

A Dual-Phase Metaheuristic Framework for the Capacitated Location-Routing Problem: Leveraging Evolutionary Path Relinking and Genetic Algorithms for Supply Chain Cost Optimization

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Abstract

The structural complexity of modern distribution networks necessitates the simultaneous optimization of strategic facility location and operational routing to mitigate suboptimalities inherent in decoupled planning. This research develops a robust two-stage metaheuristic framework to solve the Capacitated Location-Routing Problem (CLRP) by minimizing the sum of fixed depot expenditures and variable transportation costs. The first phase employs a Location-Allocation (LAP) mechanism based on Euclidean distance minimization to establish optimal depot-customer clusters. In the second phase, a high-performance Genetic Algorithm (GA) integrated with an Evolutionary Path Relinking strategy is implemented using Evolver software to refine vehicle routing plans. The model's efficacy was rigorously validated using Prins' and Prodhon's benchmark instances, specifically analyzing 50-customer configurations across varying vehicle capacities. Computational experiments demonstrate that increasing vehicle capacity and integrating decision layers significantly enhance network efficiency, resulting in substantial reductions in total logistics costs. The findings provide a scalable, analytically rigorous decision-support tool for industrial engineers seeking to optimize complex supply chain architectures under strict capacity and service-level constraints.

Keywords

CLRP Metaheuristic Synthesis, Evolutionary Path-Relinking, Dual-Phase CLRP Optimization, Evolver-GA Heuristic, Benchmark-Driven Network Design.

1. Introduction

Efficient distribution network design is a critical issue in modern supply chain management. Organizations must determine not only where to locate distribution facilities but also how to route vehicles efficiently to serve geographically dispersed customers. These two decision-facility location and vehicle routes are highly interdependent. When addressed separately, solutions often become inefficient, leading to higher logistics costs, longer delivery times, and reduced customer satisfaction. The growing complexity of supply chains, increasing e-commerce demands, and rising transportation costs make it imperative to develop integrated optimization strategies that improve overall efficiency.

The Location-Routing Problem (LRP) addresses this challenge by combining the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP). The FLP determines the optimal number and location of distribution facilities, while the VRP focuses on designing cost-efficient delivery routes. By integrating these decisions, the LRP aims to minimize the total cost of the distribution system, including depot establishment costs and transportation expenses, while satisfying operational constraints such as vehicle capacity and customer demand. Solving the LRP effectively can reduce travel distance, improve service levels, and lower overall logistics costs, which is increasingly important for sustainable, low-carbon logistics operations.

Despite its practical relevance, the LRP is computationally challenging due to its combinatorial nature. Exact optimization approaches are impractical for large-scale instances involving many customers and multiple-depot alternatives. While metaheuristic approaches have been widely applied, most existing methods for the Capacitated Location-Routing Problem (CLRP) do not fully exploit the interaction between location assignment and route optimization. This creates a research gap: efficient strategies that simultaneously optimize depot locations and vehicle routes under capacity constraints are still limited, particularly those that can balance exploration of new solutions with exploitation of promising solution regions.

To address this gap, this study proposes a dual-phase metaheuristic framework for the CLRP. In Phase 1, a location-allocation procedure assigns customers to candidate depots based primarily on distance considerations, while respecting depot capacity constraints, forming feasible service clusters. In Phase 2, a Genetic Algorithm integrated with an Evolutionary Path-Relinking strategy optimizes vehicle routes within each cluster. Path relinking explores intermediate solutions between high-quality routes, effectively balancing exploration and exploitation to enhance solution quality.

The framework is evaluated using benchmark instances from the well-known CLRP datasets developed by Prodhon and Prins, focusing on a 50-customer configuration with multiple-depot alternatives and varying vehicle capacities. Computational results demonstrate that the integrated approach significantly reduces total logistics cost and travel distance, highlighting its effectiveness as a decision-support tool for cost-efficient and sustainable distribution network design.

1.1 Objectives

The main objective of this study is to develop a practical and efficient framework for optimizing both facility location and vehicle routing in capacitated distribution networks, aiming to reduce total logistics cost and enhance service efficiency. Specifically, the research seeks to identify the most advantageous depot locations to serve customers with minimal travel distance, design vehicle routes that satisfy capacity and operational constraints, and integrate advanced metaheuristic techniques—combining Genetic Algorithms with Evolutionary Path Relinking—to solve the Capacitated Location-Routing Problem effectively. The framework is rigorously validated against established benchmark instances to ensure reliability, scalability, and practical applicability. Ultimately, this study provides industrial engineers and supply chain managers with a robust decision-support tool that unifies strategic facility placement and operational routing, delivering significant cost reductions, enhanced delivery efficiency, improved overall network performance, and supporting more sustainable logistics operations.

2. Literature Review

The Location-Routing Problem (LRP) has emerged as a critical area in supply chain and logistics management, focusing on the simultaneous optimization of facility location and vehicle routing decisions. By integrating the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP), the LRP addresses both strategic and operational aspects of distribution networks. The FLP determines the optimal number, location, and capacity of facilities to minimize establishment and operational costs, while the VRP focuses on designing cost-efficient routes for vehicles serving geographically dispersed customers. Compared with decoupled approaches, integrated LRPs have been shown to improve distribution efficiency and reduce logistics costs (Prins, 2004; Prodhon & Laporte, 2015).

The VRP has been widely studied because of its practical relevance and computational complexity. Variants such as the Vehicle Routing Problem with Time Windows (VRPTW) incorporate operational constraints like delivery schedules and vehicle capacities, reflecting real-world challenges in sectors ranging from postal delivery to healthcare logistics. Classical algorithms, including Clarke and Wright's savings heuristic, established the foundation for modern solution approaches. As problem size increases, exact optimization methods become computationally impractical, motivating the development of heuristic and metaheuristic techniques capable of generating high-quality near-optimal solutions (Dantzig & Ramser, 1959; Geir Hastle & Knut-Andreas, 2007).

Metaheuristic approaches such as Genetic Algorithms (GA), Tabu Search (TS), Simulated Annealing (SA), Scatter Search (SS), and Hill Climbing have demonstrated strong performance in solving LRPs. Genetic Algorithms emulate evolutionary processes to iteratively improve candidate solutions through crossover, mutation, and selection (Holland, 1975). Tabu Search and Scatter Search employ diversification and intensification strategies to escape local optima and explore broader solution spaces (Glover, 1977; Venkateswarlu, 2021). Simulated Annealing balances exploration and exploitation, while Hill Climbing provides efficient local improvements for smaller instances. In addition, path-relinking techniques—originally introduced within the Scatter Search framework—have been used to explore trajectories between high-quality solutions, enhancing search intensification and solution quality (Glover & Laguna, 1997).

Recent studies have extended the LRP to address practical logistics constraints. Ferreira et al. (2018) investigated capacitated LRPs using simulated annealing, while Rabbani et al. (2018) applied multi-objective metaheuristics such as NSGA-II and MOPSO to hazardous waste routing problems. Hybrid approaches combining Genetic Algorithms with local search and neighborhood exploration have achieved notable reductions in logistics costs (Yu et al., 2019; Zhang et al., 2019). Other studies have explored sustainability-oriented variants, including electric-vehicle LRPs with time windows and energy constraints (Wang et al., 2021; Zhang et al., 2022). In many of these approaches, customer allocation to depots is often performed using proximity-based clustering or location-allocation procedures similar to K-means strategies, which simplify the routing structure before route optimization.

These studies highlight the versatility of metaheuristic frameworks in addressing the LRP's computational complexity while accommodating practical operational constraints. However, they typically focus on specific variants or constraints rather than developing a generalizable framework that tightly integrates location assignment and routing decisions.

