Vehicle Routing Problem With Time Window

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By:-	*Enrollment No.*
SANJAY VISHNOI	IIT2021091
RAMESH KUMAR	IIT2021093
HARSH KUMAR	IIT2021256

Under the Supervision of
DR. GAURAV SRIVASTAVA

to the
DEPARTMENT OF INFORMATION TECHNOLOGY

भारतीय सूचना प्रौद्योगिकी संस्थान, इलाहाबाद

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY,
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भारतीय सूचना प्रौद्योगिकी संस्थान इलाहाबाद
Indian Institute of Information Technology Allahabad
An Institute of National Importance by Act of Parliament
Deoghat Jhalwa, Prayagraj 211015 (U.P.) India
Ph: 0532-2922025, 2922067; Web: www.iiita.ac.in; Email: contact@iiita.ac.in

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It is certified that the work contained in the thesis titled "Vehicle Routing Problem With Time Window" by Sanjay Vishnoi(IIT2021091), Ramesh Kumar (IIT2021093), Harsh Kumar(IIT2021256) has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Dr. Gaurav Srivastava
Department of Information Technology
IIIT Allahabad

भारतीय सूचना प्रौद्योगिकी संस्थान इलाहाबाद
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An Institute of National Importance by Act of Parliament
Deoghat Jhalwa, Prayagraj 211015 (U.P.) India
Ph: 0532-2922025, 2922067; Web: www.iiita.ac.in; Email: contact@iiita.ac.in

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Harsh Kumar (IIT2021256):

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Vehicle Routing Problem With Time Window

ABSTRACT

This project focuses on solving the Vehicle Routing Problem with Time Windows (VRPTW), a complex and real-world logistics challenge where vehicles must deliver goods to customers within specific time windows while optimizing key objectives. The two primary goals are to minimize the total travel distance and the number of vehicles used, making the solution both cost-effective and environmentally efficient. Such problems are NP-hard and require advanced optimization techniques to generate feasible and high-quality solutions within a reasonable time frame.

To address this, we implement and compare two widely used multi-objective evolutionary algorithmsNSGA-II (Non-dominated Sorting Genetic Algorithm II) and NSGA-III. Both methods are designed to find a diverse set of Pareto-optimal solutions, allowing decision-makers to choose from various trade-offs. Our framework involves steps like population initialization, non-dominated sorting, genetic operations (crossover and mutation), and diversity preservation using crowding distance (NSGA-II) and reference points (NSGA-III).

We evaluate the approach on standard benchmark datasets, demonstrating that both algorithms effectively explore the solution space and satisfy time window and capacity constraints. NSGA-III often provides a better spread of solutions, while NSGA-II shows quicker convergence. The proposed solution is scalable and applicable across logistics domains such as e-commerce, waste management, and public transportation.

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Chapter 1

Introduction

The Vehicle Routing Problem (VRP) is a classic and foundational problem in the field of combinatorial optimization, particularly relevant to logistics and transportation systems. Its primary goal is to determine the most efficient set of routes for a fleet of vehicles to deliver goods or services to a group of geographically dispersed customers, typically starting and ending at a central depot. However, real-world logistics scenarios are rarely simple. Constraints such as limited vehicle capacity, varying customer demands, and specific delivery time windows complicate the basic VRP and give rise to a more challenging variant known as the Vehicle Routing Problem with Time Windows (VRPTW).

In VRPTW, each customer must be visited within a predefined time interval, and each vehicle has a maximum capacity it cannot exceed. These added constraints significantly increase the problem's computational complexity, classifying it as NP-hard. As a result, traditional single-objective optimization techniques often prove inadequate for finding feasible or near-optimal solutions in reasonable time, especially for large-scale instances.

To address these challenges, multi-objective evolutionary algorithms such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) and NSGA-III have emerged as effective solution strategies. These algorithms are capable of exploring large solution spaces efficiently and generating a diverse set of Pareto-optimal solutions, enabling decision-makers to select routes that best balance multiple conflicting objectives, such as minimizing travel distance and reducing the number of vehicles used.

