A Synopsis

On

"MAVROS : Multi-Directional Adaptive Vehicle Routing Optimization System"

Submitted in partial fulfilment of the requirements of the Degree

Bachelor of Engineering (Artificial Intelligence and Data Science)

Submitted by:

1. **Anaanti Yati**
2. **Rishabh Bhawsar**
3. **Sahil Jadhav**

Supervisor:

Dr.(Mrs). Preeti Jain

Datta Meghe College of Engineering

Department of Artificial Intelligence and Data Science

Airoli, Navi Mumbai

(Affiliated To University of Mumbai)

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Datta Meghe College Of Engineering
Department Of Artificial Intelligence and Data Science
Airoli, Navi Mumbai.
(Affiliated To University of Mumbai)
Academic Year 2025-2026

Project Approval

This report, entitled as **”MAVROS : Multi-Directional Adaptive Vehicle Routing Optimization System”**, submitted by students,

1. Anaanti Yati
2. Rishabh Bhawsar
3. Sahil Jadhav

Is approved for the term work in partial fulfillment of the requirements of degree of ”Bachelor of Engineering, (Artificial Intelligence and Data Science)”, (CBGS Course), of ”University of Mumbai”, in semester VII during academic year 2025-2026.

1) Name and Signature of Internal Examiner:

2) Name and Signature of External Examiner:

Date:

Place: Airoli

Datta Meghe College of Engineering
Department Of Artificial Intelligence and Data Science
Airoli, Navi Mumbai.
(Affiliated To University of Mumbai)
Academic Year 2025-2026

Certificate

This is to certify that, following students

1. Anaanti Yati
2. Rishabh Bhawsar
3. Sahil Jadhav

Have satisfactorily completed the term work for project titled as **”MAVROS : Multi-Directional Adaptive Vehicle Routing Optimization System”**, undertaken at ”Datta Meghe College of Engineering, Airoli” in partial fulfillment of the requirements of degree of ”Bachelor of Engineering, (Artificial Intelligence and Data Science)”, (CBGS Course), of ”University of Mumbai”, in semester VIII during academic year 2025-2026.

Mrs. P. N. Jain	Dr. S. M. Patil	Dr. P.A.Dode
Supervisor	Head of Department	Principal

Declaration

We declare that this written submission represent our idea in our own words and other ideas and words which have been included are adequately cited and referenced from the original source. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified and idea/data/fact/source in our submission. We understand that our violation of above will be cause for disciplinary action by Institute and can also evoke penal action for the sources which have thus not been properly cited or from whom proper permission has not be taken when needed.

NAME	SIGNATURE

1. Anaanti Yati
2. Rishabh Bhawsar
3. Sahil Jadhav

Date:

Place: Airoli

Abstract

In logistics, the Vehicle Routing Problem (VRP) is an important and common challenge considerably affecting the cost-effectiveness and efficiency of numerous operations. The core objective of the VRP is to establish an optimal set of routes for a fleet of vehicles to service a specific group of clients. The VRPTW is a NP-hard discrete optimization problem and stated as a combination of both the traveling salesman problem (TSP) and the VRP. The travelling salesman problem is a classic problem which seeks the shortest possible route that a person or a vehicle must take to visit a specific group of locations. VRP is a complex version of TSP.

In essence, it involves a starting point called depot from which the vehicles depart initially and then routing and scheduling is done according to the demands under various constraints such as time window. Such problems are common in various domains, not only for transportation but also for various others like service network design, production planning, apportionment etc.

VRPTW deals with a fleet of vehicles instead of one vehicle and also finds the optimal set of routes for all the vehicles visiting a set of locations. The proposed solution method is to design efficient algorithms for the VRPTW using a combination of heuristics, local search, and evolutionary methods. Heuristics will be used to quickly find an initial, feasible solution then local search will iteratively improve this solution by making small, strategic changes. Finally, evolutionary methods will be applied to explore a wider solution space and escape local optima, leading to a robust and highly-effective algorithm. MAVROS aims to contribute a robust and scalable solution for practical application in the logistics industry.