Despite these advancements, many existing studies still treat routing optimization and facility location as partially independent stages, or they lack scalable frameworks capable of addressing both dimensions simultaneously under capacity constraints. To address this limitation, this research proposes a dual-phase metaheuristic framework in which customers are first allocated to candidate depots using a location-allocation clustering strategy, and vehicle routes are subsequently optimized using a Genetic Algorithm enhanced with Evolutionary Path-Relinking. The proposed approach is evaluated using standard benchmark instances, demonstrating its applicability to complex capacitated distribution networks.

3. Method

Transportation costs involve not only distance but also taxi fares, fuel, parking, meals, bonuses, cleaning, distribution, and phone charges that employees may incur and request reimbursement for. These costs vary depending on the distance between customers and the warehouse or product location. Longer travel times can also lead to customer dissatisfaction. To address this, the Location Vehicle Routing Problem (LRP) can be applied to find an optimized solution. LRPs determine how far each vehicle will travel, how many depots are needed, how many customers each

vehicle will serve, and the load carried. This paper focuses on reducing total vehicle travel distance. Using a meta-heuristic approach, a model is developed with a fitness function, decision variables, and strict constraints, while vehicle and depot capacities, as well as setup and distribution costs, are fixed (Figure 1- Figure 11).

This study focuses on minimizing total travel distance while meeting the following conditions:

- Each customer is served by exactly one vehicle.
- The total demand on a route does not exceed the vehicle's capacity.
- Each route starts and ends at a similar location.
- The vehicle fleet is homogeneous and unrestricted in size.

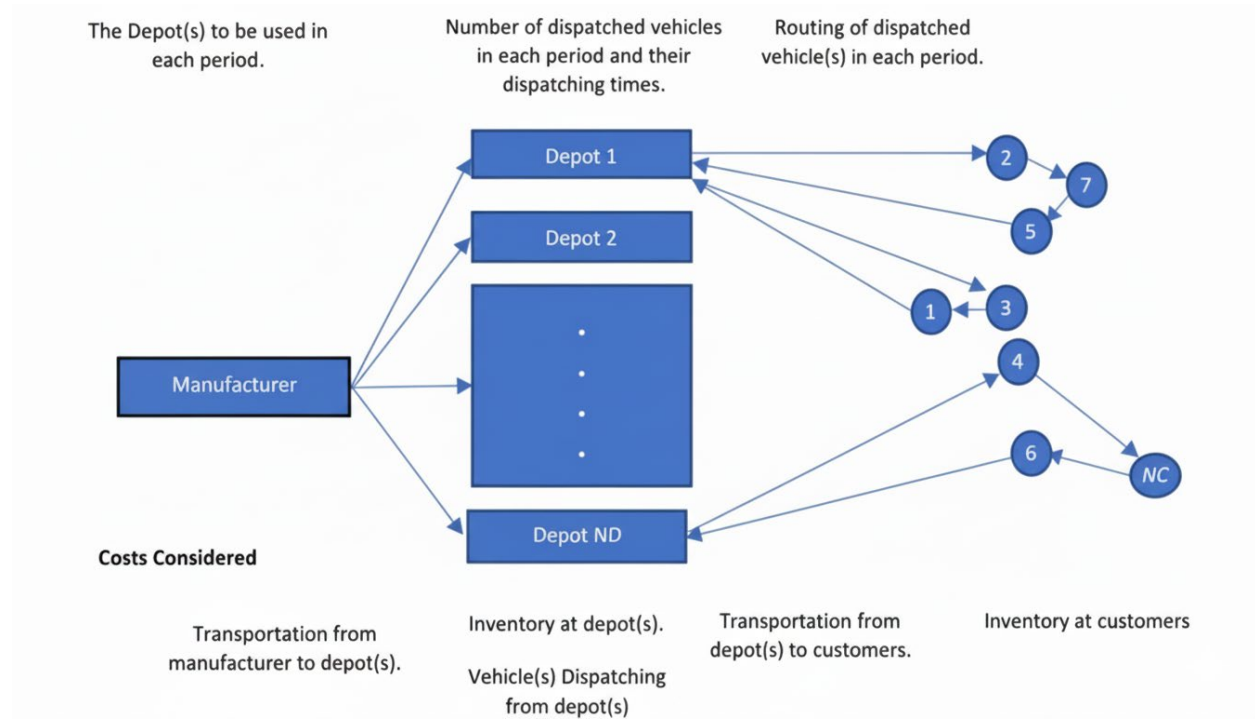


Figure 1. The mathematical model considers both decision variables and associated costs (Ahmad Sayed Saif-Eddine et al.).

The Capacitated Location-Routing Problem (CLRP) considered in this study can be modeled on a weighted, directed graph $G = (V, A, C)$, where V is the set of nodes, A is the set of arcs, and C represents traversal costs. The node set V includes a subset $I \subset V$ of m potential depots and a subset $J = V \setminus I$ of n customers. Each depot $i \in I$ has a fixed opening cost O_i and a capacity W_i , while each customer $j \in J$ has a demand d_j . A fleet of K identical vehicles, each with capacity Q and fixed operating cost F , is available. Each vehicle operates on a single route, starting and ending at a depot. The objective is to determine which depots to open, how many vehicles to use, and how to design routes that satisfy customer demand while minimizing total logistics cost.

The following constraints define the model:

- Customer Assignment: Each customer is served by exactly one vehicle and assigned to a single depot.
- Vehicle Capacity: The total demand for each route does not exceed the vehicle capacity.
- Depot Capacity: The total demand served by a depot does not exceed its capacity.
- Route Continuity: Each route starts and ends at the same depot.
- Subtour Elimination: No subtours are allowed on vehicle routes.
- Allocation Constraint: A customer can only be assigned to a depot if a route connecting them is established.

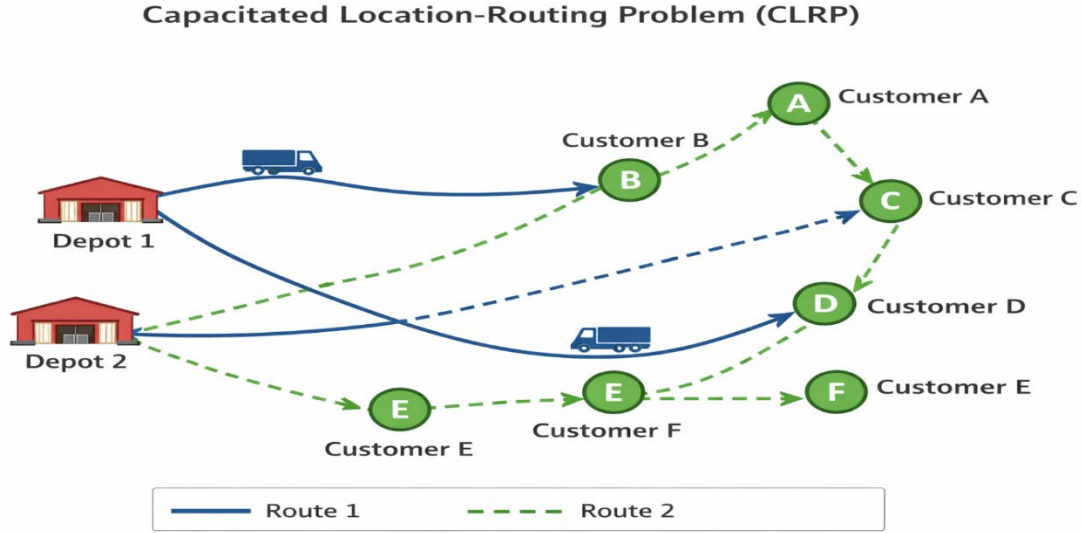


Figure 2. Capacitated Location-Routing Diagram

Let the Boolean variables be defined as:

$$y_i = \begin{cases} 1, & \text{if depot } i \text{ is opened} \\ 0, & \text{otherwise} \end{cases},$$

$$x_{ak} = \begin{cases} 1, & \text{if vehicle } k \text{ traverses arc } a \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ij} = \begin{cases} 1, & \text{if customer } j \text{ is assigned to depot } i \\ 0, & \text{otherwise} \end{cases}$$