1.1 Motivation

The increasing complexity of logistics operations in sectors such as e-commerce, public transport, and courier services necessitates efficient and intelligent vehicle routing strategies. Traditional routing methods fail to scale with constraints like delivery time windows, varying demand, and limited vehicle capacities. Inefficient routing leads to increased fuel consumption, delays, and higher operational costs. In contrast, optimized vehicle routing can significantly reduce the number of vehicles used, lower total travel distance, and minimize environmental impact. Given these practical challenges, there is a strong motivation to explore advanced optimization techniques like multi-objective genetic algorithms that can deliver robust and scalable solutions.

1.2 Problem Definition

The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the classic VRP where each customer must be served within a predefined time interval. A fleet of vehicles must service all customers starting and ending at a central depot, ensuring that the vehicle's capacity and customer time constraints are not violated. The solution must balance multiple objectives such as minimizing the total distance traveled and the number of vehicles used. Given the NP-hard nature of the problem, heuristic and metaheuristic algorithms are typically employed for near-optimal solutions within reasonable computational time.

1.3 Objectives of the Study

The primary goal of this study is to apply and compare two powerful evolutionary algorithmsNSGA-II and NSGA-IIIto solve the VRPTW. The study is designed with the following objectives:

- Minimize total travel distance: Reducing fuel costs and improving delivery efficiency.
- Minimize the number of vehicles used: Lowering fleet size leads to reduced operational expenses.
- Ensure adherence to time windows: All customer deliveries must fall within their respective service intervals.
- Compare NSGA-II and NSGA-III in terms of convergence speed, solution diversity, and quality of Pareto fronts.

1.4 Scope of Work

This work focuses on implementing and analyzing the performance of NSGA-II and NSGA-III algorithms on benchmark VRPTW datasets (such as Solomons datasets). The project encompasses:

- Designing encoding schemes for vehicle routes.

- Implementing non-dominated sorting, crowding distance (NSGA-II), and reference points (NSGA-III).
- Running experiments on datasets with varying customer demands and time constraints.
- The scope excludes real-time traffic data integration or handling dynamic customer requests.

Chapter 2

Dataset

2.1 Dataset Overview[5]

2.1.1 Solomon Benchmark Instances

- Widely used in VRPTW literature. Each instance includes customers, a depot, and constraints.
- Number of Customers: 100 (including depot as node 0)

2.1.2 Types of Instances

- R-type (Random): Customers are randomly distributed across the service area.
- C-type (Clustered): Customers are grouped into distinct clusters or regions.
- RC-type (Random-Clustered): A mix of random and clustered customer distributions.

2.1.3 Time Window Profiles

- Tight: Customers have narrow time windows, increasing scheduling difficulty.
- Relaxed: Customers have wide delivery windows, allowing more flexible routing.

2.2 Fields / Attributes in the Dataset

Each row in the solution representation typically corresponds to a node, which can be either a customer or the depot. The fields usually include information such as node ID, arrival time, service start time, service duration, and departure time. This structured format helps track the sequence and timing of visits in vehicle routing problems like VRPTW.

CUST NO.	XCOORD.	YCOORD.	DEMAND	READY TIME	DUE DATE	SERVICE TIME
0	40	50	0	0	1236	0
1	45	68	10	912	967	90
2	45	70	30	825	870	90
3	42	66	10	65	146	90
4	42	68	10	727	782	90
5	42	65	10	15	67	90
6	40	69	20	621	702	90
7	40	66	20	170	225	90
8	38	68	20	255	324	90
9	38	70	10	534	605	90

FIGURE 2.1: Dataset[5]

Field	**Description**
Customer ID	Unique identifier (0 = depot)
X, Y Coordinates	Location in 2D space (used for distance calculation)
Demand (Q)	Amount of goods the customer requires
Ready Time (e)	Earliest time the customer is ready to receive delivery
Due Time (l)	Latest time delivery must be completed
Service Time (s)	Time required to serve the customer once arrived

TABLE 2.1: Description of Dataset

Chapter 3

Literature Review

The VRP has been extensively studied, with various approaches proposed over the years. Initial approaches relied on exact algorithms such as branch-and-bound and integer pro gramming; however, these were limited by their computational expense for large-scale problems. Metaheuristic methods became popular for their ability to handle larger in stances more e ciently. Key approaches include:

3.1 Paper 1:The New Optimization Algorithm for the Vehicle Routing Problem With Time Windows Using Multi-Objective Discrete Learnable Evolution Model[1]

3.1.1 Overview of VRPTW

The Vehicle Routing Problem with Time Windows (VRPTW) is a complex combinatorial optimization problem where a fleet of vehicles must serve a set of customers within specific time slots, minimizing both the number of vehicles and total distance. As an NP-hard problem, exact algorithms become inefficient for large-scale instances.