Acknowledgment

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Contents

List of Abbreviations

Abbreviation	Description
MAVROS	Multi-Directional Adaptive Vehicle Routing Optimization System
VRPTW	Vehicle Routing Problem with Time Windows
MARL	Multi-Agent Reinforcement Learning
RL	Reinforcement Learning
GA	Genetic Algorithm
RRGA	Ruin-and-Recreate Genetic Algorithm
QAOA	Quantum Approximate Optimization Algorithm
MIH	Multiple Insertion Heuristic
MDS	Multi-Directional Search

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Chapter 1

Introduction

The VRP has long been recognized as one of the most challenging and impactful problems in operations research, forming the foundation of modern logistics optimization [1, 2]. It focuses on determining the optimal set of routes for a fleet of vehicles to serve a geographically distributed set of customers under constraints such as vehicle capacity, time windows, and service durations. The problem has numerous real-world applications across logistics, healthcare distribution, e-commerce, and public services [3]. Efficient solutions can significantly reduce transportation costs, fuel consumption, and environmental impact while improving customer satisfaction and service reliability [4, 5].

Despite decades of research, the VRPTW remains computationally complex and difficult to solve optimally. Exact algorithms such as branch-and-bound and branch-and-price become infeasible for large-scale instances due to exponential growth in the solution space [6]. Consequently, recent research has shifted toward metaheuristic and hybrid approaches that balance solution quality with computational efficiency [7, 8, 9].

MAVROS is designed to address these challenges through a three-layered hybrid metaheuristic approach. The framework combines an initial heuristic phase, a MA, and an MDS phase for local refinement [10, 11]. The initial heuristic ensures a high-quality, feasible starting solution that accelerates convergence. The MA leverages both global search through evolutionary mechanisms and localized exploitation to refine candidate solutions adaptively [12, 13].

What distinguishes MAVROS from traditional hybrid methods is its tightly integrated and adaptive optimization pipeline. The MA and MDS components exchange structural insights during runtime to maintain population diversity while ensuring convergence toward near-optimal solutions [14]. This cross-layer communication reduces the likelihood of premature convergence—a common weakness in evolutionary methods—and enhances adaptability in dynamic or uncertain routing environments [15, 16].

Finally, the MDS component acts as a derivative-free fine-tuning layer that systematically explores multiple improvement directions without gradient dependence [13, 17]. Its incorporation enhances MAVROS's ability to achieve deeper local optimality, ensuring each route is globally competitive and contextually efficient within real-world constraints such as limited fleet capacity, varying service times, and stochastic travel conditions [18].

Collectively, MAVROS demonstrates a synergistic balance between exploration and exploitation. Its hybrid design enables robust scalability for large instances while maintaining solution precision, making it highly relevant for emerging logistics domains that demand both real-time adaptability and optimization efficiency [7, 5].

1.1 Existing Systems and Their Limitations

Numerous algorithms have been developed to address the VRPTW, ranging from classical exact approaches to modern metaheuristic and learning-based frameworks. Although these methods have yielded valuable insights, they still face significant performance bottlenecks in complex, real-world environments. Some notable limitations are outlined below:

1. **Rigid objective prioritization:** Many traditional systems follow Solomon's classical objective hierarchy—minimizing the number of vehicles before optimizing distance or travel time—which is unrealistic in practical fleet operations where vehicle availability can be dynamic or outsourced [7, 8].

2. **Limited adaptability to flexible delivery points:** Most VRPTW formulations assume fixed customer locations and fail to integrate flexible or capacitated delivery nodes. This limits applicability in domains such as healthcare and disaster logistics, where on-the-fly rerouting is common [12, 19].

3. **Scalability challenges of exact algorithms:** Although exact methods like branch-and-price can provide optimal solutions, they become computationally infeasible for large instances, with fewer than 10 out of 300 benchmark datasets solvable to optimality [2, 6, 18].