The objective function minimizes the sum of depot opening costs, vehicle fixed costs, and travel costs along arcs:

$$\text{Minimize } Z = \sum_{i \in I} O_i y_i + \sum_{k \in K} \sum_{a \in A} C_a x_{ak} + \sum_{k \in K} \sum_{a \in \delta^+(I)} F x_{ak}$$

Subject to:

1. Each customer is visited once: $\sum_{i \in I} z_{ij} = 1, \quad \forall j \in J$
2. Vehicle capacity: $\sum_{j \in J} d_j x_{ak} \leq Q, \quad \forall k \in K$
3. Route continuity: $\sum_{a \in \delta^+(v)} x_{ak} - \sum_{a \in \delta^-(v)} x_{ak} = 0, \quad \forall v \in V, \forall k \in K$
4. Subtour elimination: $\sum_{a \in L(S)} x_{ak} \leq |S| - 1, \quad \forall S \subseteq J, \forall k \in K$
5. Depot allocation: $\sum_{j \in J} z_{ij} \leq W_i, \quad \forall i \in I$
6. Boolean constraints: $y_i, x_{ak}, z_{ij} \in \{0,1\}$

The CLRP generalizes the classical Vehicle Routing Problem (VRP). When $m = 1$, it reduces to a VRP. Additional complexity arises from selecting depots, assigning customers to depots, and sequencing routes simultaneously, making exact solutions computationally infeasible for large instances. Only small instances can be solved optimally using commercial linear programming solvers, while linear relaxations provide weak lower bounds.

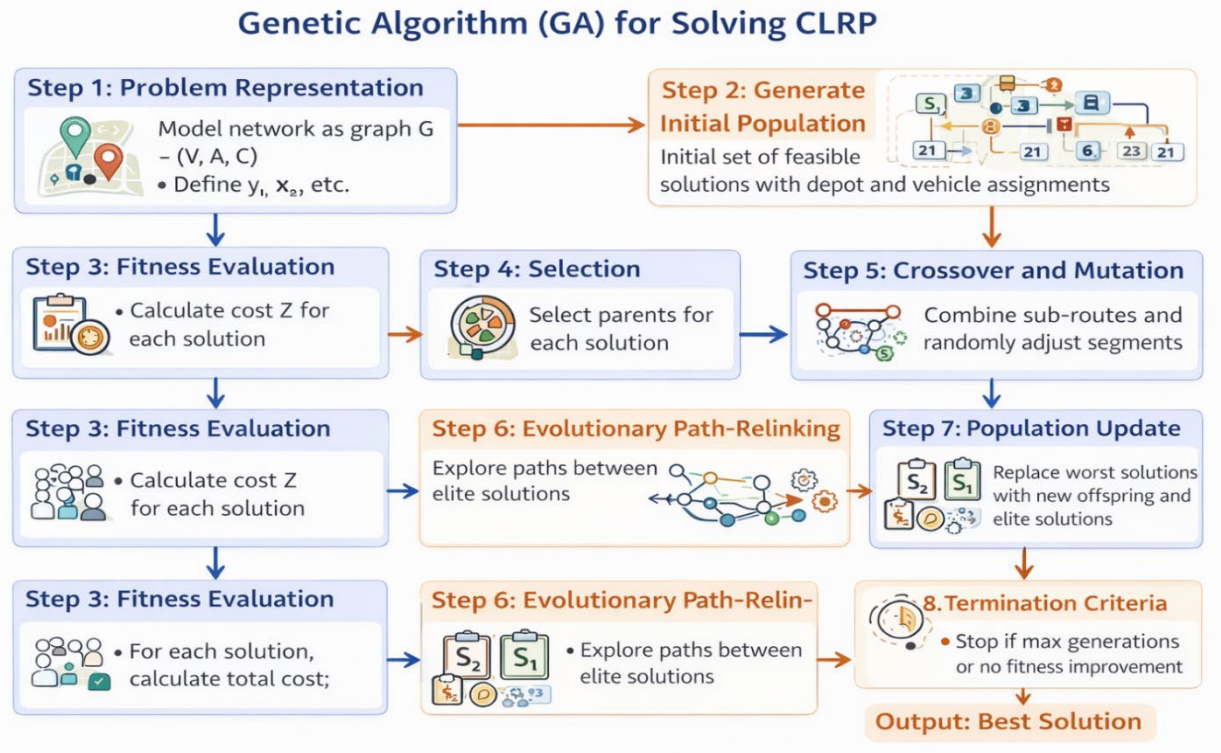


Figure 3. Steps of Genetic Algorithm (GA) for Solving CLRP

4. Data Collection

The primary objective of this study is to identify the optimal location for a distribution center such that the maximum number of clients can be served with the minimum number of vehicles traveling the shortest possible distance. To evaluate the effectiveness of the proposed genetic algorithm (GA) and to analyze the parameters influencing vehicle allocation at each depot, a benchmark instance from the Multi-Depot Vehicle Routing Problem (MDVRP) literature was adapted (http://prodhonc.free.fr/Instances/instances_us.htm). This adaptation was necessary to align the benchmark with the specific requirements of the present case study.

The selected benchmark contains detailed information on client numbers (ranging from 20 to 200), depot counts, vehicle capacities, and the associated costs for depots and vehicles. For this study, fifty clients were selected, alongside five potential depot locations, each with varying vehicle capacities. Customers were then reorganized to minimize the distance between clients and depots. Notably, this analysis does not consider service time at depots or with clients, nor transportation costs from the manufacturer to depots. To investigate the effect of vehicle availability on routing decisions, the number of vehicles at each depot was adjusted according to demand.

A heuristic approach was adopted to solve the location-routing problem (LRP), dividing it into two main phases:

- Location-Allocation Problem (LAP)
- Vehicle Routing Problem (VRP)

LAP Phase – Customer Allocation to Depots: In this phase, each customer is initially assigned to the nearest depot based on radial distance, provided that the depot's capacity constraint is not exceeded. If a capacity violation occurs, the customer is reassigned to an alternative depot that minimizes the cost function. The output of this step is a customer-facility incidence matrix, where an entry is marked as 1 if customer i is assigned to depot j . Distances were calculated using the Euclidean formula, and allocation was implemented using conditional logic in Excel.

Following allocation, a distribution list was generated, representing the number of customers assigned to each depot. This list was then sorted in descending order to assist in determining depot requirements. A lower bound on the number

of depots was established, independent of the actual spatial distribution of customers and depots. In cases where a depot served fewer than five clients, employees were reassigned to the nearest depot.

VRP Phase – Route Optimization: The VRP phase redistributes customers within each cluster to evaluate feasible routing solutions that satisfy total customer demand while respecting vehicle capacity. Given the complexity of this problem, manual route planning becomes challenging, especially as problem scale increases exponentially.

Rubific software was used to optimize routes based on distance or travel time while assigning drivers appropriately. The process was executed in two steps:

- **Excel Formulation** – The VRP model was implemented in Excel. Coordinates and demand were named ranges, and the INDEX function was used to dynamically link customer data. Capacity constraints were addressed using conditional logic, and distances were calculated using the Euclidean formula.
- **Evolver Implementation** – After formulating the problem in Excel, Evolver was employed to optimize routes. The model definition interface allowed specification of target cells, adjustable cell ranges, and constraints. The primary objective was to minimize the total distance traveled while using the fewest vehicles. Customer demand and vehicle capacity were enforced as hard constraints. The genetic algorithm was configured with a population size of 50 and ran for 20,000 generations. Randomized variations in crossover, mutation rates, and vehicle capacities were introduced to explore solution space.

The optimization process involved a local search technique, simulating initial solutions across multiple crossover and mutation scenarios. Feasible steps were accepted if they improved the objective function, while suboptimal alternatives were discarded. This iterative approach continued until the best possible solution, given the constraints, was identified (Table 1).

