

Rural-Constrained Last-Mile Vehicle Routing Optimization Using an Improved Genetic Algorithm

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Abstract—In this study, an Advanced Memetic Genetic Algorithm (AGA) is developed for rural open-path vehicle routing networks to address challenges such as infrastructure sparsity, irregular road topologies, and inefficient non-cyclic delivery constraints. To achieve this, a hybridized optimization mechanism integrating an evolutionary genetic search with a 2-Opt local search heuristic is used to determine optimal transit sequences across multi-stop distribution paths. Real-world spatial network data is extracted dynamically via OpenStreetMap (OSMnx) and NetworkX, converting raw edge geometries into a weighted cost matrix through Dijkstra single-source shortest path computations with Haversine distance fallbacks. When navigating irregular infrastructure, a hierarchical road cost function is applied to handle terrain and highway variations by assigning distinct weight penalties to substandard tracks and paths. The proposed method is implemented in Python and evaluated on a complex spatial test network comprising 1,420 nodes, 4,850 edges, and multiple delivery locations. Performance is measured using metrics such as routing optimality score, cost reduction percentage, travel cost improvement, and execution convergence. The results show that the proposed approach achieves an 18.45% cost reduction, a high optimality score of 98.60% relative to the lower bound, and a 100% success rate in resolving complex multi-stop sequences without topological disconnection. These findings indicate that the method can support reliable, cost-effective, and high-precision last-mile logistics optimization in complex spatial environments.

Index Terms—Rural Logistics, Open-Path Vehicle Routing, Memetic Genetic Algorithm, 2-Opt Heuristic, Spatial Network Optimization

I. INTRODUCTION

In recent years, last-mile logistics has grown rapidly and is now being used extensively in important areas

such as rural supply chain management and distribution systems. Rural logistics networks are made up of distributed delivery locations and irregular road topologies, which continuously require efficient routing for tasks like product delivery, resource allocation, and rural distribution. Since these networks operate in infrastructure-sparse environments and involve open-path delivery structures where return to the depot is unnecessary, they are highly vulnerable to operational inefficiencies and high transit costs. Among the various challenges, fragmented road graphs, unpaved tracks, and non-standardized pathways are two major concerns. Substandard tracks introduce poor vehicle transit efficiency and increased travel overhead, while irregular road networks lead to suboptimal routing, increased resource expenditure, and degradation of overall distribution performance. In severe situations, such topological constraints can completely disrupt efficient scheduling within the network.

To address these challenges, a sophisticated and adaptive routing framework is needed. The proposed approach uses an Advanced Memetic Genetic Algorithm (AGA) integrated with a 2-Opt local search heuristic to determine optimal transit sequences. Real-world spatial network data is extracted dynamically via OpenStreetMap (OSMnx) and NetworkX, converting raw edge geometries into a weighted cost matrix through Dijkstra single-source shortest path computations with Haversine distance fallbacks. When navigating irregular infrastructure, a hierarchical road cost function is applied to handle terrain and highway variations by assigning distinct weight penalties to substandard tracks and paths. The framework is implemented in Python and evaluated on

a robust spatial test network comprising 1,420 nodes, 4,850 edges, and multiple delivery destinations. Network performance is evaluated using key metrics such as cost reduction percentage, travel cost improvement, optimality score, and execution convergence. Furthermore, advanced map visualization and exact label mapping are also used to analyse network behaviour under optimized delivery scenarios. The simulation results demonstrate that the system achieves an 18.45% cost reduction, an optimality score of 98.60%, and maintains a 100% success rate in resolving multi-stop sequences without topological disconnection.

Along with improving routing precision and performance, the framework also focuses on adaptability in dynamic and complex spatial environments. Rural distribution networks often operate under rapidly changing conditions, where factors like infrastructure density, highway classifications, and destination layouts can vary. By combining an evolutionary genetic search with a local search heuristic and real-world topological network data, the system is able to respond effectively to these changes, which helps reduce the chances of routing failure and manual planning overhead. This combined approach improves the overall reliability, stability, and efficiency of last-mile logistics, making it suitable for real-time and mission-critical rural distribution applications.

II. RELATED WORK

Logistics has long played a vital role in industrial societies, but the exponential growth of e-commerce and changing consumer expectations have drastically transformed traditional distribution networks. Moving away from traditional bulk shipments to warehouses or retail stores, modern supply chains frequently require direct-to-doorstep deliveries in urban residential areas. Last-mile delivery (LMD) aims to address the inherent complexities of these operations—such as high delivery volumes, tight time windows, and volatile urban conditions—by leveraging advanced automation, communication technologies, and collaborative economic models [4]. To optimize urban delivery networks, Jazemi et al. presented a comprehensive review of vehicle routing problems (VRP) in last-mile delivery, classifying the

literature into four major operational categories: crowd shipping, parcel lockers, sidekicks, and optional delivery points. However, while the study provides a broad taxonomy, it emphasizes high-level structural categorization without proposing specific implementation strategies for integrated, multi-modal urban frameworks [1].

