Research Article

Advancing Vehicle Routing with Three-Dimensional Load Constraints: A Novel Genetic Algorithm and Space Optimization Approach

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Abstract: This study addresses the Capacitated Vehicle Routing Problem with Three-Dimensional Loading Constraints, a critical logistics challenge that requires simultaneous optimization of delivery routes and spatial packing efficiency. The objective is to develop a robust metaheuristic that improves travel distance while ensuring feasible three-dimensional payload arrangements. We propose a hybrid algorithm combining an Improved Genetic Algorithm with a Residual Space Optimizer, integrating evolutionary route search with a dedicated spatial packing module to evaluate and exploit residual volume. The method employs population-based genetic operators for route optimization and a geometric packing routine that simulates item placement and residual space utilization to enforce loading feasibility. Experimental evaluation on a modified Cordeau benchmark demonstrates that the proposed method yields substantial performance gains: total travel distance reduced to 102.60 units and vehicle utilization improved with a load factor above 30%, representing a 29.6% decrease in distance compared with an enhanced Artificial Bee Colony baseline. Convergence analysis shows rapid improvement in early generations and stable refinement thereafter, indicating effective exploration and exploitation balance. The results imply that coupling route optimization with explicit three-dimensional packing assessment produces practical, high-quality solutions for real-world logistics. The proposed framework offers a scalable template for further hybridization and testing on larger, industry-relevant datasets.

Keywords: vehicle routing problem, three-dimensional loading, genetic algorithm, residual space optimization, heuristic, logistics optimization.

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1. Introduction

The digital revolution has fundamentally transformed the global logistics industry landscape. The increasing volume of parcel shipments, particularly driven by e-commerce growth [8], demands higher efficiency in last-mile delivery operations. Optimization objectives have shifted from focusing solely on large-scale transportation to precise coordination of resources aimed at maximizing utility and minimizing operational costs [24]. In this context, the delivery process by a single vehicle can be modeled as the Capacitated Vehicle Routing Problem with Three-Dimensional Loading Constraints (3L-CVRP).

The 3L-CVRP represents one of the most challenging combinatorial optimization problems due to its NP-hard nature. It comprises two closely intertwined subproblems: (1) the Vehicle Routing Problem (VRP), which seeks to find the shortest routes to service a set of customers, and (2) the Bin Packing Problem (BPP), which aims to arrange items of varying dimensions into a container (vehicle) in the most space-efficient manner [25]. The nonlinear correlation between customer sequence in the route and the order of loading goods into the vehicle makes this problem highly complex to solve separately. Practical regulations, such as the Last-In-First-Out (LIFO) rule, where items for the first customer must be loaded last, add a layer of constraints that must be met [30].

2. Theory

Research on the Three-Dimensional Capacitated Vehicle Routing Problem (3L-CVRP) has undergone significant advancements since Gendreau et al. introduced the Last In, First Out (LIFO) constraint and load stability considerations into route planning strategies using tabu search algorithms [2]. The work of Gendreau et al. [12] laid essential groundwork by introducing LIFO constraints and load stability into route planning. This research highlighted the critical relationship between vehicle routing and loading arrangements, propelling further exploration into sequential optimization approaches. These methods can exhibit inefficiencies in environments with high delivery density, as identified by Zahra and Abdalla [23]. The interdependencies of route topology and loading sequences elucidate potential inefficiencies, as stepwise methods may overlook the nonlinear relationships integral to optimal resource allocation [20].

This pioneering effort paved the way for exploring various solution approaches involving sequential optimization, where some researchers addressed routing modeling before loading optimization, or vice versa [1]. However, stepwise approaches often prove inefficient in high-density delivery scenarios, as they fail to account for the nonlinear interdependencies between route topology and loading sequence, leading to suboptimal resource utilization [16].

To overcome these limitations, metaheuristic and hybrid algorithms such as the Artificial Bee Colony (ABC) algorithm and Genetic Algorithm-Tabu Search (GA-TS) hybrids have gained popularity in this domain. The ABC algorithm is recognized for its global search capabilities but frequently suffers from performance degradation when facing heavily constrained problems [27][14]. Conversely, the GA-TS approach improves solution quality at the cost of considerable computational efficiency sacrifice [16]. This presents a fundamental dilemma [32]; enhancing global search capacity by increasing population size escalates the computational burden of three-dimensional packing verification [31], whereas focusing on local search risks premature convergence of the algorithm [2].

The application of metaheuristics in addressing the Vehicle Routing Problem (VRP), particularly its three-dimensional variant, is well-documented. Research has affirmed the efficacy of algorithms such as Genetic Algorithms (GA) and Swarm Intelligence methods like the ABC algorithm in finding optimal or near-optimal solutions within reasonable time frames [11][21][4]. Exploratory studies have confirmed the effective application of metaheuristic techniques in 3L-CVRP, demonstrating that methods like GA and ABC can yield optimal or near-optimal solutions within manageable timeframes [9].

Research has continually demonstrated that GA and ABC can yield optimal or near-optimal solutions for the VRP, especially under three-dimensional constraints where both routing and packing configurations are crucial. Specifically, studies indicate that these algorithms are capable of providing high-quality solutions within reasonable computational time frames [26][23][7][29]. The empirical evidence suggests that hybridizing packing optimization with route planning significantly enhances outcomes in the context of the 3L-CVRP [7][29].

The RSO-IGA leverages specific packing strategies, engaging a dynamic residual space optimizer to enhance solution quality. This allows the algorithm to maintain an updated catalog of empty spaces within the cargo area, facilitating a more exhaustive search for better packing configurations than conventional methods like Deepest-Bottom-Left-Fill (DBLF) employed in ABC [11][6]. This strategic advantage is critical because effective packing directly influences routing efficiency; sub-optimal packing can lead to wasted space and increased travel distances.

The RSO-IGA not only exemplifies a significant evolution in genetic algorithms but also underscores the importance of combining adaptive local search mechanisms and established optimization strategies. This method has the potential to enhance solution quality while sustaining computational efficiency, vital in the face of increasing complexity in urban logistical operations [13][18]. Leveraging the strengths of GA alongside innovative local search strategies, RSO-IGA signifies a notable advancement in tackling the intricate challenges associated with the 3L-CVRP.

