safety compliance are required. Moreover, the model could be leveraged in disaster response logistics, such as emergency LPG deployment to shelters or recovery zones, where timely, constraint-aware delivery is critical. These real-world applications highlight the model's relevance for infrastructure resilience and energy governance.

Table 5. Comparison of Constraint Compliance Between Real and Optimized Routes (Time Windows, Capacity, and Loading Considerations)

T	Tm	P	PC (Rp)	TD	DU	TC (Rp)	T	Tm	P	PC (Rp)	TD	DU	TC (Rp)
		Real Route Data-Vehicle 1							*Optimized Route Data-Vehicle 1*				
1	10:22	1	10000	57.80	650.00	81498	1	10:37	0	0	78.40	560.00	110544
2	12:19	0	0	61.80	390.00	87138	2	13:23	0	0	93.70	470.00	132117
3	13:52	0	0	42.40	370.00	59784	3	15:54	0	0	84.30	440.00	118863
4	15:55	0	0	45.10	610.00	63591	4	17:44	1	10000	52.30	430.00	73743
5	17:46	2	20000	45.60	490.00	64296	5						
6							6						
7							7						
8							8						
TOTAL	*17:46*	*3*	*30000*	*252.7*		*356307*	*TOTAL*	*17:44*	*1*	*10000*	*308.70*		*435267*
		Real Route Data-Vehicle 2							*Optimized Route Data-Vehicle 2*				
1	09:27	0	0	57.10	170.00	80511	1	11:00	0	0	97.60	550.00	137616
2	10:53	0	0	40.80	320.00	57528	2	13:26	0	0	72.50	520.00	102225
3	12:17	0	0	43.10	290.00	60771	3	15:57	0	0	82.10	480.00	115761
4	13:30	0	0	34.00	290.00	47940	4						
5	15:29	0	0	68.70	320.00	96867	5						
6							6						
7							7						
8							8						
TOTAL	*15:29*	*0*	*0*	*243.7*		*343617*	*TOTAL*	*15:57*	*0*	*0*	*252.20*		*355602*
		Real Route Data-Vehicle 3							*Optimized Route Data-Vehicle 3*				
1	11:19	0	0	113.00	680.00	159330	1	09:57	0	0	72.80	330.00	102648
2	12:30	0	0	37.10	270.00	52311	2	11:43	0	0	63.30	330.00	89253
3	12:57	0	0	16.80	80.00	23688	3	12:56	0	0	35.80	300.00	50478
4	13:41	0	0	29.20	120.00	41172	4	14:34	0	0	53.40	360.00	75294
5	14:38	0	0	38.70	130.00	54567	5	16:00	0	0	43.10	350.00	60771
6	15:40	0	0	49.60	70.00	69936	6	17:15	0	0	44.30	230.00	62463
7	18:57	1	20000	117.20	620.00	165252	7						
8							8						
TOTAL	*18:57*	*1*	*20000*	*401.6*		*566256*	*TOTAL*		*0*	*0*			*440907*
		Real Route Data-Vehicle 4							*Optimized Route Data-Vehicle 4*				
1	09:23	1	10000	47.25	370.00	66623	1	08:54	0	0	28.40	250.00	40044
2	10:27	0	0	52.80	140.00	74448	2	10:17	0	0	59.70	250.00	84177
3	11:27	0	0	56.00	80.00	78960	3	11:24	0	0	43.80	250.00	61758
4	12:03	0	0	31.20	70.00	43992	4	12:46	0	0	62.10	230.00	87561
5	12:52	0	0	32.80	170.00	46248	5	13:30	0	0	23.60	200.00	33276
6	13:53	0	0	44.30	180.00	62463	6	14:41	0	0	52.50	200.00	74025
7	14:51	0	0	44.20	150.00	62322	7	15:47	0	0	48.30	200.00	68103
8	15:30	0	0	27.60	120.00	38916	8	16:29	0	0	19.40	220.00	27354
TOTAL	15:30	1	10000	336.15		473972	TOTAL	16:29	0	0	337.80		476298

[a] Notes: T= Trip, Tm=Time, P=Penalty, PC=Penalty Costs; TD=Total Distance; DU=Delivery Unit; TC= Total costs

Beyond serving as a practical decision-support tool for logistics planners and energy distributors, the proposed model also offers important interdisciplinary contributions. From the lens of operations research, it advances the development of hybrid metaheuristics for solving high-dimensional, multi-constrained problems. For transportation engineering, the model provides a practical framework for route planning, vehicle assignment, and service level optimization. From the perspective of sustainable urban development, the efficient use of resources, reduced fuel consumption, and improved service reliability support cleaner and more equitable city logistics. These implications reflect the broader utility of the model beyond LPG delivery systems.

Nevertheless, we acknowledge several limitations. The current model assumes static demand and deterministic travel conditions. Future research should explore dynamic routing scenarios that incorporate real-time traffic information, weather conditions, and stochastic customer demand to enable more responsive and adaptive decision-making. Additionally, the model could be extended into a multi-objective VRP framework, balancing trade-offs between cost, environmental impact, service level, and energy efficiency. Interdisciplinary extensions involving environmental modeling, dynamic optimization under uncertainty, and policy integration are also promising directions to further enhance the applicability and societal impact of this approach.

Acknowledgment

The authors gratefully acknowledge the financial support from the Institute for Research and Community Service, Universitas Pembangunan Nasional Veteran Yogyakarta, through the International Collaborative Research Grant No. 125/UN62.21/DT.07.00/2024. The authors also extend their sincere appreciation to the editor and anonymous reviewers for their valuable comments and constructive suggestions, which have significantly improved the quality of this manuscript.

Declarations

Author contribution. N.I. and R.A.C.L. contributed to the conceptualization, data curation, and methodology of the study. The investigation was carried out by N.I., R.A.C.L., and S.H.A.-R., while resources were provided by all three. R.A.C.L., A.M.K., and Y.L were responsible for software development, with visualization handled by R.A.C.L. The manuscript was written collaboratively by N.I., R.A.C.L., and S.H.A.-R. Project administration and funding acquisition were managed by N.I. All authors have reviewed and approved the final version of the manuscript for publication

Funding statement. The authors gratefully acknowledge the financial support provided by the Institute for Research and Community Service at Universitas Pembangunan Nasional Veteran Yogyakarta, under the International Collaborative Research Grant No. 125/UN62.21/DT.07.00/2024

Conflict of interest. The authors declare no conflict of interest.

Additional information. Additional supporting information is available for download at https://bit.ly/4cN3WfV (accessed on 10 December 2024).

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