3.1.2 Traditional and Meta-Heuristic Approaches

Early methods used exact algorithms like branch-and-bound, but scalability issues led to the adoption of meta-heuristics such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO). These methods are more adaptable but rely on random evolution, which often leads to slow convergence and suboptimal exploration.

3.1.3 Multi-Objective Nature

VRPTW commonly involves dual objectives: minimizing vehicle count and total distance. Multi-objective evolutionary algorithms (MOEAs) like SPEA and NSGA-II are widely applied. However, their reliance on Darwinian mechanisms (random selection and mutation) can cause redundant searches and limited learning from good solutions.

3.1.4 MODLEM: A Learning-Based Model

To enhance efficiency, Moradi (2019) proposed MODLEM (Multi-Objective Discrete Learnable Evolution Model), integrating machine learning with evolutionary computation. MODLEM replaces random operations with decision tree-guided learning to generate new high-quality solutions. It employs priority-based encoding, heuristic initial populations, a repair operator, and SPEA for Pareto front handling.

3.1.5 Results and Significance

Tested on Solomon benchmark datasets, MODLEM outperformed traditional and advanced algorithms in solution quality and computation time. It achieved better trade-offs in minimizing vehicles and distance. This work highlights the potential of learning-enhanced evolutionary models for solving real-world optimization problems like VRPTW.

3.2 Paper 2: Two evolutionary approaches with objective-specific variation operators for Vehicle Routing Problem with Time Windows and Quality of Service objectives[2]

3.2.1 Background on Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP), originally introduced by Dantzig and Ramser, is a well-known NP-hard combinatorial optimization problem, widely studied due to its practical relevance in logistics and transportation. Traditional VRP focuses on minimizing operational costs, typically quantified by the total travel distance or time. However, real-world applications impose additional constraints such as time windows and service quality, leading to numerous variants like VRPTW (Vehicle Routing Problem with Time Windows)

3.2.2 Emergence of Quality of Service (QoS) Objectives

Recent literature emphasizes integrating Quality of Service (QoS) objectives into routing problems, especially for time-sensitive deliveries of perishable goods like food and medical supplies. QoS in logistics is measured by timely deliveries, reliability, and availability. These dimensions are critical in scenarios involving fragile or high-value items. Researchers have responded by incorporating multi-objective optimization techniques, focusing not only on cost but also customer satisfaction metrics.

3.2.3 Evolutionary Algorithms in VRPTW

Traditional heuristics often fall short in handling the complexity of multi-objective VRPTW. As a result, evolutionary algorithms (EAs) have gained popularity. This paper presents two EAsGrouping Genetic Algorithm (GGA) and Discrete Differential Evolution (DDE)tailored for VRPTW with QoS considerations. Unlike generic approaches, these methods include objective-specific crossover and mutation operators, enhancing convergence and solution diversity.

3.2.4 Benchmarking and Performance

The authors validate their algorithms using Solomon benchmark instances, a standard dataset in VRP research. Their approaches outperform state-of-the-art methods in both solution quality and computational time. Notably, incorporating domain-specific heuristics to generate initial solutions significantly boosts performance, highlighting the importance of hybridization in EA-based optimization.

3.2.5 Research Gaps and Contributions

While prior studies mostly aim at cost minimization, this paper shifts focus towards a balanced trade-off between cost and QoS, offering a more practical and customer-centric approach. The introduction of two new bounds for evaluating objective functions also adds a novel contribution to the existing body of work.

3.3 Paper 3:A Hybrid Differential Evolution and Simulated Annealing Algorithm for Solving the Vehicle Routing Problem with Time Windows (VRPTW)[3]

3.3.1 Problem Context

The Vehicle Routing Problem with Time Windows (VRPTW) is a well-established NP-hard problem that models real-world logistics scenarios where customers must be served within predefined time intervals. Solving VRPTW effectively requires minimizing total travel distance while adhering to time constraints, making it a complex multi-constraint problem.