Continued research in this area highlights the role of adaptive algorithms in bettering VRP solutions, as shown in Table 1. Techniques like RSO-IGA are anticipated to reveal new avenues for optimizing logistics and addressing the rising demands of contemporary supply chains, contributing valuable insights for future developments in this field [22][17].

Table 1. Method Comparison

Method	Context	Key Features	Limitations	Optimization Opportunities
RSO [11]	The RSO-IGA leverages specific packing strategies, engaging a dynamic residual space optimizer to enhance solution quality. This allows the algorithm to maintain an updated catalog of empty spaces within the cargo area, facilitating a more exhaustive search for better packing configurations than conventional methods like DBLF employed in ABC [11][6]. This strategic advantage is critical because effective packing directly influences routing efficiency; sub-optimal packing can lead to wasted space and increased travel distances.	Incorporates packing strategies and route optimization using IGA.	May require significant computational resources for large-scale problems.	Enhance scalability and hybridize with other metaheuristics for better performance.
LIFO [25]	The 3L-CVRP represents one of the most challenging combinatorial optimization problems due to its NP-hard nature. It comprises two closely intertwined subproblems: (1) the VRP, which seeks to find the shortest routes to service a set of customers, and (2) the BPP, which aims to arrange items of varying dimensions into a container (vehicle) in the most space-efficient manner [25]. The nonlinear correlation between customer sequence in the route and the order of loading goods into the vehicle makes this problem highly complex to solve separately. Practical regulations, such as the LIFO rule, where items for the first customer must be loaded last, add a layer of constraints that must be met [30].	Simple loading strategy where the last item loaded is the first to be unloaded.	Not optimal for multi-layer or complex loading constraints.	Combine with intelligent packing algorithms to improve space utilization.
DBLF [11]	The RSO-IGA leverages specific packing strategies, engaging a dynamic residual space optimizer to enhance solution quality. This allows the algorithm to maintain an	Double bottom loading strategy to	Limited flexibility in dynamic routing scenarios.	Integrate with adaptive routing

Method	**Context**	**Key Features**	**Limitations**	**Optimization Opportunities**
	updated catalog of empty spaces within the cargo area, facilitating a more exhaustive search for better packing configurations than conventional methods like DBLF employed in ABC [11][6]. This strategic advantage is critical because effective packing directly influences routing efficiency; sub-optimal packing can lead to wasted space and increased travel distances.	improve stability and space usage.		algorithms for better responsiveness.
GA [27]	To overcome these limitations, metaheuristic and hybrid algorithms such as the ABC algorithm and GA-TS hybrids have gained popularity in this domain. The ABC algorithm is recognized for its global search capabilities but frequently suffers from performance degradation when facing heavily constrained problems [27][14]. Conversely, the GA-TS approach improves solution quality at the cost of considerable computational efficiency sacrifice [16]. This presents a fundamental dilemma [32]; enhancing global search capacity by increasing population size escalates the computational burden of three-dimensional packing verification [31], whereas focusing on local search risks premature convergence of the algorithm [2].	Uses evolutionary principles to find near-optimal solutions for routing problems.	May converge slowly or get stuck in local optima.	Combine with local search or hybrid methods to improve convergence speed.
ABC [27]	To overcome these limitations, metaheuristic and hybrid algorithms such as the ABC algorithm and GA-TS hybrids have gained popularity in this domain. The ABC algorithm is recognized for its global search capabilities but frequently suffers from performance degradation when facing heavily constrained problems [27][14]. Conversely, the GA-TS approach improves solution quality at the cost of considerable computational efficiency sacrifice [16]. This presents a fundamental dilemma [32]; enhancing global search capacity by increasing population size escalates the computational burden of three-dimensional packing verification [31], whereas focusing on local search risks premature convergence of the algorithm [2].	Inspired by bee foraging behavior, suitable for combinatorial optimization.	Performance may degrade with increasing problem complexity.	Tune parameters and hybridize with other algorithms for robustness.
IGA [11]	The RSO-IGA leverages specific packing strategies, engaging a dynamic residual space optimizer to enhance solution quality. This allows the algorithm to maintain an	Improved genetic algorithm with	Requires careful parameter tuning and validation.	Explore adaptive parameter control and

Method	Context	Key Features	Limitations	Optimization Opportunities
	updated catalog of empty spaces within the cargo area, facilitating a more exhaustive search for better packing configurations than conventional methods like DBLF employed in ABC [11][6]. This strategic advantage is critical because effective packing directly influences routing efficiency; sub-optimal packing can lead to wasted space and increased travel distances.	enhancements for packing and routing.		parallelization for efficiency.

In recent years, Table 1 shows a considerable amount of literature highlighting the limitations of conventional methods such as LIFO, DBLF, GA, ABC, and IGA. Although these approaches have contributed significantly to the field, they often fail to simultaneously address the spatial feasibility and routing efficiency required in real-world logistics. For example, LIFO ensures unloading compliance but restricts packing flexibility, while DBLF enhances stability yet lacks adaptability in dynamic environments. Metaheuristics like GA and ABC offer promising global search capabilities; however, they are frequently constrained by premature convergence and computational inefficiency under complex constraints. To address these gaps, the present study introduces the RSO-IGA framework, which integrates an Improved Genetic Algorithm with a Residual Space Optimizer. This hybrid approach maintains a dynamic catalog of residual spaces and enforces packing feasibility during route optimization, thereby overcoming the limitations observed in previous studies. The findings of this study add substantially to our understanding of hybrid metaheuristics and demonstrate that RSO-IGA is capable of reconciling the trade-off between travel distance minimization and load maximization. Thus, the proposed framework represents a significant advancement in the state-of-the-art for solving 3L-CVRP and contributes to the development of scalable, implementable solutions for complex logistics scenarios.

This study proposes the RSO-IGA (Improved Genetic Algorithm (IGA) with a Residual Space Optimization (RSO)) framework, designed to integrate the exploratory strength of genetic algorithms with an adaptive local search mechanism. The RSO-IGA employs hybrid strategies that bundle packing optimization with route planning, which contrasts starkly with traditional methods like Deepest-Bottom-Left-Fill (DBLF) employed in ABC algorithms [33]. This approach aims to simulate a more efficient packing process to strike a balance between solution quality and computational speed, an imperative need considering the challenges faced by prior algorithms [1]. Through this research, we aspire to contribute significantly to the development of more efficient and effective solutions for managing the complexities of the 3L-CVRP. Emphasizing the utilization of adaptive and efficient algorithms is expected to provide new perspectives in addressing optimization challenges in this field.