4. **Excessive runtime in sequential hybrid models:** Many hybrid or multi-phase algorithms require extensive computation time for convergence, making them impractical for real-time or large-scale operations [5, 11].

5. **Insufficient handling of dynamic constraints:** Several metaheuristic frameworks lack real-time adaptability to fluctuating demands, traffic variations, and environmental factors, leading to suboptimal routing decisions [14, 16].

These limitations highlight the need for a next-generation hybrid system that balances computational efficiency with solution precision. MAVROS, by integrating heuristic initialization, MA, and MDS, provides a unified and adaptive framework capable of addressing the real-world complexities of VRPTW.

1.2 Aims and Objectives

MAVROS aims to address the limitations of existing VRPTW algorithms by introducing a hybrid metaheuristic framework that optimizes vehicle routing for complex, real-world logistics scenarios.

Problem Statement: Current VRPTW solutions struggle with scalability, adaptability to dynamic constraints, and balancing exploration and exploitation, leading to suboptimal or infeasible solutions for large-scale or complex logistics problems. MAVROS seeks to overcome these challenges by providing a robust, scalable, and adaptive framework that delivers near-optimal routing solutions efficiently.

Aim: To develop a hybrid metaheuristic framework that integrates heuristic initialization, MA, and MDS to deliver efficient, high-quality, and scalable solutions for complex VRPTW instances, minimizing total travel costs while respecting real-world constraints.

Objectives:

1. Develop an initial solution heuristic that generates high-quality, feasible starting solutions for VRPTW instances, ensuring a strong foundation for further optimization.

2. Implement an MA that combines global search capabilities of GA with local refinement procedures to explore a diverse solution space effectively.

3. Integrate an MDS mechanism to fine-tune solutions locally, ensuring near-optimal results by balancing exploration and exploitation.

4. Enable the framework to handle dynamic constraints, such as varying customer demands, flexible delivery locations, and traffic conditions, ensuring applicability in real-world scenarios like healthcare logistics or urban delivery systems.
5. Evaluate MAVROS against benchmark VRPTW instances (e.g., Gehring and Homberger datasets) to demonstrate efficiency, scalability, and solution quality.

1.3 Organization of the Report

This report provides a comprehensive analysis of MAVROS, from problem motivation to validated performance. **Chapter 2** reviews VRPTW literature, covering RL, hybrid metaheuristics, decomposition methods, and emerging trends like quantum computing and drone deliveries, highlighting challenges such as scalability and computational complexity. **Chapter 3** presents the MAVROS system design, detailing MIH for initial route construction and MDS for optimization, along with the architecture, workflow, algorithm, and tools, emphasizing a modular, extensible framework implemented with Python, OR-Tools, and React.js.

Chapter 2

Literature Survey

The VRPTW has remained one of the most intensively studied optimization problems due to its importance in logistics, urban freight distribution, and intelligent transportation systems. In the last five years, research has diversified into RL, hybrid metaheuristics, matheuristics, decomposition strategies, and practical extensions such as EVs, drones, and quantum computing. This chapter organizes the literature from 2020 to 2025 into key methodological categories, highlighting the strengths, limitations, and trade-offs of recent contributions.

2.1 RL Approaches

RL has become a promising paradigm for VRPTW due to its ability to learn adaptive decision-making strategies. Nazari and Soleymani [1] demonstrated a deep RL framework for capacitated VRP, showing competitive solution quality without handcrafted heuristics. However, their approach required extensive training and struggled with generalization to significantly larger problem sizes. Phiboonbanakit et al. [2] advanced this line by integrating RL with heuristic rules, improving convergence stability. Yet, hybridization increased model complexity, and tuning the interaction between learning and rule-based components was non-trivial.

A more recent trend involves MARL. Bi et al. [3] proposed a MARL framework for truck–drone VRPTW, where multiple agents coordinated heterogeneous deliveries. The model achieved better adaptability in multi-modal environments, but scalability and communication overhead among agents posed challenges. Overall, RL approaches show strong potential for dynamic VRPTW but remain computationally expensive and heavily reliant on large-scale training data.