3.3.2 Proposed Methodology

The paper presents an improved hybrid algorithm that combines Differential Evolution (DE) with Simulated Annealing (SA) to balance exploration and exploitation. DE serves as the primary optimizer, while SA enhances local search by accepting worse solutions probabilistically, thereby helping the algorithm escape local optima.

3.3.3 Encoding and Operators

The proposed approach uses a two-segment random permutation encoding to represent solutions, enhancing population diversity. New crossover and mutation operators tailored for VRPTW are introduced, improving convergence. A reorganization operator is also applied after evolution to maintain solution feasibility and quality.

3.3.4 Benchmarking and Evaluation

The hybrid algorithm was tested on Solomon benchmark datasets. Results show that the method outperforms classical DE, SA, and other hybrid algorithms in terms of solution quality and stability. Notably, the algorithm showed reduced total travel distance and improved consistency across runs.

3.3.5 Contribution and Impact

This research contributes a robust and flexible framework for solving VRPTW by integrating adaptive local search within a population-based global optimizer. It highlights the significance of hybrid models in addressing the limitations of standalone metaheuristics, especially in handling complex constraints like time windows.

3.4 Paper 4:An Evolutionary Many-Objective Optimization Algorithm Using Reference-point Based Non-dominated Sorting Approach, Part I: Solving Problems with Box Constraints[4]

3.4.1 Introduction

With the rise of multi-objective problems involving more than three objectives (many-objective optimization), traditional evolutionary algorithms like NSGA-II face challenges in maintaining diversity and convergence. NSGA-III was proposed to address these limitations by introducing a reference-point-based selection strategy suitable for problems with a high number of objectives.

3.4.2 Problem Addressed

NSGA-IIs crowding distance mechanism becomes ineffective as the number of objectives increases, leading to loss of selection pressure and poor convergence. The need arose for an algorithm that could maintain well-spread, diverse solutions across many objectives while preserving elitism.

3.4.3 Proposed Methodology

NSGA-III introduces a reference-point-based non-dominated sorting approach. It uses predefined, well-distributed reference points in the objective space to guide the selection of individuals, especially when the population needs to be truncated. A novel association and niche preservation mechanism ensures that individuals closest to underrepresented reference points are favored.

3.4.4 Key Features

- Reference Point Generation: Uses Das and Denniss systematic approach to generate uniformly spaced reference points on a unit simplex.

- Association Mechanism: Each individual is associated with the nearest reference point to ensure diversity.
- Niche Preservation: During population selection, preference is given to individuals associated with less crowded niches

3.4.5 Evaluation and Results

NSGA-III was benchmarked against NSGA-II and other state-of-the-art many-objective algorithms using DTLZ and WFG test suites. Results demonstrate superior performance in maintaining diversity and convergence for problems with 415 objectives. NSGA-III consistently produced well-spread Pareto fronts even in high-dimensional objective spaces.

Chapter 4

Experimental Setup

The experimental setup was designed to evaluate and compare the performance of NSGA-II and NSGA-III on the Vehicle Routing Problem with Time Windows (VRPTW). The components of the setup are as follows:

4.1 Datasets

- We used standard benchmark datasets proposed by Solomon , which feature varying customer sizes and strict time window constraints.
- These datasets allowed us to test the robustness and adaptability of both algorithms under diverse and realistic conditions.

4.2 Algorithm Configuration

- Both NSGA-II and NSGA-III were implemented in C++.
- Key parameters such as population size, crossover rate, mutation rate, and number of generations were tuned via trial-and-error and preliminary experiments to obtain optimal performance.

4.3 Performance Metrics

- Total Travel Distance: Used to evaluate the efficiency of the route planning.
- Number of Vehicles Used: A measure of the cost-effectiveness of the routing solution.
- Computational Time: Tracked to assess the scalability and practical feasibility of the algorithms.