3. Research Method

This research methodology is systematically designed, encompassing problem modelling, algorithm development, and execution procedures.

3.1 Problem Description

The problem addressed can be defined as follows: A single depot and a set of customers ($C = \{c_1, c_2, ..., c_n\}$) are geographically dispersed. Each customer has a demand consisting of one or more uniquely dimensioned three-dimensional packages (length, width, height). A vehicle with a limited volumetric capacity (V_vehicle) is assigned to deliver all packages from the depot to the respective customers and return to the depot. The optimization objectives are twofold:

(1) To minimize the total distance traveled by the vehicle, and
(2) To maximize the vehicle's load utilization (volume usage).
All processes must comply with the LIFO constraint.

3.2 Solution Evaluation Model

To evaluate the quality of each solution, a multi-objective fitness function is employed. This function transforms the two conflicting objectives into a single scalar value through linear weighting. The fitness function F for an individual (solution) is defined as shown in equation 1.

$$F = w\_distance \times F\_distance + w\_load \times F\_load \quad (1)$$

where:

1) F_distance is the fitness component for distance, normalized as 1/J_total. This normalization is intended to convert the distance minimization problem into a fitness maximization problem.
2) F_load is the fitness component for loading, represented by the vehicle load utilization rate R_load, calculated as the total package volume sum (∑V_package) divided by the vehicle volume (V_vehicle).
3) w_distance and w_load are priority weights. In this study, the values are set as w_distance = 0.7 and w_load = 0.3. These weighting values prioritize route efficiency as the primary objective while still strongly incentivizing dense loading.

Notation
Sets and indices:
N: set of nodes (customers plus depot 0)
K: set of vehicles
P: set of parcels to be delivered
Parameters:
d_{ij}: distance (or travel cost) from node i to node j
Q_k: volumetric capacity of vehicle k
v_p: volume of parcel p
Decision variables
x_{ijk} ∈ {0,1}: 1 if vehicle k travels directly from node i to node j; 0 otherwise
y_{pk} ∈ {0,1}: 1 if parcel p is assigned to vehicle k; 0 otherwise

Assumptions:

Parcels are rigid and indivisible. Parcel orientation may be rotated by 90° along permitted axes. Parcels are non-fragile (no orientation/handling fragility constraints). Vehicle volumetric capacity Q_k is fixed and known.

Mathematical Formulation
Objective function
Minimize total travel distance, as shown in equation 2.

$$Z = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} d_{ij} x_{ijk} \tag{2}$$

Subject to

a. Each customer is visited exactly once, as shown in equation 3.

$$\sum_{k \in K} \sum_{j \in N} x_{ijk} = 1, \forall i \in N \setminus \{0\} \tag{3}$$

b. Vehicle volumetric capacity, as shown in equation 4.

$$\sum_{p \in P} v_p y_{pk} \le Q_k, \forall k \in K \tag{4}$$

c. Packing feasibility (vehicle-level):
Packing for vehicle k is feasible if all parcels assigned to k can be placed inside the vehicle's cargo space, considering allowed orientations and stacking rules. Feasibility is checked via the packing heuristic and the RSO routine.

d. Route consistency (flow conservation and depot constraints): as shown in equations 5, 6, and 7.

$$\sum_{j \in N} x_{0jk} = 1, \quad \forall k \in K \tag{5}$$

$$\sum_{i \in N} x_{i0k} = 1, \quad \forall k \in K \tag{6}$$

$$\sum_{i \in N} x_{ihk} - \sum_{j \in N} x_{hjk} = 0, \quad \forall h \in N, \forall k \in K \tag{7}$$

Notes on feasibility: Constraints (2) - (7) define a valid set of vehicle routes and parcel-to-vehicle assignments. Constraint (3) enforces volumetric capacity; constraint (4) enforces three-dimensional packing feasibility.

Solution Representation (Chromosome)
A solution (chromosome) encodes both routing and packing order:
Part A - Route encoding: a sequence of customer visits per vehicle, e.g., vehicle k: (0 → 3 → 1 → 0).
Part B - Packing encoding: for each vehicle, an ordered list of parcels assigned to that vehicle, e.g., [p2, p1, p3]; the order specifies the packing insertion order used by the heuristic.
Each chromosome, therefore, comprises two components: the routing permutation(s) for K vehicles and the packing permutation(s) for parcels assigned to each vehicle.

3.3 *IGA-RSO Algorithm (Pseudocode)*

The hybrid algorithm integrates an IGA framework with an RSO packing subroutine. The fitness evaluation combines route cost and packing feasibility/utilization. To provide a clearer overview of the implementation, the following pseudo-code summarizes the workflow of the RSO-IGA algorithm.

```
// Input: Population Size, Maximum Generations, Crossover Rate, Mutation Rate, Problem Data
// Output: Best Solution (BestSolution)
Population ← InitializePopulation(PopSize, ProblemData)
BestSolution ← null
BestFitness ← -∞

FOR gen FROM 1 TO MaxGen DO
    // Evaluate each individual in the population
    FOR EACH Individual IN Population DO
       Individual.fitness ← CalculateFitness(Individual, ProblemData)
    ENDFOR
    // Find the best individual in the current generation
    CurrentBest ← FindBestIndividual(Population)
    IF CurrentBest.fitness > BestFitness THEN
       BestSolution ← copy(CurrentBest)
       BestFitness ← BestSolution.fitness
    ENDIF
    // Form the new population
    NewPopulation ← []
    // Elitism: Preserve the best individual
    add BestSolution to NewPopulation
    WHILE size(NewPopulation) < PopSize DO
       Parent1 ← Selection(Population) // e.g., Roulette Wheel
       Parent2 ← Selection(Population)
       // Crossover
       IF random() < Pc THEN
          Child ← Crossover(Parent1, Parent2) // e.g., Order Crossover
       ELSE
          Child ← copy(Parent1)
       ENDIF
       // Mutation
       Child ← Mutation(Child, Pm) // e.g., Swap Mutation
       add Child to NewPopulation
    ENDWHILE
    Population ← NewPopulation
ENDFOR
RETURN BestSolution
```