Table 1. Core Worksheet Structure

Sheet	Key Formulas/Features	Purpose
Coordinates	$=\text{SQRT}((X2-X1)^2+(Y2-Y1)^2)$	Distance matrix (all pairs)
Demands	$\text{INDEX}(\text{Retailers}, \text{Sequence_Cell})$	Dynamic customer lookup
Assignment	$\text{IF}(\text{CumLoad} \leq \text{Capacity}, 1, \text{NewVan})$	LAP incidence + vehicle spawn
TotalDist	$\text{SUMPRODUCT}(\text{DistMatrix}, \text{Assignment})$	Evolver target (minimize)

This setup creates the binary customer-depot matrix from LAP, feeding sorted clusters to VRP. Evolver links via toolbar: adjustable cells (sequence order), constraints ($=\text{vans} \leq \text{demand/capacity}$), GA settings (pop 50, 20k gens). Post-run reports log best routes per benchmark instance like 50-5-1 (3 depots).

Evolver Optimization Flow

- Define model: target TotalDist cell (Min), variables as retailer order.
- Add constraints: $\text{CumLoad} \leq \text{Capacity}$; max vans.
- Run 4 GA variants (crossover/mutation tweaks); select global best.

Progress window tracks runtime/best values; Watcher exports trials log for analysis.

Benchmark Instances and Vehicle Allocation: Eight instances from Prin's benchmark were used: 50-5-1, 50-5-1b, 50-5-2, 50-5-2b, 50-5-2BIS, 50-5-2bBIS, 50-5-3, and 50-5-3b. Differences among instances include vehicle capacities (70 or 150 units) and variations in X and Y coordinates.

The number of depots required to satisfy demand was determined for each instance:

- Instances 50-5-1 and 50-5-1b: 3 depots
- Instances 50-5-2 and 50-5-2b: 4 depots

- Instances 50-5-2BIS and 50-5-2Bbis: 2 depots
- Instances 50-5-3 and 50-5-3b: 3 depots

Depots were labeled A, B, C, D, and E for clarity. This structured approach ensures consistent and efficient assignment of clients to depots and facilitates the optimization of vehicle routing under varying capacity constraints.

5. Results and Discussion

This research proposes a novel mathematical approach to minimize the overall logistics cost. Extensive data collection and multiple randomized analyses were conducted to reduce the potential error and improve the robustness of the results.

5.1 Numerical Result

Instances 50-5-1 (Population 50, Iterations 20,000): For the 50-5-1 benchmark, the LAP procedure selected three depots (A, C, D) to serve 50 customers. The VRP model determined customer assignments, vehicle routes, and total travel distances. Some customers were reassigned to the nearest depots to optimize routing. With a vehicle capacity of 70, Evolver optimization showed that 12 vehicles were required to serve all customers while minimizing total distance (Table 2- Table 16).

Table 2. Total and Optimum Cost for Instance 50-5-1

Combination	Crossover	Mutation	Total Cost for Depot A	Total Cost for Depot C	Total Cost for depot D	Total Cost	Optimum Solution for GA
First	0.40	0.08	14,943.76	9,590.28	14,559.64	39,093.68	39,070.68
Second	0.90	0.02	14,950.92	9,578.84	14,576.28	39,106.04	
Third	0.60	0.35	15,042.68	9,626.92	14,548.08	39,217.68	
Forth	0.80	0.01	14,956.92	9,676.52	14,551.08	39,184.52	

Table 3. Vehicle Travel Route for Instance 50-5-1

No of Vehicle	Vehicle Travel Route (50-5-1)					Distance Traveled	Distance Traveled by Depot	Depot
1	16	2	19	34		28.04	146.94	A
2	14	39	3	17		45.67		
3	30	37	8	20	45	49.14		
4	50	47	5	28		24.1		
5	6	33	24			30.21	137.46	C
6	40	42	27	29		36.82		
7	36	32	13	18		47.06		
8	38	23	31	22	44	23.37		
9	4	7	49			38.7	122.77	D
10	10	26	41	15	35	31.24		
11	9	25	46	43		39.7		
12	12	11	48	21	1	13.14		
Total Distance Traveled							407.17	

Instances 50-5-1b (Population 50, Iterations 20,000): For the instance benchmark, the LAP procedure selected three depots (A, C, D) to serve 50 customers. The VRP model determined customer assignments, vehicle routes, and total travel distances. Some customers were reassigned to the nearest depots to optimize routing. With a vehicle capacity

of 150, Evolver optimization showed that 6 vehicles were required to serve all customers while minimizing total distance.

Table 4. Total and Optimum Cost for Instance 50-5-1b

Combination	Crossover	Mutation	Total Cost for Depot A	Total Cost for Depot C	Total Cost for depot D	Total Cost	Optimum Solution for GA
First	0.40	0.08	12,590.68	7,269.58	12,249.30	32,109.52	32,104.32
Second	0.90	0.02	12,590.68	7,268.90	12,254.80	32,114.42	
Third	0.60	0.35	12,640.46	7,286.38	12,280.20	32,207.06	
Forth	0.80	0.01	12,590.68	7,264.38	12,261.70	32,116.74	

Table 5. Vehicle Travel Route for Instance 50-5-1b

No of Vehicle	Vehicle Travel Route (50-5-1b)										Distance Traveled	Distance Traveled by Depot	Depot
1	14	16	2	19	34	39	3	47			68.34	117.34	A
2	17	30	37	8	20	45	5	28			49		
3	27	13	18	38	23	31	22	44	6		82.72	117.69	C
4	33	24	40	42	29	36	32				34.97		
5	25	7	9	35	4	41	26	15			60.3	96.13	D
6	10	12	11	1	21	48	43	49	46		35.83		
Total Distance Traveled												331.16	

Instances 50-5-2 (Population 50, Iterations 20,000): In this instance, four depots served the customers located closest to them. Only one customer was reassigned from depot A to depot E. Each vehicle has a capacity of 70 units. A total of 13 vehicles were required to serve all customers. A hard constraint was observed at depot E

Table 6. Total and Optimum Cost for Instance 50-5-2

Combination	Crossover	Mutation	Total Cost for Depot B	Total Cost for Depot C	Total Cost for depot D	Total Cost for Depot E	Total Cost	Optimum Cost for GA
First	0.40	0.08	14,469.70	12,183.01	19,093.60	12,444.22	58,190.57	58,152.68
Second	0.90	0.02	14,469.70	12,183.01	19,120.40	12,439.96	58,213.07	
Third	0.60	0.35	14,469.70	12,171.46	19,075.20	12,445.81	58,162.17	
Forth	0.80	0.01	14,469.70	12,183.01	19,071.60	12,477.34	58,201.61	

Table 7. Vehicle Travel Route for Instance 50-5-2

No of Vehicle	Vehicle Travel Route (50-5-2)					Distance Traveled	Distance Traveled by Depot	Depot
1	35	36	27			21.26	53.9	B
2	26	49	50	39		26.4		
3	47	41	48			6.24		
4	33	46	29			36.54	77.82	C
5	43	45	38	30		30.04		
6	42	31	32	28		11.24		
7	13	12	24			24.02	92.14	D
8	19	20	14	10		25.44		
9	9	7	25	11		33.6		
10	22	6	23	5	21	9.08	122.32	E
11	18	4	3			43.2		
12	2	34	40	16	1	49.5		
13	15	17	8	37	44	29.62	346.18	
Total Distance Traveled								

Instances 50-5-2b (Population 50, Iterations 20,000): the standard capacity of a car is 150. Evolver contains no hard constraints. We need seven vehicles for this. All data are same as 50-5-2 except van capacity.