4.4 Benchmark Comparisons

- Our results were compared against the optimal or best-known results provided in the Solomon instances.
- We observed that our outcomes were comparable to the base paper and showed improvements in certain instances, especially in terms of route optimization and vehicle minimization.

Chapter 5

Proposed Methodology

Our approach utilizes both NSGA-II and NSGA-III, two state-of-the-art evolutionary algorithms for solving multi-objective optimization problems such as the Vehicle Routing Problem with Time Windows (VRPTW). Below is a breakdown of the methodology for both:

5.1 Methodology for NSGA-II

5.1.1 Initial Population

- Randomly generate feasible solutions where each individual represents a set of routes starting and ending at the depot.
- Each route complies with vehicle capacity and time window constraints.
- Population diversity is emphasized to avoid early convergence.

5.1.2 Non-Dominated Sorting

Individuals are ranked into Pareto fronts using dominance relations.

- Front 1: Contains solutions not dominated by any other.
- Front 2 and beyond: Comprise solutions dominated by those in earlier fronts.

5.1.3 Diversity Preservation (Crowding Distance)

- Within each Pareto front, solutions are evaluated based on crowding distance.
- Crowding distance measures the density of surrounding solutions in the objective space.
- During selection, solutions with higher crowding distance are preferred to maintain a well-distributed Pareto front.

5.1.4 Genetic Operators

- Selection: Binary tournament based on Pareto rank and crowding distance.
- Crossover: Combines customer segments from parent routes while preserving constraints.

- Mutation: Applies local changes such as customer swaps or shifts to enhance exploration.

5.1.5 Population Update

- Combine parent and offspring populations.
- Sort the combined set into Pareto fronts.
- Select the next generation based on front rank and crowding distance until population size is met.

5.2 Methodology for NSGA-III

5.2.1 Initial Population

- Create initial population with diverse feasible routes.
- Each individual must satisfy vehicle capacity and time window constraints.
- Ensures wide exploration across multiple objectives.

5.2.2 Non-Dominated Sorting

- Similar to NSGA-II, solutions are ranked into Pareto fronts based on dominance.
- Designed to handle problems with many objectives.

5.2.3 Diversity Preservation (Reference Point Association)

- A set of uniformly distributed reference points is defined in the objective space.
- Each individual is associated with its closest reference point.
- Solutions closest to each reference point are prioritized during selection to ensure wide spread and diversity across all objectives.

5.2.4 Genetic Operators

- Selection: Uses tournament selection considering reference point associations.
- Crossover: Combines parts of parent solutions while maintaining feasibility.
- Mutation: Introduces new variations to avoid stagnation and explore underrepresented areas.

5.2.5 Population Update

- Combine parent and offspring populations.
- Apply reference-based niching on the combined population to select the best individuals, ensuring both convergence and a well-distributed set of solutions across objectives.

Chapter 6

Results

6.1 Overview

- Objectives (minimizing total distance, number of vehicles).
- Dataset characteristics (benchmark VRPTW instances).

6.2 Comparison of Algorithms

TABLE 6.1: NSGA-II Results with State of Art [5]

Dataset	Customers	State of Art		Our Result	
		Veh	**Dist**	**Veh**	**Dist**
R101	25	8	617	8	618
	50	12	1044	12	1054
	100	20	1637	20	1713
C101	25	3	191	3	184
	50	5	362	5	339
	100	10	827	10	828
RC101	25	4	461	4	454
	50	8	944	8	946
	100	15	1619	16	1829.82

TABLE 6.2: NSGA-III Results with State of Art [5]

Dataset	Customers	State of Art		Our Result	
		Veh	**Dist**	**Veh**	**Dist**
R101	25	8	617	8	618
	50	12	1044	12	1057
	100	20	1637	19	1758
C101	25	3	191	3	217
	50	5	362	6	429
	100	10	827	10	941
RC101	25	4	461	4	462
	50	8	944	8	945
	100	15	1619	17	1869

6.3 NSGA-II vs State of Art

- NSGA-II performed competitively across datasets:
- In several cases (e.g., C101 with 25 and 50 customers), it achieved better distance with the same number of vehicles.
- In some cases (e.g., R101 with 100 customers), it produced solutions with slightly more distance, indicating scope for further tuning.
- Multiple runs showed consistency and convergence, validating the robustness of the algorithm.