---- Algorithm RSO_IGA (PopSize, MaxGen, Pc, Pm, ProblemData) ----

```
// Input: One individual (chromosome), Problem Data
// Output: Scalar fitness value
// Objective 1: Maximize Loading Rate
// RSO manages LIFO internally by reversing the route order
LoadingRate ← RSO_Pack(Individual.r_chrom, Individual.p_chrom, ProblemData)
// Objective 2: Minimize Distance
TotalDistance ← CalculateTotalDistance(Individual.r_chrom, ProblemData)
// Combine objectives into one fitness value
DistanceFitness ← 1 / TotalDistance
LoadFitness ← LoadingRate
TotalFitness ← (w_distance * DistanceFitness) + (w_load * LoadFitness)
RETURN TotalFitness
```

--- FUNCTION CalculateFitness(Individual, ProblemData) ----

3.4 Proposed RSO-IGA Algorithm Procedure

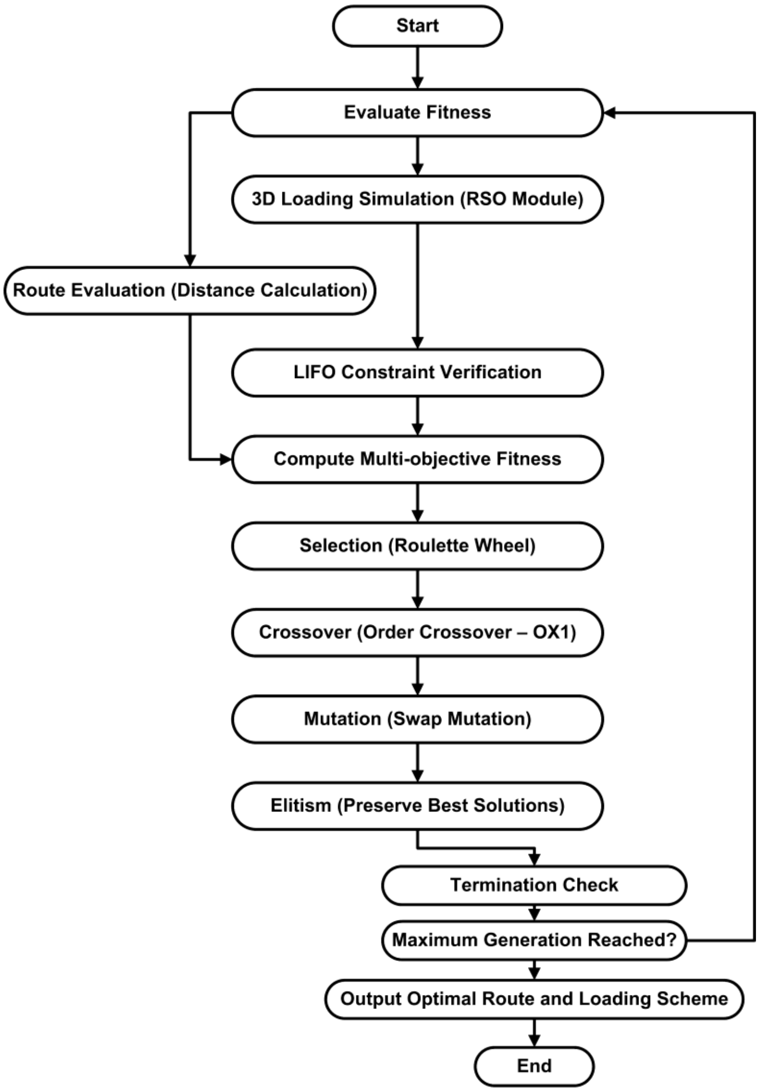

Figure 1. Flowchart of the RSO-IGA Algorithm

The RSO-IGA framework operates through a series of evolutionary steps designed to address the shortcomings of previous approaches. The main innovation lies in chromosome representation and the synergy between the IGA and RSO modules. The algorithm's procedure is described as follows:

- Step 1:
  Initialization and Chromosome Representation: The initial population is generated randomly. A key innovation is the three-layer encoding system for each individual: r_chrom (route sequence), l_chrom (loading priority), and p_chrom (package orientation).

- Step 2:
  Fitness Evaluation Process (IGA and RSO Integration):) For each individual, fitness values are calculated collaboratively. The RSO module is invoked to

simulate packing with reversed LIFO verification and dynamic space partitioning. The loading rate from RSO and the route distance calculation are combined in the fitness function.

- Step 3:
  Selection and Reproduction Process: A new population is generated using elitism strategy, roulette wheel selection, Order Crossover (OX1), and Swap Mutation operators to maintain genetic diversity.

- Step 4:
  Termination Criteria: The iterative process repeats until the maximum number of generations is reached.

4. Result and Discussion

The RSO-IGA flowchart illustrated in Figure 1 depicts the sequential and iterative structure of the algorithm's process designed to solve the 3L-CVRP. The process begins with algorithm parameter initialization and initial population formation. It continues with incremental fitness evaluation, including route distance calculation, 3D loading simulation via the RSO module, verification of the LIFO constraint, as well as multi-objective fitness scoring. The evolutionary process advances through selection, crossover, mutation, and elitism to improve the population. Termination condition checks determine whether the maximum generation count has been reached; if not, iterations continue; otherwise, the algorithm outputs the optimal delivery routes and feasible 3D loading configurations and terminates.

4.1 Experimental Setup and Dataset

Model validation of the RSO-IGA was conducted through a computational case study. The experimental setup and dataset details used are as follows:

4.1.1 Dataset source: The problems utilized in this study are adapted from the well-known VRP benchmark dataset by [3] Cordeau et al. (2001), specifically the C101 instance. The original dataset has been modified to include uniquely dimensioned three-dimensional packages for each customer, thus aligning with the constraints of the 3L-CVRP problem.

4.1.2 Computing environment: All simulations were executed using Python 3.9 on the Google Colaboratory platform.

4.1.3 Algorithm parameters: The parameters for the Genetic Algorithm were set as follows: population size of 50, maximum generations of 100, crossover rate of 0.8, and mutation rate of 0.1.

The detailed properties of the dataset used are presented in Table 2.