Table 8. Total and Optimum Cost for Instance 50-5-2b

Combination	Cross over	Mutation	Total Cost for Depot B	Total Cost for Depot C	Total Cost for Depot D	Total Cost for Depot E	Total Cost	Optimum Cost for GA
First	0.40	0.08	12,343.17	11,076.06	16,865.60	11,235.06	51,519.93	51,500.81
Second	0.90	0.02	12,343.17	11,076.06	16,857.30	11,235.06	51,511.61	
Third	0.60	0.35	12,343.17	11,076.34	16,887.40	11,235.06	51,541.95	
Forth	0.80	0.01	12,343.17	11,076.06	16,846.50	11,235.06	51,500.81	

Table 9. Vehicle Travel Route for Instance 50-5-2b

No of Vehicle	Vehicle Travel Route (50-5-2b)										Distance Traveled	Total Distance Traveled by Depot	Depot
1	35	36	27	26	47	41	48	50	39	49	35.17	35.17	B
2	30	42	32	28	31	45	38	33			55.95	69.03	C
3	46	29	43								13.08		
4	7	25	11	21	5	6	23	22	12		43.97	71.76	D
5	13	9	10	24	19	20	14				27.8		
6	2	15	3	4	18	1	16	17			57.96	81.03	E
7	8	34	40	37	44						23.07		
Total Distance Traveled												256.99	

Instances 50-5-2BIS (Population 50, Iterations 20,000): In this instance, two distribution centers were required to serve the customer demand. A hard constraint was observed at depot A. The fleet consisted of a total of 12 vans. Three customers who were initially closest to depot C were reassigned to depot D. Each van has a capacity of 70 units.

Table 10. Total and Optimum Cost for Instance 50-5-2BIS

Combination	Crossover	Mutation	Total Cost for Depot A	Total Cost for Depot D	Total Cost	Optimum Cost for GA
First	0.40	0.08	14,064.56	15,752.68	29,817.24	29,738.40
Second	0.90	0.02	14,060.78	15,699.46	29,760.24	
Third	0.60	0.35	14,199.68	15,776.44	29,976.12	
Forth	0.80	0.01	14,038.94	15,742.06	29,781.00	

Table 11. Vehicle Travel Route for Instance 50-5-2BIS

No of vehicle	Vehicle Travel Route (50-5-BIS)						Distance Traveled	Total Distance Traveled by Depot	Depot
1	27	49	41				61.99	230.54	A
2	28	31	42	32			47.02		
3	35	43	47	26	37		35.54		
4	36	40	48	44			40.2		
5	29	39	30	33			36.69		
6	38	50	46	34	45		9.1		
7	9	25	24				8.85	103.25	D
8	17	3	23	6			20.26		
9	18	7	15	11			13.71		
10	19	14	5	12	16		24.66		
11	8	20	21	10			15.41		
12	13	2	22	4	1		20.36		
Total Distance								333.79	

Instances 50-5-2bBIS (Population 50, Iterations 20,000): In this instance, according to the distance calculations, depots D and E served all customers. A total of six vans were required to solve this instance. Each van has a capacity of 150 units, and no hard constraints were observed.

Table 12. Total and Optimum Cost for Instance 50-5-2bBIS

Combination	Crossover	Mutation	Total Cost for depot D	Total Cost for depot E	Total Cost	Optimum Cost for GA
First	0.40	0.08	10,910.04	10,926.24	21,836.28	21,804.00
Second	0.90	0.02	10,929.66	10,902.06	21,831.72	
Third	0.60	0.35	11,048.91	10,993.14	22,042.05	
Forth	0.80	0.01	10,942.95	10,893.96	21,836.91	

Table 13. Vehicle Travel Route for Instance 50-5-2bBIS

No of vehicle	Vehicle Travel Route (50-5-bBIS)									Distance Traveled	Total Distance Traveled by Depot	Depot
1	21.0	19.0	11.0	10.0	9.0	15.0	8.0	12.0		34.8	69.8	D
2	18.0	23.0	1.0	7.0	3.0	16.0	13.0	25.0	2.0	27.1		
3	6.0	4.0	22.0	5.0	24.0	20.0	17.0	14.0		7.8		
4	40.0	48.0	28.0	50.0	44.0	32.0	42.0	35.0		50.6	109.9	E
5	30.0	43.0	34.0	45.0	27.0	39.0	38.0	49.0	41.0	43.6		
6	26.0	31.0	47.0	37.0	29.0	33.0	36.0	46.0		15.7		
Total Distance											179.7	

Instances 50-5-3 (Population 50, Iterations 20,000): In this instance, three depots were used to serve fifty customers. No hard constraints were observed, and a total of 13 vans were required for this instance. Each vehicle has a capacity of 70 units

Table 14. Total and Optimum Cost for Instance 50-5-3

Combination	Crossover	Mutation	Total Cost for Depot A	Total Cost for Depot B	Total Cost for Depot C	Total Cost	Optimum Cost for GA
First	0.40	0.08	17,756.64	18,469.12	16,491.75	52,717.51	52,675.67
Second	0.90	0.02	17,752.44	18,458.40	16,541.60	52,752.44	
Third	0.60	0.35	17,770.60	18,466.40	16,618.10	52,855.10	
Forth	0.80	0.01	17,757.08	18,431.48	16,538.50	52,727.06	

Table 15. Vehicle Travel Route for Instance 50-5-3

No of vehicle	Vehicle Travel Route (50-5-3)					Distance Traveled	Total Distance Traveled by Depot	Depot
1	21.00	23.00	25.00			22.70	72.61	A
2	28.00	19.00	27.00	22.00		24.79		
3	29.00	18.00	20.00	24.00		20.11		
4	17.00	16.00	30.00			5.00		
5	3.00	13.00	36.00			34.10	149.62	B
6	14.00	7.00	5.00	2.00		36.12		
7	11.00	6.00	10.00	4.00	1.00	54.34		
8	8.00	9.00	15.00	12.00		25.06		
9	32.00	38.00	31.00			43.77	166.55	C
10	43.00	41.00	35.00	40.00		43.04		
11	34.00	47.00	39.00	26.00		30.71		
12	46.00	44.00	37.00	42.00		23.67		
13	48.00	45.00	49.00	33.00	50.00	25.36		
Total Distance							388.78	

Instances 50-5-3b (Population 50, Iterations 20,000): In this instance, three depots were used to serve the fifty customers. No hard constraints were observed, and a total of 7 vans were required for this instance. Each vehicle has a capacity of 150 units. The remaining data is the same as in instance 50-5-3 (Table 16 and Table 17).

Table 16. Total and Optimum Cost for Instance 50-5-3b

Combination	Crossover	Mutation	Total Cost for Depot A	Total Cost for Depot B	Total Cost for Depot C	Total Cost	Optimum Cost for GA
First	0.40	0.08	15,591.16	16,038.70	14,048.79	45,678.65	45,673.53
Second	0.90	0.02	15,586.04	16,072.58	14,086.32	45,744.94	
Third	0.60	0.35	15,589.62	16,065.22	14,212.11	45,866.95	
Forth	0.80	0.01	15,603.12	16,059.06	14,048.79	45,710.97	

Table 17. Vehicle Travel Route for Instance 50-5-3b

No of vehicle	Vehicle Travel Route (50-5-3b)									Distance Traveled	Total Distance Traveled by Depot	Depot
1	17	16	30	24	20	18	22	27	29	40.46	62.02	A
2	21	23	25	28	19					21.56		
3	8	1	9	12	15	7	14			66.11	102.85	B
4	3	11	13	36	6	2	5	4	10	36.73		
5	50	31	38	32	43	41	35	40		80.21	129.93	C
6	34	47	39	26	46	44	37	42	48	41.82		
7	45	49	33							7.89		
Total Distance											294.80	

5.2 Graphical Results

The graphical representation shows the optimal routes obtained for each benchmark instance. The routes illustrate how customers are assigned to depots and served by vehicles while minimizing the total travel distance. The solution ensures that vehicle capacity constraints are satisfied and that each route starts and ends at the assigned depot.