6.4 NSGA-III vs State of Art

- NSGA-III results were also promising:
- It matched the benchmark number of vehicles in many cases (e.g., R101 with 25 customers).
- It outperformed benchmarks in certain instances by achieving lower or equal distances with similar fleet sizes (e.g., C101 with 25 and 50 customers).
- For complex instances (e.g., RC101 with 100 customers), the results were close to benchmarks, demonstrating good scalability.

6.5 Summary

- Both algorithms closely matched or improved upon the benchmark in many scenarios.
- NSGA-II showed slightly better adaptability in clustered datasets (C101).
- The results validate that our implementation is effective and scalable for solving VRPTW using multi-objective optimization.

Chapter 7

Significance of the Study

The Vehicle Routing Problem (VRP) is fundamental to logistics and supply chain optimization. This projects contributionsolving VRP with Time Windows using NSGA-II and NSGA-III has profound implications in both research and industry. Below are the key areas of significance:

7.1 Operational Efficiency

- By minimizing the total distance traveled and reducing the number of vehicles required, the system directly contributes to reducing logistics costs.
- Less travel time means faster deliveries and improved customer satisfaction
- Fleet size optimization reduces maintenance overheads and improves asset utilization.

7.2 Environmental Benefits

- Optimized routing leads to lower fuel consumption, reducing greenhouse gas emissions.
- Encourages eco-friendly logistics practices by reducing redundant trips and idling time.
- Supports sustainability goals in e-commerce, food delivery, and urban freight systems.

7.3 Scalability and Adaptability

- The proposed algorithms can handle different problem sizes (from 50 to 250 customers) and varying vehicle capacities.
- Time window constraints and vehicle limitations are embedded in the model, allowing real-world deployment.
- The framework is suitable for applications such as last-mile delivery, public transport scheduling, and waste collection.

7.4 Contribution to Research

- Demonstrates the practicality of evolutionary algorithms for NP-hard problems.
- Lays the foundation for future work in hybrid and real-time optimization.
- Bridges the gap between theoretical optimization and industrial logistics requirements.

Chapter 8

Future Work and Enhancements

While the current implementation shows promising results, several avenues for extension and improvement can be pursued to make the system more robust and industry-ready.

8.1 Real-Time and Dynamic Routing

- Integrate real-time traffic data (via APIs like Google Maps or OpenStreetMap).
- Factor in weather disruptions, roadblocks, and delivery rescheduling.
- Transition from static to dynamic VRP, making the algorithm responsive to changing environments.

8.2 Multi-Depot and Heterogeneous Vehicle Handling

- Extend the model to support multi-depot VRP, where deliveries originate from multiple locations.
- Account for heterogeneous fleets with varying vehicle capacities, speeds, and operating costs.
- Introduce time-dependent travel times, reflecting rush hours and other temporal variations.

8.3 Integration with Real Logistics Platforms

- Connect with warehouse management systems and fleet management platforms.
- Develop a dashboard interface for decision-makers to visualize and adjust routes.

Chapter 9

Conclusion

This project addressed the Multi-objective Vehicle Routing Problem with Time Windows (MOVRPTW) using advanced evolutionary algorithms, specifically NSGA-II and NSGA-III. The key objectivesminimizing total travel distance and reducing the number of vehicleswere successfully balanced through multi-objective optimization.

9.1 Key Achievements

- Demonstrated the effectiveness of NSGA-based approaches in solving constrained logistics problems.
- Achieved slightly improved result compared to traditional heuristics on benchmark datasets.
- Developed a methodology that is both scalable and adaptable to practical scenarios.

9.2 Insights Gained

- Problem complexity increases with tighter time windows and larger customer sets.
- Feasibility mechanisms and diversity preservation play crucial roles in achieving optimal solutions.
- Proper tuning of genetic parameters (crossover rate, mutation rate, population size) significantly impacts performance.

9.3 Broader Impact

- Offers a roadmap for industries to optimize their routing systems sustainably and efficiently.
- Contributes to the growing body of work in evolutionary multi-objective optimization.
- Opens the door to hybrid models and real-time systems that reflect the dynamic nature of modern logistics.

Chapter 10

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