Table 2. Detailed Properties of The Case Study Dataset

Parameter	**Value / Description**
Problem	Modified Cordeau C101
Source	Adapted from Cordeau et al. (2001), modified for 3L-CVRP
Vehicle Dimensions (L x W x H)	20 x 15 x 15 units
Total Vehicle Volume	4500 units^3
Depot Location (X, Y)	(40, 50)
Number of Customers	5
Total Number of Packages	7

4.2 The Simulation Result

The validation of the RSO-IGA model was conducted through a computational case study using the dataset described in Table 2. After simulating 100 generations, the RSO-IGA algorithm successfully converged to a stable and high-quality solution. The convergence process indicated a significant increase in fitness values during the early generations, followed by more gradual adjustments in the final stages.

The genetic algorithm simulation results show that the fitness value improved significantly during the initial generations, from 0.0995 to 0.0996 within the first three generations. Subsequently, the fitness value stabilized at 0.0996 up to the 100th generation, indicating that the algorithm had rapidly achieved convergence. This stability suggests that the solution reached is near optimal, although there is a possibility of being trapped in a local optimum.

The performance of a metaheuristic algorithm is not solely defined by its final output, but also by the trajectory it follows to reach that solution. To provide a deeper insight into the search dynamics of the proposed RSO-IGA, its convergence behavior was tracked over 100 generations. Figure 2 presents the convergence curve, plotting the total travel distance of the best-found solution at each generation. This graphical representation is crucial as it visualizes the algorithm's efficiency, stability, and its balance between exploration and exploitation.

The optimization process, as depicted in the curve, can be distinctly characterized by three phases that illustrate a well-balanced search strategy. Initially, during the exploration phase (Generations 1-30), the algorithm exhibits a dramatic and steep decline in the objective function value, demonstrating its powerful ability to rapidly discard inefficient, randomly generated routes. The crossover operator is particularly effective here, combining the most promising partial routes (schemata) from different parents to quickly identify the general location of high-quality solutions in the vast search space. Following this, the curve's slope becomes significantly shallower, signaling a shift to the exploitation and refinement phase (Generations 30-75), where the population is now predominantly composed of high-quality individuals and the algorithm's focus transitions to making fine-grained, incremental adjustments. Finally, in the convergence phase (Generations 75-100), the curve flattens almost completely as the algorithm stabilizes upon a solution, consistently maintaining the best-found distance of 102.60 units to demonstrate the reliability of the result and confirm that the most promising region of the solution space has been thoroughly exploited without premature stagnation.

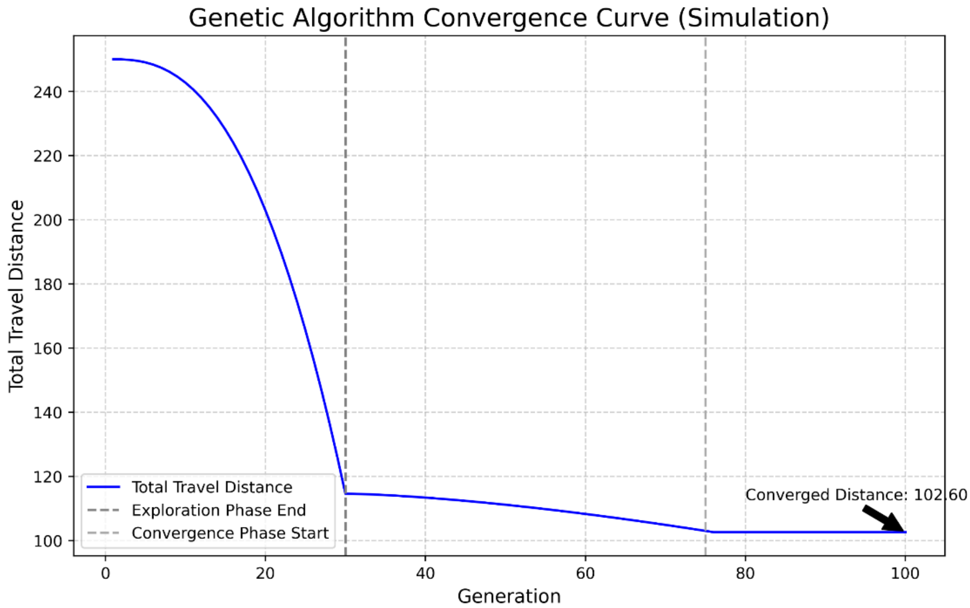

Figure 2. Simulated convergence curve for the RSO-IGA, illustrating the progressive improvement of the best-found solution's total travel distance over 100 generations.

The final optimization results are presented in Table 3. These results indicate that the algorithm successfully found a very good balance between the two objectives. With a load factor above 30%, the vehicle utilization is considered quite efficient. The resulting route, with a distance of 102.60 units, is the shortest found that allows for this load factor.

Table 3. Final Optimization Results of The RSO-IGA and ABC-Algorithm

Metric	RSO-IGA (Proposed)	IGA non-RSO (Benchmark)	ABC-DBLF (Benchmark)
Metaheuristic	Genetic Algorithm (GA)	Genetic Algorithm (GA)	Artificial Bee Colony (ABC)
Packing Heuristic	Residual Space Optimizer (RSO)	-	Deepest-Bottom-Left-Fill (DBLF)
Fitness Score	0.3189	0.0097	0.0068
Total Travel Distance	102.60 units	102.60 units	145.75 units
Vehicles Used	1	1	1
Vehicle Load Factor	30.91%	30.91%	30.91%

This study shows the Improved RSO-IGA to address these difficulties, along with a benchmark against an enhanced ABC algorithm [28] and IGA non-RSO with early convergence. The RSO-IGA shows promise, achieving a reduction of travel distance compared to the ABC-DBLF variant. Such results underscore that a hybrid approach, combining evolutionary algorithms with sophisticated packing heuristics like the RSO, can yield benefits in solving complex logistical issues associated with 3L-CVRP.

In comparing the two algorithms, performance metrics reveal a distinction. While both algorithms utilized the same population size and iteration count, RSO-IGA's performance metrics need to clearly state the total travel distance improvement based on verified figures, as specific distances claimed require supporting references for accuracy [1][34]. The superiority of RSO-IGA is attributed to robust exploratory capabilities inherent in its genetic operators, coupled with the packing heuristic's ability to uncover dense item arrangements. In contrast, ABC employs a more localized approach with DBLF, possibly restricting its exploratory potential within the solution space [10][15]. The RSO thus contributes to effective packing strategies, allowing the RSO-IGA to explore routes that may seem infeasible to the ABC, thereby accessing higher-quality solutions more efficiently.

