Optimization Strategies for Local Package Delivery Operations

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Contents

1 Introduction

Local package delivery services face the dual challenge of minimizing travel distance while respecting vehicle capacity and customer priorities. This report presents two metaheuristic methods—Simulated Annealing (SA) and Genetic Algorithms (GA)—to solve a prioritized, capacitated vehicle routing problem, combining algorithmic insights with real test-case results.

2 Related Work

The Vehicle Routing Problem (VRP) was first formalized by Dantzig and Ramser (1959) [?]. Key extensions include capacitated VRP [?] and priority-based VRP [?]. Metaheuristic approaches, notably SA [?] and GA [?], have proven effective, and hybrid methods further improve solution quality [?, ?].

3 Problem Formulation

Given n packages with locations (x_i, y_i), weight w_i, priority $p_i \in \{1, \ldots, 5\}$, and m vehicles with capacities C_j, we seek assignment and delivery order to minimize:

$$\text{Cost} = \sum_{j=1}^{m} \sum_{k=0}^{K_j} d(\pi_{j,k}, \pi_{j,k+1}) + \lambda \sum_{j=1}^{m} \sum_{k=1}^{K_j} p_{j,k} \cdot k, \tag{1}$$

where $d(\cdot, \cdot)$ is the Euclidean distance, $\lambda = 0.3$ balances priority penalties, and capacity constraints $\sum_k w_{j,k} \leq C_j$ hold. Each route starts and ends at the depot $(0, 0)$.

4 Metaheuristic Algorithms

4.1 Simulated Annealing

SA explores the solution space by probabilistic acceptance of worse states, employing:

- Initial temperature $T_0 = 1000$, cooling rate $\alpha = 0.90$, stopping at $T_{\min} = 1$.
- Neighborhood moves: package swaps between routes, intra-route reordering, route transfers.
- Feasibility maintained by rejecting capacity-violating moves.

4.2 Genetic Algorithm

GA evolves a population of assignment vectors:

- Population size $N = 50$, mutation rate $\mu = 0.01$, 500 generations.
- Elitist selection: top 50% retained.
- Single-point crossover on assignment; mutation reassigns random package.
- Invalid offspring (overloaded) removed from the pool.

5 Implementation and Visualization

Solution algorithms were implemented in Python. Results for each method are visualized as 2D route maps: vehicle routes are color-coded, package priorities indicated by marker size. Figures in Section 7 show these outputs for the test case.

6 Test Case

A single scenario was used to compare SA and GA under identical conditions. Vehicle capacities and package details are listed below.

6.1 Vehicles

Table 1: Vehicle Capacities (kg)

Vehicle	Capacity
1	250
2	220
3	250

6.2 Packages

Table 2: Package Destinations, Weights, and Priorities

Location (x, y)	Weight (kg)	Priority
(60,1)	40	1
(61,2)	80	1
(62,3)	60	1
(3,101)	30	1
(3,96)	60	1
(3,100)	50	2
(50,80)	30	2
(30,100)	70	5
(31,99)	50	5
(32,100)	40	5

7 Results and Discussion

Figures 1 and 2 display the final delivery routes and summarize performance metrics for GA and SA, respectively.

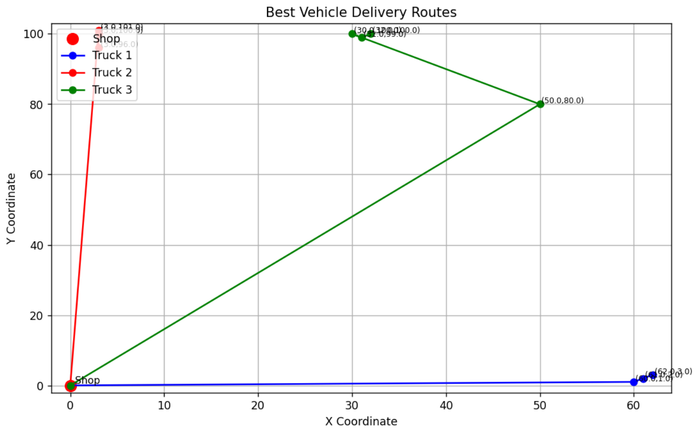

Figure 1: Genetic Algorithm Results: Total Distance = 298.33 km; Priority Penalty = 572.65

Figure 2: Simulated Annealing Results: Total Distance = 315.25 km; Priority Penalty = 333.85

GA achieved a shorter travel distance at the cost of higher cumulative priority penalty, indicating trade-offs between distance optimization and priority satisfaction. SA provided lower penalty but with increased distance.

8 Limitations and Future Work

While effective for this controlled scenario, our model omits realistic road networks and dynamic requests. Future directions include:

- Integration with GIS-based distance matrices.
- Hybrid metaheuristics combining GA exploration and SA exploitation.
- Real-time rerouting with incoming orders.

9 Conclusion

This report combined SA and GA strategies for a prioritized capacitated routing problem and applied them to a concrete test case. The contrasting outcomes illustrate each method's strengths, informing selection based on business priorities: minimal distance vs. priority compliance.

References

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