2.2 Hybrid Evolutionary and GA

Metaheuristics such as ACO and GAs continue to provide strong solutions for VRPTW. Ratanavilisagul and Kosolsombat [10] improved ACO by adding customer selection, elimination, and re-initialization strategies. This enhanced exploration but required delicate balance between diversification and solution stability. Similarly, Maroof et al. [4] introduced a hybrid GA for logistics optimization, achieving significant gains in solution quality. Yet, as with many GA-based approaches, computational overhead increased with population size, and performance was sensitive to parameter tuning.

Tan et al. [7] contributed a multi-objective EA for VRPTW under uncertainty. Their model handled stochastic variations in time windows effectively but at the cost of additional runtime. These works collectively highlight the trade-off between solution robustness and computational complexity in evolutionary approaches.

2.3 Distributed, Parallel, and Decomposition-Based Methods

Scalability has driven the development of parallel and decomposition-based frameworks. Khoo and Mohammad [12] designed a two-phase distributed RRGA, which improved runtime and solution quality across benchmarks. However, their method was highly parameter-sensitive, and communication overhead limited scalability in larger distributed systems.

Truden et al. [14] proposed a matheuristic decomposition approach along the time dimension, which allowed efficient handling of large instances. Santini et al. [5] explored general decomposition strategies for large-scale heuristics, showing how problem partitioning accelerates search while maintaining accuracy. Both approaches underscored a common trade-off: decomposition simplifies computation but risks losing global interactions among routes.

2.4 Matheuristics and Exact Algorithms

Integrating mathematical programming with heuristics has been another major trend. Rodríguez et al. [8] introduced a hybrid matheuristic for the 3D loading VRPTW, combining routing with packing decisions. Their approach improved realism but required significant computational effort. Vahedi-Nouri et al. [11] proposed a bi-objective matheuristic for collaborative electric VRPTW, balancing cost efficiency with environmental goals. While effective, solving two objectives simultaneously increased algorithmic complexity.

On the exact side, Sahin and Yaman [6] developed a branch-and-price algorithm for the heterogeneous fleet, multi-depot, multi-trip VRPTW. While capable of producing optimal solutions, the method was limited to moderately sized instances, highlighting the classic scalability trade-off of exact methods. Overall, matheuristics strike a balance between solution quality and runtime, but integration with multiple constraints often leads to higher computational requirements.

2.5 Real-World VRPTW Extensions: Contactless, EV, and Drone Delivery

Real-world challenges have pushed VRPTW research into new domains. Chen et al. [9] studied contactless delivery during the COVID-19 pandemic, emphasizing safe logistics. While practical, the model was highly context-specific and less generalizable post-pandemic. Chen et al. [13] investigated autonomous EV routing with charging and parking coordination, showing integration of grid constraints with routing. However, grid stability requirements increased computational complexity.

Vahedi-Nouri et al. [11] addressed sustainability with a collaborative electric VRPTW, but balancing collaboration efficiency and battery constraints proved challenging. Yang et al. [18] modeled post-disaster truck–drone routing using a two-stage stochastic approach. The framework handled uncertainty but was computationally intensive. Cheng et al. [20] further extended the two-echelon truck–drone VRPTW for patrol operations, demonstrating flexibility but facing synchronization challenges between drones and trucks. Collectively, these works show how extending VRPTW to practical scenarios increases realism at the cost of higher model complexity and computational demand.

2.6 Quantum and Emerging Approaches

Exploration of unconventional paradigms has also begun. Azad et al. [15] applied QAOA to VRPTW, highlighting quantum computing's potential for combinatorial optimization. While promising, the approach is limited by current hardware capacity and small-scale applicability. These early experiments show future directions but remain far from practical deployment.