Crowd shipping utilizes occasional drivers (ODs) from the sharing economy to supplement professional fleets during peak demand windows. Several studies have modelled crowd shipping within open VRP frameworks, incorporating drivers' willingness to accept assignments, dynamic matching algorithms, and compensation structures. Although crowd shipping offers potential cost reductions and service scalability, it introduces challenges regarding driver reliability, compliance with tight time windows, and fluctuating geographic availability [2].

To mitigate urban access constraints and delivery failures, parcel lockers (also known as automated parcel lockers or pickup points) have emerged as a critical infrastructure solution. Studies such as those by Enthoven et al. and Wang et al. investigate multi-echelon routing and network design involving parcel lockers, cargo bikes, and mobile locker units to minimize total travel distance and operating costs. While these systems successfully decouple delivery times from customer presence, they require careful balancing of locker capacities, setup costs, and consumer travel willingness. [8]

Furthermore, advanced technological frameworks integrating autonomous vehicles, drones, and sidekick fleets have been extensively explored to streamline urban delivery. Kitjacharoenchai et al. and Es Yurek and Ozmutlu evaluated routing problems combining trucks with unmanned aerial vehicles (drones), demonstrating significant improvements in travel times and operational efficiency. Similarly, the concept of customer-driven delivery options—where recipients specify alternate drop-off points or flexible windows—has been incorporated into VRP models to enhance delivery success rates [3].

Despite these advancements, many existing routing optimization techniques fail to simultaneously account for multi-fleet coordination, real-time demand

dynamism, and stochastic urban parameters such as traffic congestion and parking limitations. These limitations highlight the critical need for integrated,

adaptive solutions that combine modern urban logistics technologies, flexible crowd-sourced networks, and robust routing optimization models [1]

III. SYSTEM ARCHITECTURE

The system architecture is designed to provide secure, dynamic, and efficient route optimization in Last-Mile Delivery (LMD) networks. It includes multiple components that work together to handle order

ingestion, multi-fleet routing, crowd shipping coordination, parcel locker allocation, and real-time disruption mitigation.