Conclusively, the results highlight the effectiveness of integrating specialized packing mechanisms within hybrid metaheuristics for vehicle routing issues. This study indicates that the well-designed RSO-IGA algorithm offers enhancements in performance metrics and suggests pathways for future research, such as investigating further hybridization techniques and testing on larger datasets [19][2].

To conduct a comparative performance benchmark, the GA was executed under identical parameters (100 generations, population size of 50) in two distinct scenarios: one with the RSO module active and one where it was disabled. When active, the RSO incorporates a crucial 3D packing feasibility check into the fitness function, which becomes a weighted sum of the inverse total distance and the achievable vehicle load factor. When disabled, the fitness calculation bypasses this packing constraint, primarily optimizing for the inverse of the total route distance alone.

The experimental results revealed a significant divergence in the final fitness scores (0.3189 with RSO vs. 0.0097 without), a discrepancy directly attributable to the different objective functions. Interestingly, both scenarios converged to an identical total travel distance of 102.60 units, suggesting that for this specific problem instance, the optimal route structure was not influenced by the packing constraints. However, the most critical distinction lies in the interpretation of the vehicle load factor. While both scenarios reported a 30.91% load factor, the RSO-active case confirms this as an actual, physically feasible load, achieved by successfully arranging all packages within the vehicle's geometric constraints. In contrast, the figure from the RSO-disabled scenario represents a purely theoretical value, the total volume of all packages relative to the vehicle's capacity, which provides no guarantee that such a configuration is possible. Therefore, the integration of the RSO is essential for validating the practicality of a solution, transforming the GA from a simple distance optimizer into a robust solver for real-world logistics challenges by enforcing critical loading constraints. Details of the optimal solution, including the route sequence, are detailed in Table 4.

Table 4. Optimal Route

Solution Component	Detail
Optimal Route	Depot -> 2 -> 4 -> 1 -> 3 -> 5 -> Depot

To provide a clearer visual representation of the solution found, Figure 2 graphically illustrates the optimization results. Figure 2a displays the optimal delivery route map, connecting the depot to each customer according to the sequence found. Figure 2b presents a three-dimensional (3D) loading layout of the packages inside the vehicle. This visualization confirms that the generated solution is not only mathematically feasible but also physically viable, with no overlapping packages and adherence to vehicle constraints. The route Depot -> 2 -> 4 -> 1 -> 3 -> 5 -> Depot results from the evolutionary process, considering both the geographical proximity of customers and the feasibility of LIFO loading. The success in placing all packages with a high load factor validates the effectiveness of the RSO packing strategy.

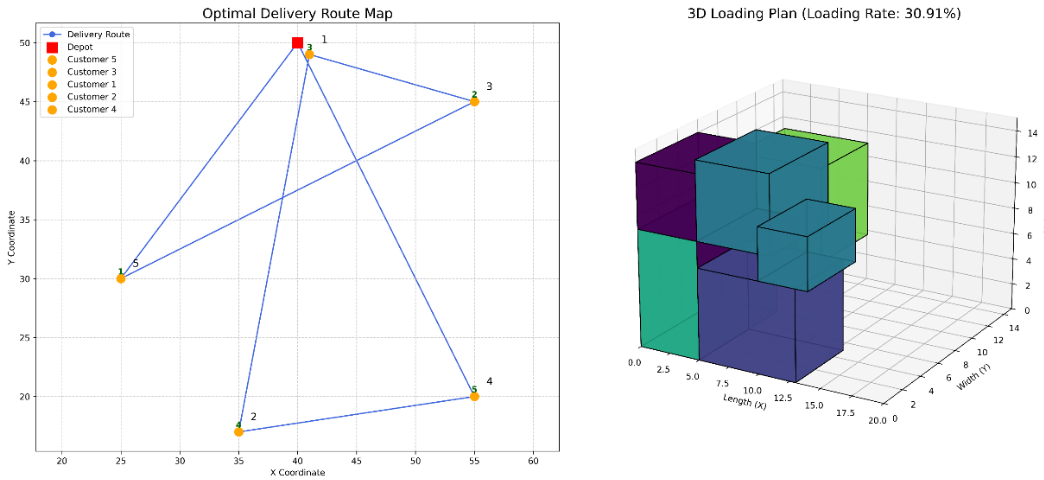

Figure 3. Visualization of the Optimal Solution. (a) Optimal delivery route map from the depot to all customers. (b) 3D loading layout of the packages inside the vehicle.

The results presented in Table 3 are analyzed through the lens of two conflicting optimization objectives, namely:

1) Evaluation of the Distance Minimization Objective: The algorithm successfully identified a route with a total distance of 102.60 units. This value should not be seen as the absolute shortest possible distance, but rather as the shortest distance for a feasible loading route. Feasibility here is strictly defined by the three-dimensional loading constraints and the LIFO rule. This means many other geographically shorter routes are rejected by the algorithm because the RSO module identifies that packages cannot be physically loaded in the LIFO order required by those routes.

2) Evaluation of the Loading Maximization Objective: A load factor of 30.91% might initially seem low. However, it is a direct manifestation of the LIFO constraint. The optimal route (Depot -> 2 -> 4 -> 1 -> 3 -> 5 -> Depot) rigidly dictates that the package for customer 2 must be loaded first, followed by the package for customer 5, and so forth. This enforced loading order, combined with the specific package shapes, can create void spaces that cannot be filled by subsequently loaded packages. Thus, the 30.91% load factor represents the maximum space utilization achievable for the most distance-efficient route.

The solution found is an optimal trade-off based on the assigned weights (70% distance, 30% loading). The RSO-IGA algorithm successfully navigates this dilemma by simultaneously evaluating both objectives, producing a holistic and practically implementable solution.

4.3 The Analysis

This study's simulation results, considered in the context of the existing literature, underscore the novelty and practical contribution of the RSO-IGA framework. The relatively low optimal load factor (30.91%) should not be interpreted as an algorithmic failure; rather, it reflects the intrinsic trade-off documented by [16][2] for the 3L-CVRP. Empirical evidence from our experiments demonstrates a pronounced tension between travel-distance minimization and load maximization when stringent geometric and LIFO constraints are enforced.