2.7 Observations

From 2020 to 2025, VRPTW research shows a clear shift towards hybridization, parallelization, and problem diversification. RL [1], [2], [3], evolutionary algorithms [10], [4], [7], and decomposition frameworks [12], [14], [5] represent dominant streams. At the same time, practical extensions such as contactless services [9], EV routing [13], and truck–drone collaboration [18], [20] reflect adaptation to real-world challenges. Quantum computing [15] opens speculative but exciting directions.

The common limitations remain: parameter sensitivity in heuristics, scalability bottlenecks in exact and hybrid methods, training overhead in RL, and high computational demands in real-world extensions. Future work must focus on adaptive frameworks that balance scalability, robustness, and practical constraints, ensuring VRPTW solutions are not only optimal in theory but also feasible in real deployments.

Chapter 3

System Design

3.1 Architecture

3.1.1 Architecture Overview

The system design defines an architecture that combines heuristic and metaheuristic techniques to effectively solve the Vehicle Routing Problem with Time Windows (VRPTW). The workflow begins with gathering essential inputs such as customer locations, delivery quantities, service times, depot details, and vehicle capacities. These inputs are pre-processed to check feasibility, standardize the data format, and prepare structured datasets suitable for optimization. Once ready, the Multiple Insertion Heuristic (MIH) is employed to generate an initial feasible routing plan. MIH constructs routes by progressively inserting customers into vehicle paths at positions that minimize incremental costs while respecting capacity and time-window constraints.

Following this, the architecture integrates Multidirectional Search (MDS) as an optimization phase. MDS enhances the MIH-generated routes by exploring multiple local neighborhoods, aiming to reduce total travel distance, balance fleet utilization, and improve overall solution quality without violating constraints. The modular design supports additional optimization methods and benchmarking against solvers like Google OR-Tools.

In addition to the optimization modules, the design incorporates an evaluation layer where solution effectiveness is measured using metrics like total distance traveled, number of vehicles deployed, and adherence to time schedules. Results can be presented through route visualizations and tabular summaries, ensuring clarity for both technical analysts and non-technical stakeholders. The framework is also designed for extensibility: future improvements may include traffic-aware routing, adaptive handling of dynamic customer requests, and real-time re-optimization. This multi-layered design promotes scalability, adaptability, and practical usability for logistics and distribution systems.