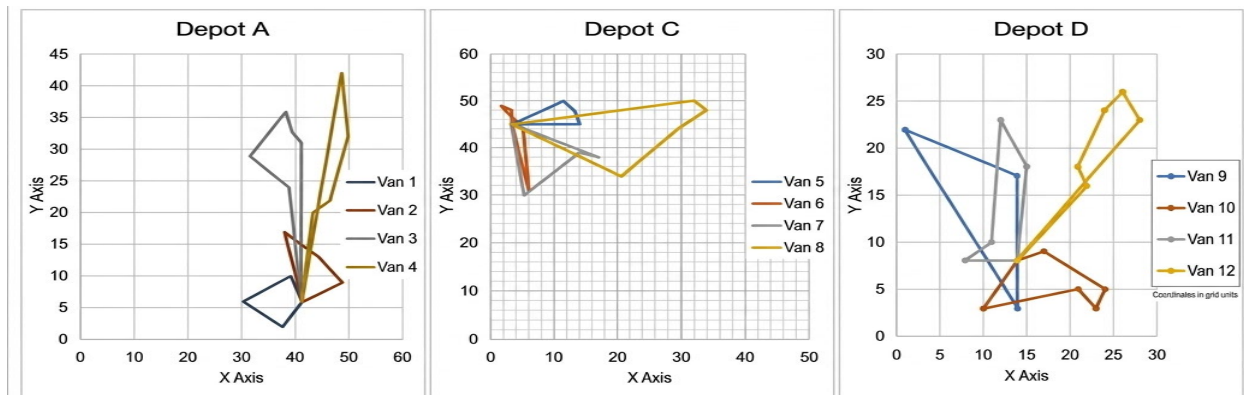


Figure 4. Optimal travel routes and graphical representation of the best solution for the 50-5-1 benchmark instance.

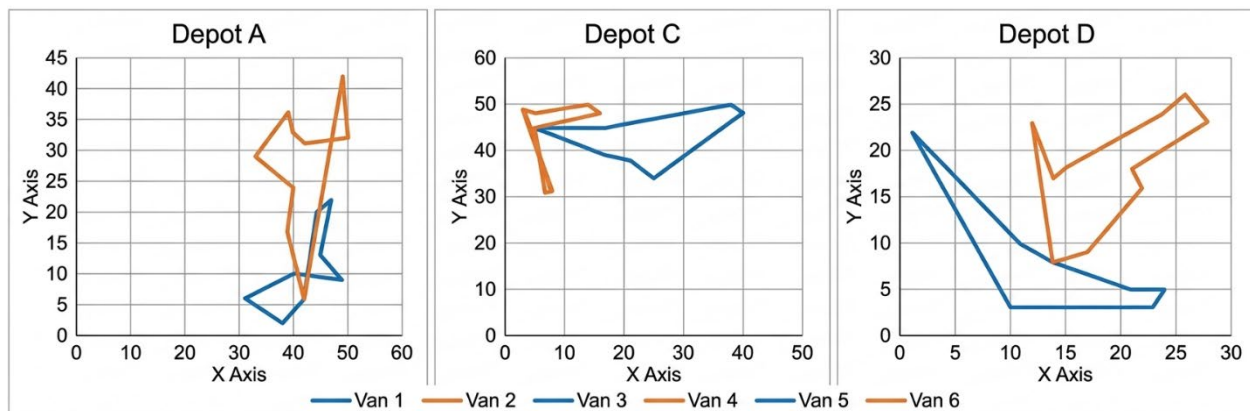


Figure 5. Optimal travel routes and graphical representation of the best solution for the 50-5-1b benchmark instance.

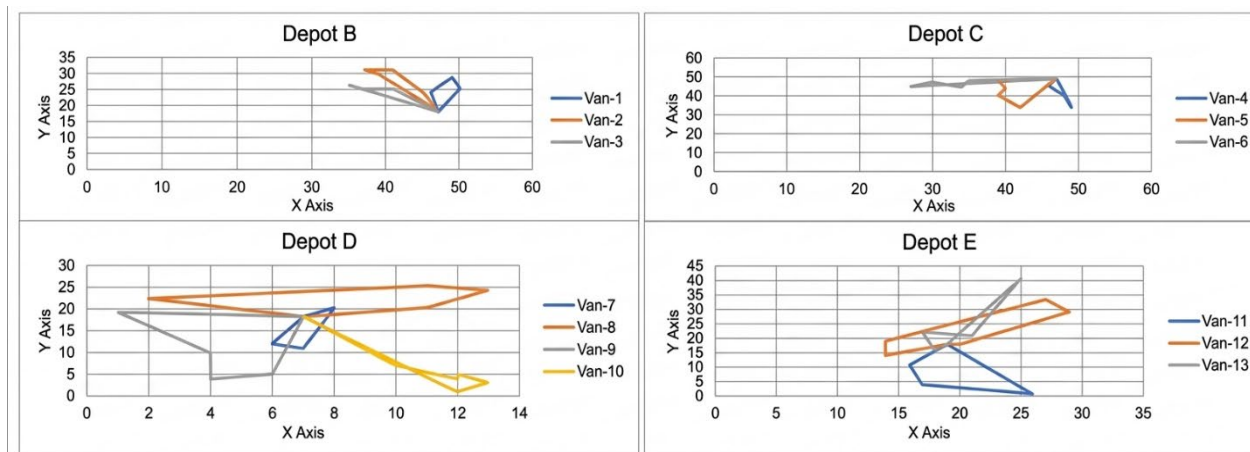


Figure 6. Optimal travel routes and graphical representation of the best solution for the 50-5-2 benchmark instance.

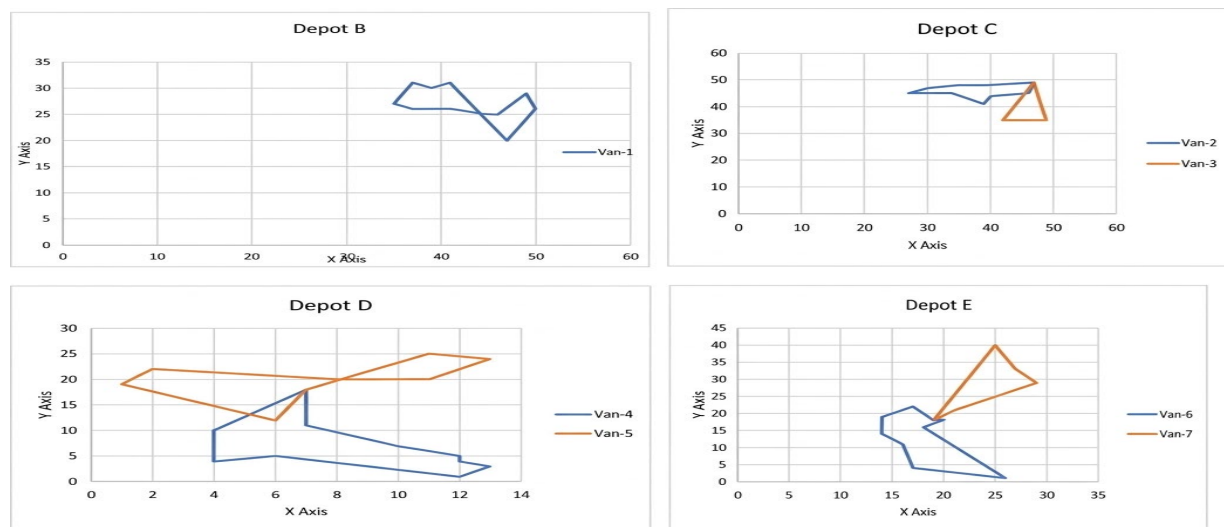


Figure 7. Optimal travel routes and graphical representation of the best solution for the 50-5-2b benchmark instance.