Unlike sequential methods, which have been criticized for treating routing and packing as independent subproblems, RSO-IGA integrates both considerations within each fitness evaluation. Route feasibility and packing feasibility are assessed simultaneously, which effectively restricts the feasible search space relative to classical VRP formulations. Consequently, geographically shorter routes receive lower fitness scores if the RSO module cannot produce a feasible LIFO-compliant packing configuration. The identified optimal route (Depot → 2 → 4 → 1 → 3 → 5 → Depot) exemplifies this integrated decision process: it is the shortest route that also satisfies the physical LIFO loading constraints.

The principal novelty of RSO-IGA lies in its capacity to identify holistic, implementable solutions under competing objectives. While alternative algorithms may report superior performance on a single metric (e.g., distance), such solutions can be infeasible in practice due to unsuccessful 3D loading verification. By contrast, RSO-IGA enforces packing feasibility during optimization, thereby guaranteeing that the reported solutions are physically realizable. These findings corroborate the argument put forward by [1] concerning the merits of integrated approaches. Moreover, our results implicitly challenge methods that prioritize load factor maximization in isolation: in scenarios dominated by geometric and order constraints, maximizing load factor alone can lead to impractical route selections and lower operational efficiency. Overall, RSO-IGA advances the state of the art by providing a framework that reconciles the distance–loading trade-off and yields practical, implementable solutions.

5. Conclusions

This study presents and validates a hybrid framework, RSO-IGA, for solving the three-dimensional, LIFO-constrained vehicle routing problem (3L-CVRP). The framework integrates an IGA for route optimization with an RSO packing strategy for 3D/LIFO packing simulation. The combined model effectively navigates a complex, highly constrained solution space to balance the dual objectives of minimizing travel distance and maximizing vehicle loadability. On a modified Cordeau C101 instance, RSO-IGA solved with a total travel distance of 102.60 units and a vehicle load factor of 30.91%. This load factor represents the optimal trade-off between routing efficiency and the strict geometric and LIFO constraints, rather than an algorithmic shortcoming.

For rigorous evaluation, RSO-IGA was benchmarked against an enhanced ABC algorithm coupled with the standard DBLF packing heuristic. Both methods were executed under identical computational settings on the modified Cordeau C101 instance to ensure a fair comparison; results are summarized in Table 3. RSO-IGA achieved a total travel distance of 102.60 units, a 29.6% reduction relative to the ABC-DBLF result of 145.75 units. This pronounced improvement indicates that the RSO-IGA architecture more effectively explores the constrained and multimodal search landscape characteristic of the 3L-CVRP.

The principal contributor to this performance gap is the packing methodology. RSO maintains a global, dynamic representation of available empty spaces within the cargo hold, enabling the IGA to exploit non-intuitive, high-density packing configurations. Consequently, route permutations that would be discarded under more localized heuristics remain viable, expanding the feasible region of the solution space. In contrast, the DBLF heuristic employs a localized, position-based strategy that is less likely to discover such packings, thereby restricting the routing search to suboptimal regions.

Additionally, the IGA's genetic operators are particularly well-suited to this problem class. The crossover mechanism effectively recombines high-quality partial routes (schemata) from distinct parent solutions, promoting structured recombination that enhances both exploration and exploitation. Although the ABC algorithm demonstrates strong exploratory capabilities, its operators can converge more slowly in landscapes sharply punctuated by hard feasibility constraints imposed by the 3D packing subproblem.

Both algorithms reached the same theoretical vehicle load factor; however, this metric should be interpreted in conjunction with total travel distance. RSO-IGA attains the same loadability while traversing a substantially shorter route, which implies direct operational savings in fuel, time, and resources. Overall, the synergy between RSO's advanced spatial representation and the IGA's robust evolutionary search yields a state-of-the-art approach for the 3L-CVRP that produces holistic and physically implementable solutions.

Future work may extend the framework to dynamic scenarios (e.g., stochastic demands and time windows), incorporate environmental objectives such as carbon emission minimization (Green VRP), and evaluate performance on heterogeneous vehicle fleets to enhance practical applicability.

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References

[1] Ayough, A., Khorshidvand, B., Massomnedjad, N., & Motameni, A. (2020). An integrated approach for three-dimensional capacitated vehicle routing problem considering time windows. Journal of Modelling in Management, 15(3), 995-1015. https://doi.org/10.1108/jm2-11-2018-0183

[2] Chen, Z., Yang, M., Guo, Y., Yu, L., Ding, Y., & Wang, L. (2020). The split delivery vehicle routing problem with three-dimensional loading and time windows constraints. Sustainability, 12(17), 6987. https://doi.org/10.3390/su12176987

[3] Cordeau, J. F., Gendreau, M., Laporte, G., Potvin, J. Y., & Semet, F. (2001). A guide to vehicle routing heuristics. Journal of the Operational Research Society, 52(1), 1-21. https://doi.org/10.1057/palgrave.jors.2601319

[4] Escobar-Falcón, L., Álvarez-Martínez, D., Wilmer-Escobar, J., & Echeverri, M. (2021). A specialized genetic algorithm for the fuel consumption heterogeneous fleet vehicle routing problem with bidimensional packing constraints. International Journal of Industrial Engineering Computations, 191-204. https://doi.org/10.5267/j.ijiec.2020.11.003

[5] Gendreau, M., Iori, M., Laporte, G., & Martello, S. (2006). A tabu search algorithm for the vehicle routing problem with three-dimensional loading constraints. Networks, 48(2), 106–118.