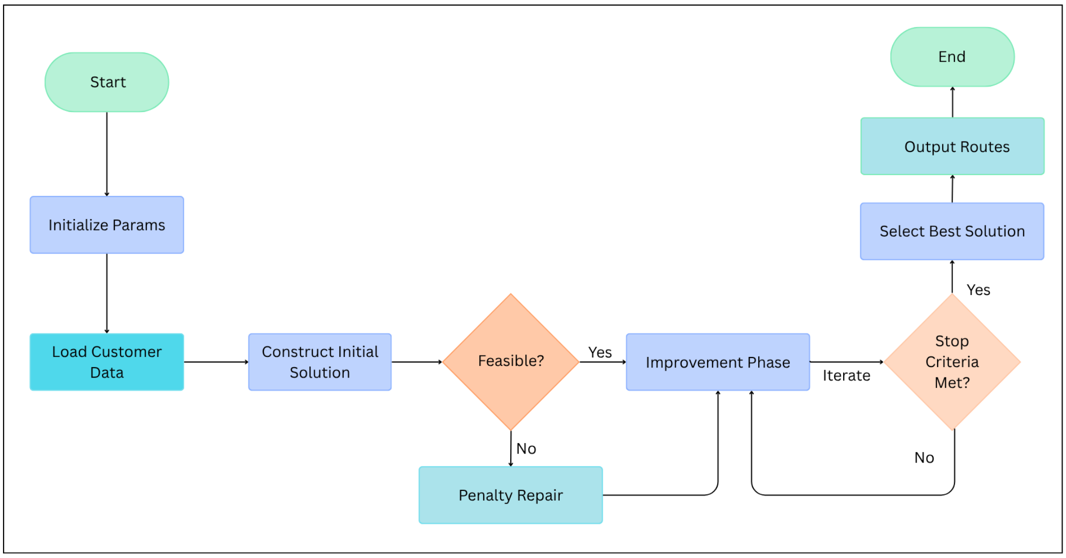

Figure 3.1.1: Architecture Flow of MIH–MDS Based VRPTW Solution

Workflow Steps

1. **Parameter Initialization:** Define vehicle capacity, fleet size, time windows, and optimization settings.
2. **Data Loading:** Load customer data (locations, demands, service times, time windows), depot location, and distance/travel time matrices.
3. **Initial Solution (MIH):** Construct feasible routes using MIH.
4. **Feasibility Check:** Verify routes for capacity, time windows, and maximum duration.
5. **Penalty Repair (if infeasible):** Adjust routes to restore feasibility.
6. **Improvement Phase (MDS):** Optimize routes via MDS with local neighborhood exploration.
7. **Stopping Criteria Evaluation:** Check convergence or maximum iterations.
8. **Solution Selection:** Choose the best routing plan.
9. **Output Generation:** Present optimized results via maps, schedules, and performance metrics.