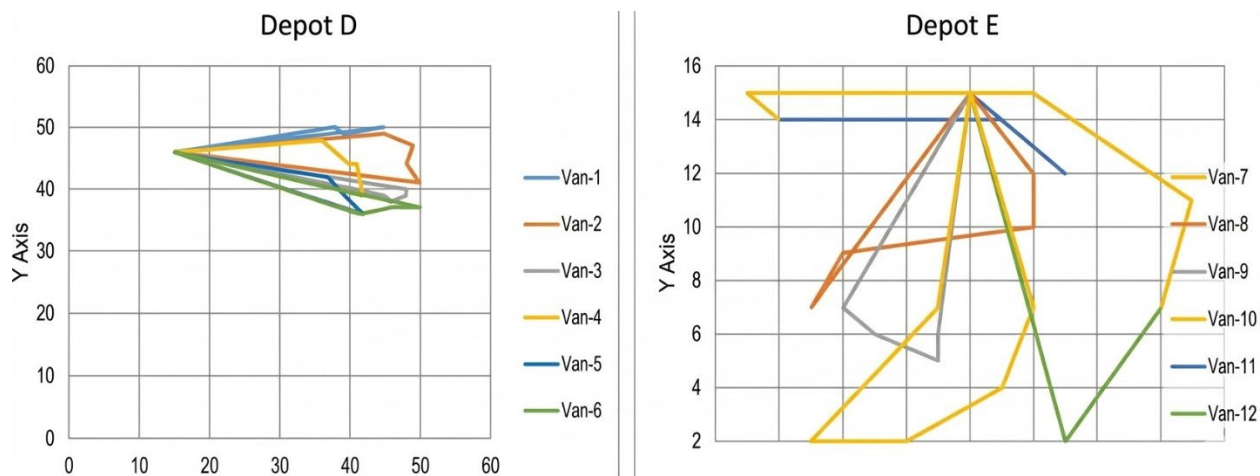


Figure 8. Optimal travel routes and graphical representation of the best solution for the 50-5-2BIS benchmark instance.

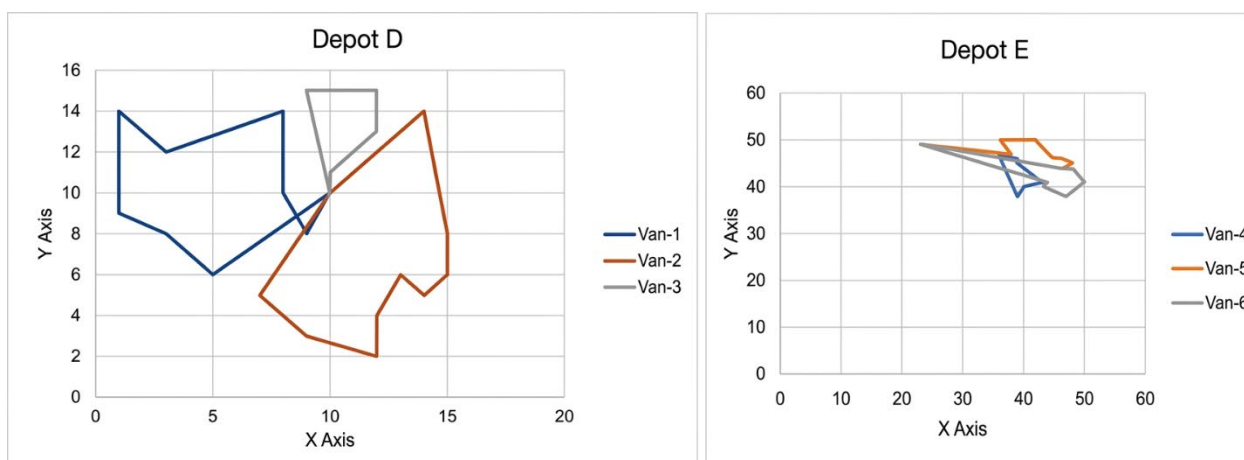


Figure 9. Optimal travel routes and graphical representation of the best solution for the 50-5-2bBIS benchmark instance.

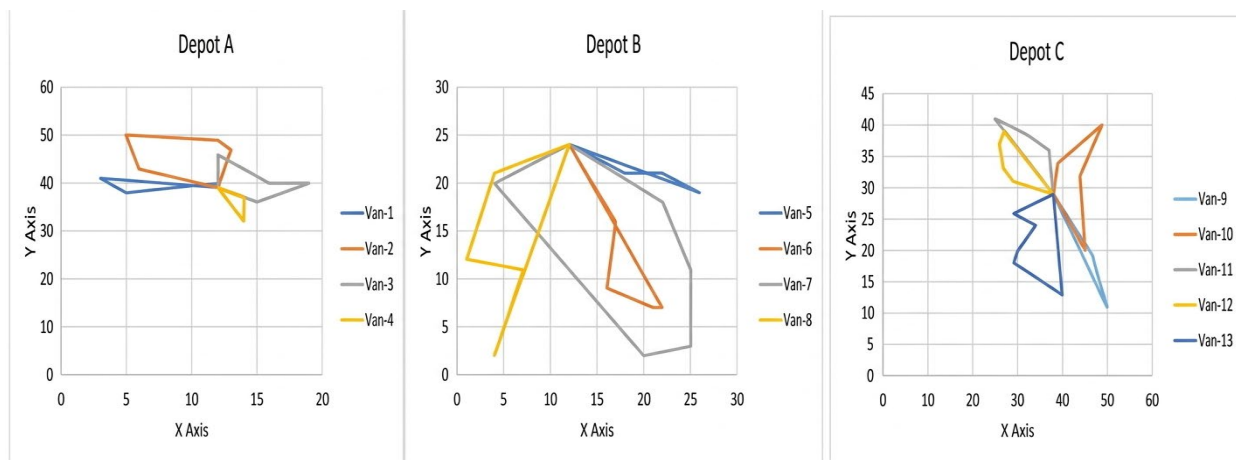


Figure 10. Optimal travel routes and graphical representation of the best solution for the 50-5-3 benchmark instance.

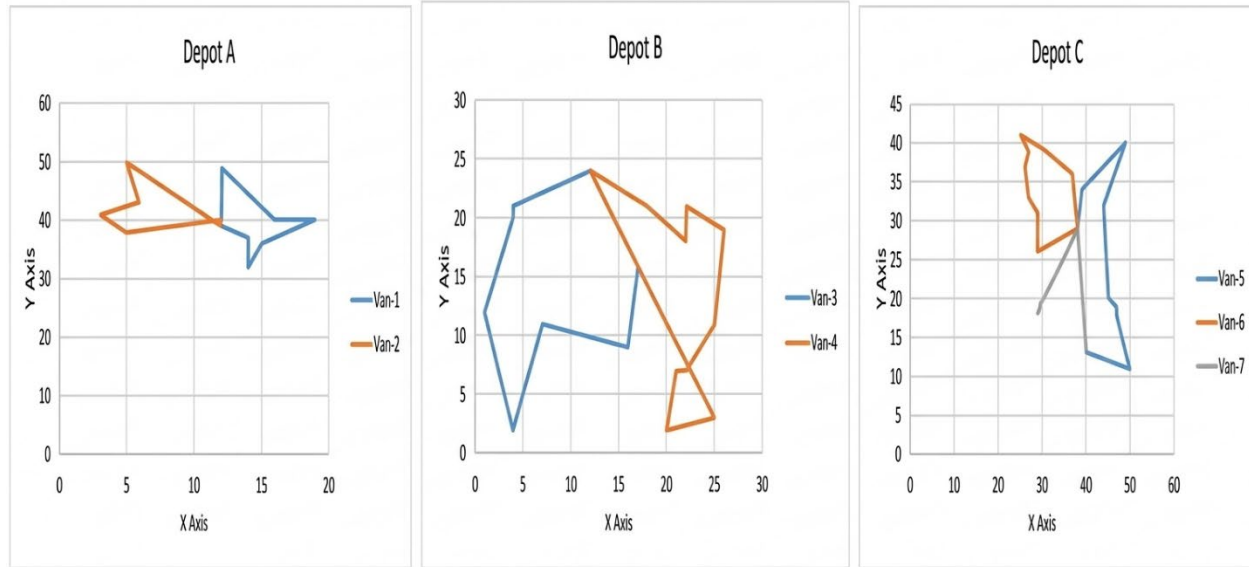


Figure 11. Optimal travel routes and graphical representation of the best solution for the 50-5-3b benchmark instance.