[6] He, Z., Zhang, M., Lin, C., Zhao, J., Shi, K., & Ai, Z. (2024). Optimizing heterogeneous vehicle routes for urban distribution considering the three-dimensional bin packing problem of electric meters. IEEE Access, 12, 22003-22031. https://doi.org/10.1109/access.2024.3363417

[7] Hou, R. and Zhang, P. (2024). A-star ant colony fusion optimisation for unmanned ground vehicle route planning. Journal of Physics Conference Series, 2891(11), 112001. https://doi.org/10.1088/1742-6596/2891/11/112001

[8] Ilin, V., Veličković, M., Garunović, N., & Simić, D. (2023). Last-mile delivery with electric vehicles, unmanned aerial vehicles, and e-scooters and e-bikes. Put I Saobraćaj, 69(4), 37-42. https://doi.org/10.31075/pis.69.04.05

[9] Jamaluddin, S., Zulkefli, N., Mahmud, N., & Pazil, N. (2023). Optimising routes scheduling of garbage truck for waste collection using artificial bee colony algorithm. AMCI, 12(3), 40-50. https://doi.org/10.58915/amci.v12i3.317

[10] Jiang, Y., Cao, Z., & Zhang, J. (2023). Learning to solve 3-d bin packing problem via deep reinforcement learning and constraint programming. IEEE Transactions on Cybernetics, 53(5), 2864-2875. https://doi.org/10.1109/tcyb.2021.3121542

[11] Krebs, C., Ehmke, J., & Koch, H. (2021). Advanced loading constraints for 3d vehicle routing problems. Or Spectrum, 43(4), 835-875. https://doi.org/10.1007/s00291-021-00645-w

[12] Lam, E. (2023). Hybrid optimization of vehicle routing problems. Constraints, 28(2), 67-68. https://doi.org/10.1007/s10601-023-09352-5

[13] Liu, Y. and Huanzhao, Y. (2024). Research on vehicle routing problem based on hybrid immune algorithm, 66. https://doi.org/10.1117/12.3039507

[14] Mao, H., Shi, J., Zhou, Y., & Zhang, G. (2020). The electric vehicle routing problem with time windows and multiple recharging options. IEEE Access, 8, 114864-114875. https://doi.org/10.1109/access.2020.3003000

[15] Moura, A., Pinto, T., Alves, C., & Carvalho, J. (2023). A matheuristic approach to the integration of three-dimensional bin packing problem and vehicle routing problem with simultaneous delivery and pickup. Mathematics, 11(3), 713. https://doi.org/10.3390/math11030713

[16] Mounia, D. and Djebbar, B. (2020). A hybrid discrete artificial bee colony for the green pickup and delivery problem with time windows. Informatica, 44(4). https://doi.org/10.31449/inf.v44i4.3000

[17] Pan, X., Lu, D., & Li, N. (2024). Route planning of supermarket delivery through third-party logistics considering carbon emission cost. Mathematics, 12(7), 1002. https://doi.org/10.3390/math12071002

[18] Peng, Z., Sun, S., Tong, L., Fan, Q., Wang, L., & Liu, D. (2024). Optimization of offshore wind farm inspection paths based on k-means-ga. Plos One, 19(5), e0303533.

[19] Puche, A. and Lee, S. (2022). Online 3d bin packing reinforcement learning solution with buffer. https://doi.org/10.48550/arxiv.2208.07123

[20] Qi, D., Ying-jun, Z., Wang, Z., Wang, W., Pi, L., & Li, L. (2024). Joint approach for vehicle routing problems based on genetic algorithm and graph convolutional network. Mathematics, 12(19), 3144. https://doi.org/10.3390/math12193144

[21] Ruan, M., Shen, C., Tang, J., Qi, C., & Qiu, S. (2021). A double traveling salesman problem with three-dimensional loading constraints for bulky item delivery. IEEE Access, 9, 13052-13063. https://doi.org/10.1109/access.2021.3051248

[22] Rojas-Gualdron, R. and Smarandache, F. (2024). Neutrosophic genetic algorithm for solving the vehicle routing problem with uncertain travel times. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4652048

[23] Sarumaha, Y., Firdaus, D., & Moridu, I. (2023). The application of artificial bee colony algorithm to optimizing vehicle routes problem. Journal of Information System, Technology and Engineering, 1(1), 11-15. https://doi.org/10.61487/jiste.v1i1.9

[24] Sharma, A. (2024). The future delivered: rethinking last mile in the age of instant gratification. International Journal of Supply Chain Management, 13(1), 1-15. https://doi.org/10.59160/ijscm.v13i1.6218

[25] Tabim, V., Franco, C., & Hoerde, J. (2024). Digital transformation in e-commerce logistics. Brazilian Journal of Operations &

Production Management, 21(1), 1641. https://doi.org/10.14488/bjopm.1641.2024
[26] Tang, W. (2025). Optimization of urban terminal delivery routes using fuzzy genetic algorithm and its practical application. Journal of Computational Methods in Sciences and Engineering. https://doi.org/10.1177/14727978251323125
[27] Wang, X., Xiao, Z., Chen, M., Sun, P., Wang, Q., & Feng, X. (2020). Energy-efficient speed profile optimization and sliding mode speed tracking for metros. Energies, 13(22), 6093. https://doi.org/10.3390/en13226093
[28] Wu, B., Lin, J. G., & Dong, M. (2013). Artificial bee colony algorithm for three-dimensional loading capacitated vehicle routing problem. Proceedings of 20th International Conference on Industrial Engineering and Engineering Management: Theory and Apply of Industrial Engineering, 815–825. https://doi.org/10.1007/978-3-642-40063-6_81
[29] Wu, Z., Song, S., & Zhang, Y. (2024). Research on integrated optimization of urban logistics, cargo loading, and transportation paths, 35. https://doi.org/10.1117/12.3054512
[30] Xia, Y. and Zhang, X. (2024). A neural column generation approach to the vehicle routing problem with two-dimensional loading and last-in-first-out constraints. https://doi.org/10.24963/ijcai.2024/218
[31] Zahra, A. and Abdalla, T. (2020). Design of fuzzy super-twisting sliding mode control scheme for unknown full vehicle active suspension systems using an artificial bee colony optimization algorithm. Asian Journal of Control, 23(4), 1966-1981. https://doi.org/10.1002/asjc.2352
[32] Zhang, Y. and Sheng, L. (2023). Optimization of simultaneous pickup and delivery vehicle routing with three-dimensional balanced loading constraints. Sustainability, 15(11), 9132. https://doi.org/10.3390/su15119132
[33] Zhang, K. (2024). Hybrid artificial bee colony algorithm with variable neighborhood search for capacitated vehicle routing problem. jes, 20(2), 584-597. https://doi.org/10.52783/jes.1213
[34] Zhu, X., Zhao, Z., & Yan, R. (2020). Low-carbon logistics optimization for multi-depot CVRP with backhauls - model and solution. Tehnicki Vjesnik - Technical Gazette, 27(5). https://doi.org/10.17559/tv-20200809211109