3.2 Algorithm and Process Design

3.2.1 Algorithm Overview

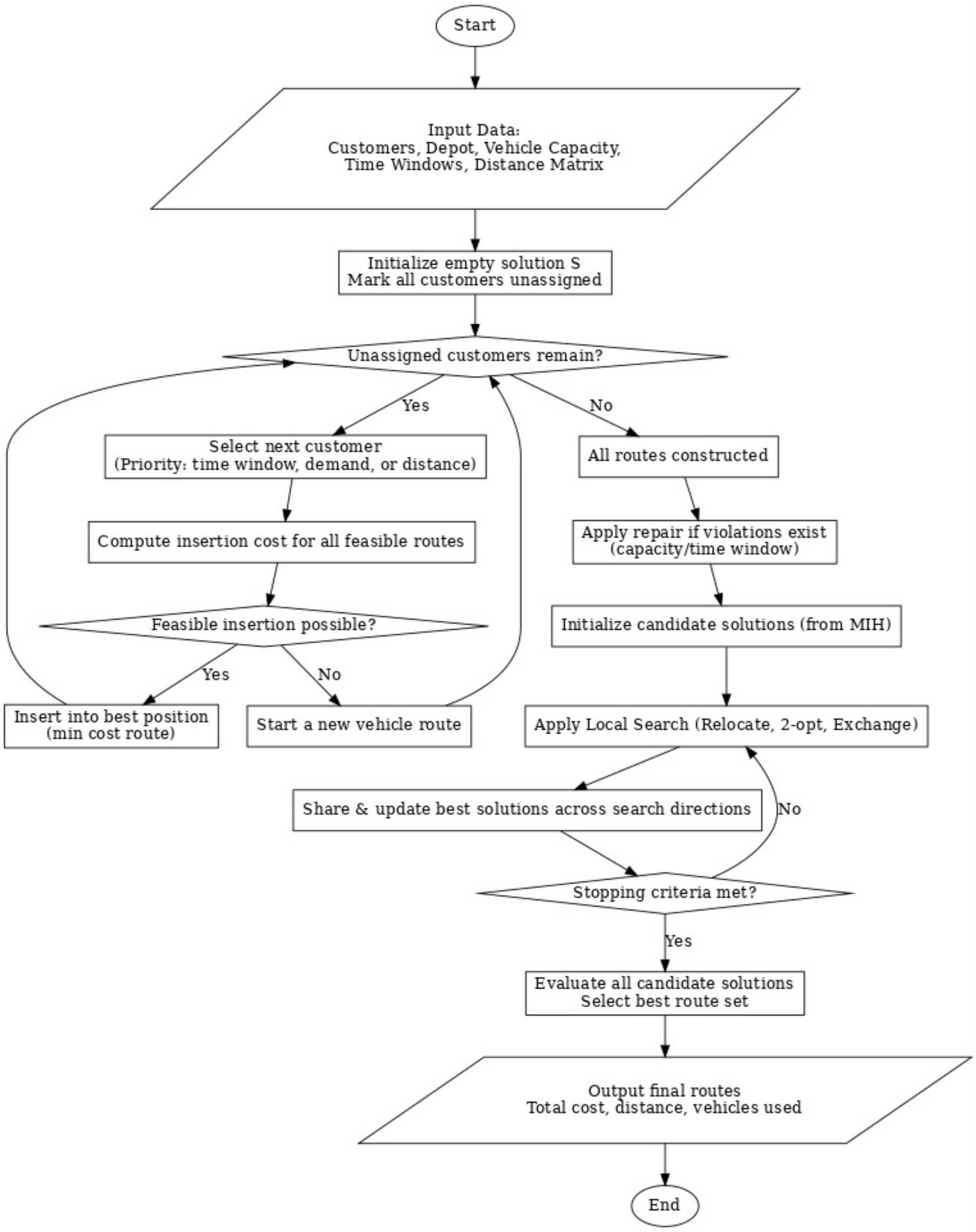

Figure 3.2.1: Algorithmic Workflow of the MIH–MDS Optimization Process

3.2.2 Input and Output Specification

Inputs: Customer data (ID, coordinates, demand, service times, time windows), depot info (location, operation times), vehicle info (capacity, fleet size, optional max route duration), distance/travel time matrix, algorithm parameters (insertion cost weights, penalties, optimization limits).

Outputs: Optimized vehicle routes minimizing distance/time, respecting constraints. Metrics include total distance, total time, fleet utilization, and feasibility (capacity and time windows).

3.2.3 Algorithm Design

Input: Customer set (C) with demands, time windows, service times, depot (D), vehicle capacity (Q), fleet size, travel time/distance matrix.

Output: Optimized routes minimizing total distance while satisfying all constraints.

Steps:

1. **Initialization:** Load customer data and mark all as unassigned. Initialize empty solution set S.

2. **Initial Solution (MIH):** While unassigned customers remain, select next customer (earliest time window, largest demand, or depot proximity). Compute insertion cost for feasible routes and insert at minimum cost. If no feasible insertion, start new vehicle route.

3. **Feasible Complete Solution:** Ensure all routes satisfy capacity and time windows. Apply penalty-based repair if violations exist.

4. **Improvement (MDS):** Initialize candidates from MIH. Apply local moves (relocation, 2-opt, exchange) to reduce cost. Share best solutions across directions to diversify/exploit. Continue until stopping criteria met.

5. **Select Best Solution:** Evaluate all MDS candidates; select routes with minimum total cost.

6. **Output Final Routes:** Display vehicle routes, compute total distance, total time, and fleet usage.

3.2.4 Tools and Technologies

Core Tools:

1. Python: Main language for MAVROS framework.
2. Jupyter Notebook/Lab: Rapid prototyping, experimentation, reproducible reports.

Libraries and Algorithms:

1. OR-Tools: Routing solver for VRPTW.
2. NumPy: Numerical computations (distance/cost calculations).
3. Pandas: Data manipulation/preprocessing.
4. NetworkX: Modeling network graphs.
5. Matplotlib: Visualizations for routes and metrics.

UI and Visualization:

1. Flask/Django: Web backend for route optimization and data management.
2. React.js/HTML/CSS/JS: Frontend dashboards, route visualization, optimization results.

3.3 Software Stack

1. Frontend: React.js or lightweight HTML/CSS/JS for route visualization.
2. Backend: Flask/Django for computation requests, data management, API endpoints.
3. Database: MongoDB (primary) or PostgreSQL (optional).
4. Optimization/ML: OR-Tools + Python-based heuristics (MIH) + MDS for solution refinement.
5. Visualization: Matplotlib, NetworkX for maps and performance charts.
6. Version Control: GitHub for source code management.

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