5.3 Results Analysis

Based on the Prins benchmark data, eight problem instances were analyzed to determine the optimal routing solution. The experiments were conducted using a maximum of 20,000 iterations in Evolver. Different combinations of crossover and mutation rates were tested using the Genetic Algorithm (GA) and compared with the OptQuest optimization method (Table 18).

Table 18. Comparison of Total Travel Distance Using GA and OptQuest for Prins Benchmark Instances

Instances	Combination	Crossover	Mutation	Total distance travelled	Instances	Combination	Crossover	Mutation	Total distance travelled
50-5-1	First	0.4	0.08	146.94	50-5-2BIS	First	0.4	0.08	234.81
	Second	0.9	0.02	148.73		Second	0.9	0.02	234.18
	Third	0.6	0.35	171.67		Third	0.6	0.35	257.33
	Fourth	0.8	0.01	150.23		Fourth	0.8	0.01	230.54
	Optquest			150.23		Optquest			241.01
50-5-1b	First	0.4	0.08	117.34	50-5-2bBIS	First	0.4	0.08	69.78
	Second	0.9	0.02	117.34		Second	0.9	0.02	76.32
	Third	0.6	0.35	142.23		Third	0.6	0.35	116.07
	Fourth	0.8	0.01	117.34		Fourth	0.8	0.01	80.75
	Optquest			123.67		Optquest			65.91
50-5-2	First	0.4	0.08	53.9	50-5-3	First	0.4	0.08	73.66
	Second	0.9	0.02	53.9		Second	0.9	0.02	72.61
	Third	0.6	0.35	53.9		Third	0.6	0.35	77.15
	Fourth	0.8	0.01	53.9		Fourth	0.8	0.01	73.77
	Optquest			53.9		Optquest			73.66
50-5-2b	First	0.4	0.08	35.17	50-5-3b	First	0.4	0.08	64.58
	Second	0.9	0.02	35.17		Second	0.9	0.02	62.02
	Third	0.6	0.35	35.17		Third	0.6	0.35	63.81
	Fourth	0.8	0.01	35.17		Fourth	0.8	0.01	70.56
	Optquest			35.17		Optquest			59.77

The results indicate that GA and OptQuest produced very similar solutions, with only minor differences in the total travel distance. In most cases, the best GA solutions were very close to the OptQuest results. Since heuristic algorithms may produce slightly different outcomes for the same input parameters, multiple runs were considered and the average performance was evaluated. Overall, the results demonstrate that both approaches are effective for solving complex LRP instances where exact methods become computationally expensive. The obtained solutions are therefore considered near-optimal for the tested benchmark instances (Table 19).

Table 19. Summary of GA Results for Prins Benchmark Instances
(Depots, Vehicles, Capacity, and Total Distance)

Instances	Number of Depots	Number of Vehicles	Total Distance for GA	Vehicle Capacity	Cost Decrease Percentage
50-5-1	3	12	407.17	70	
50-5-1B	3	6	331.16	150	18.67%
50-5-2	4	13	346.18	70	
50-5-2b	4	7	256.99	150	25.76%
50-5-2BIS	2	12	333.79	70	
50-5-2bBIS	2	6	179.71	150	
50-5-3	3	13	388.78	70	
50-5-3b	3	7	294.8	150	24.17%

The results show that the Genetic Algorithm (GA) effectively determines the optimal number of depots, vehicles, and routing distances for different benchmark instances. When vehicle capacity increases from 70 to 150, the number of required vehicles decreases significantly, which also reduces the total travel distance. This improvement is reflected in the cost decrease percentages, such as 18.67% for instance 50-5-1B, 25.76% for 50-5-2b, and 24.17% for 50-5-3b. Overall, higher vehicle capacity leads to fewer vehicles and lower total routing distances, demonstrating that GA provides efficient and near-optimal solutions for the Location Routing Problem.

5.4 Proposed Improvements

This study has several limitations related to the data and assumptions used in the analysis. The research relies entirely on Prins benchmark instances, which may not fully represent real-world logistics conditions. As a result, several practical cost factors were not considered in the model.

Additional operational costs such as taxi fares, fuel, parking, meals, bonuses, cleaning, distribution expenses, and communication costs were not included in the analysis. The results are based on theoretical modeling; therefore, the outcomes may differ when applied in real-world situations. The dataset has certain constraints. For example, cost values were scaled (multiplied by 1000) for vehicle capacities of 70 and 150, which simplifies the complexity found in real logistics operations. The benchmark dataset is relatively old and does not necessarily reflect current logistics environments.

Despite these limitations, the study provides useful insights for transportation planning and distribution network design. The proposed approach can help improve supply chain efficiency by optimizing depot locations and vehicle routing. For more accurate results in future research, real operational data and more advanced software tools should be used. In addition, demand forecasting could be incorporated to determine the optimal number of depots, vehicles, and customer allocations more precisely.

5.4 Validation

To validate the effectiveness of the proposed approach, the results obtained from the Genetic Algorithm (GA) were compared with the solutions generated by the OptQuest optimization tool using the same benchmark instances from the Prins dataset. The comparison focused on key performance indicators such as total travel distance, number of

depots used, and number of vehicles required. The results indicate that the GA solutions are very close to those obtained from OptQuest, showing only small variations in total travel distance across different instances.

To further examine the reliability of the results, multiple runs of the GA were conducted with the same parameter settings (population size = 50 and maximum iterations = 20,000). The average total distance obtained from these runs was compared with the OptQuest results. A simple statistical hypothesis test was considered where the null hypothesis assumed that there is no significant difference between the GA results and the OptQuest solutions. The observed differences in the objective values were minimal, suggesting that the null hypothesis cannot be rejected at the commonly accepted significance level.

This validation indicates that the proposed GA-based method produces stable and near-optimal solutions for the Location Routing Problem. The close agreement between the GA results and the OptQuest outcomes confirms that the proposed approach is suitable for solving complex routing and depot location decisions in logistics systems.

6. Conclusion

This study addressed the Location Routing Problem (LRP) with the objective of minimizing total travel distance while determining the optimal number of depots, vehicles, and route paths. A Genetic Algorithm (GA)-based approach was developed and applied to benchmark instances derived from Prins' dataset. The proposed model considered depot selection, customer allocation, vehicle capacity constraints, and routing decisions simultaneously to obtain efficient distribution solutions.

The experimental results demonstrate that the proposed method successfully determines feasible depot locations and vehicle routes while minimizing total travel distance. The findings confirm that increasing vehicle capacity reduces the number of vehicles required and improves routing efficiency. The solutions generated by the Genetic Algorithm were also validated through comparison with OptQuest results, showing very small differences in total distance. This indicates that the proposed approach produces reliable and near-optimal solutions for complex logistics problems.

All research objectives set at the beginning of the study have been achieved. The model effectively identifies optimal depot allocation, determines customer distribution among depots, and generates efficient vehicle routing plans under capacity constraints. The study also demonstrates the applicability of meta-heuristic techniques for solving large-scale logistics optimization problems where exact methods are computationally expensive.

The key contribution of this research lies in integrating location and routing decisions within a Genetic Algorithm framework and applying it to benchmark datasets to evaluate performance under different vehicle capacities and parameter settings. The results provide useful insights for improving distribution network design and transportation planning. The proposed approach can support decision-makers in developing more efficient logistics systems and reducing operational costs in supply chain operations.

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Biographies

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