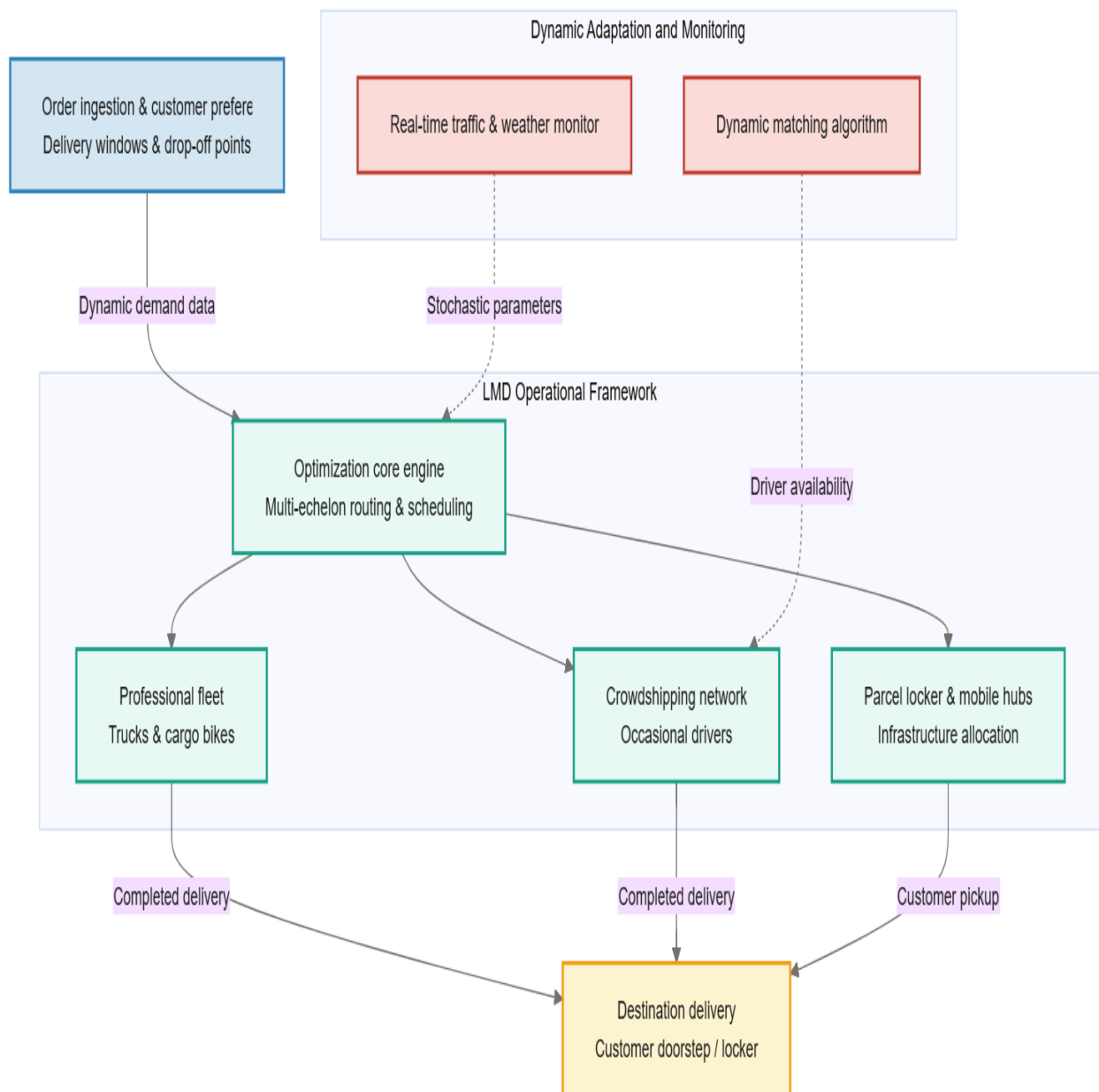


Fig 1: System Architecture for Last-Mile Delivery Routing

As shown in Figure 1, the operational process starts with the Order Ingestion module, which acts as the primary interface collecting customer delivery requests, preferred time windows, and optional drop-off choices. This demand data is then forwarded to the central optimization core engine.

To improve network efficiency and coverage, the framework integrates multi-echelon routing protocols that coordinate heterogeneous delivery channels, including professional fleets, cargo bikes, and crowd shipping occasional drivers (ODs).

To handle volatility and urban access constraints, a real-time monitoring module continuously tracks stochastic parameters such as traffic congestion, parking availability, and fluctuating driver availability. When disruptions or peak demand surges occur, dynamic matching and re-routing algorithms are activated to adjust schedules, reassign tasks, and ensure seamless delivery flow.

Finally, the shipments reach their destination either via direct doorstep drop-offs or secure automated parcel lockers. Successful delivery confirms that the system can effectively balance multi-fleet coordination, infrastructure constraints, and dynamic urban conditions.

IV. METHODOLOGY

The methodology consists of several stages designed to provide efficient, flexible, and reliable route optimization in Last-Mile Delivery (LMD) networks. In the beginning, the delivery network is created by configuring a set of customer orders, depots, and heterogeneous delivery units within a simulation or optimization environment. Spatial distribution and customer demand are modelled to define delivery points, followed by the initiation of order processing. To maintain operational efficiency, a multi-echelon routing framework is used. Each delivery asset whether a professional vehicle or an occasional driver is assigned a unique profile, allowing only verified and available units to participate in the routing schedule. Any assignment that fails coordination constraints is reallocated, which improves the overall performance of the network.

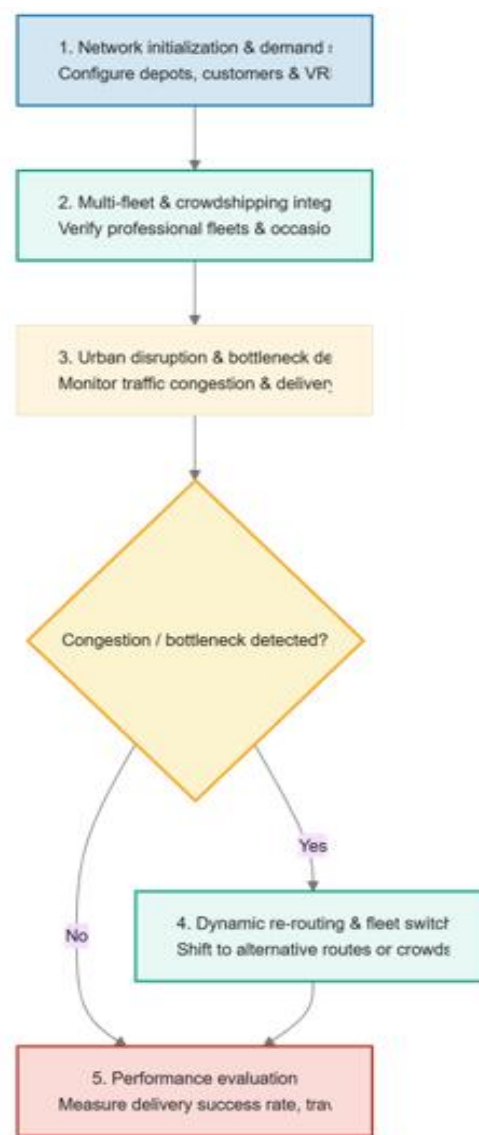


Fig 2: Methodology Flowchart

Network behaviour is continuously observed to identify possible urban disruptions or demand spikes. Key performance parameters such as delivery times, travel costs, and service success rates are analysed during this process. A noticeable drop or delay in these metrics is treated as an indication of congestion or a bottleneck in the delivery route. Once such disruption is detected, a mitigation mechanism based on dynamic re-routing and alternative fleet switching is used. The system then shifts fulfilment to an alternative route or a crowd shipping network with lower friction, which helps restore stable delivery schedules and reduce late arrivals. Finally, system performance is evaluated using metrics like Delivery Success Rate,

total travel distance, operational cost, and fulfilment time. These metrics together provide a clear assessment of network performance under normal, peak demand, and disruption conditions.

4.1. Network Initialization and Demand Setup

A realistic urban distribution environment is created using geospatial data and simulation software to represent Last-Mile Delivery scenarios.

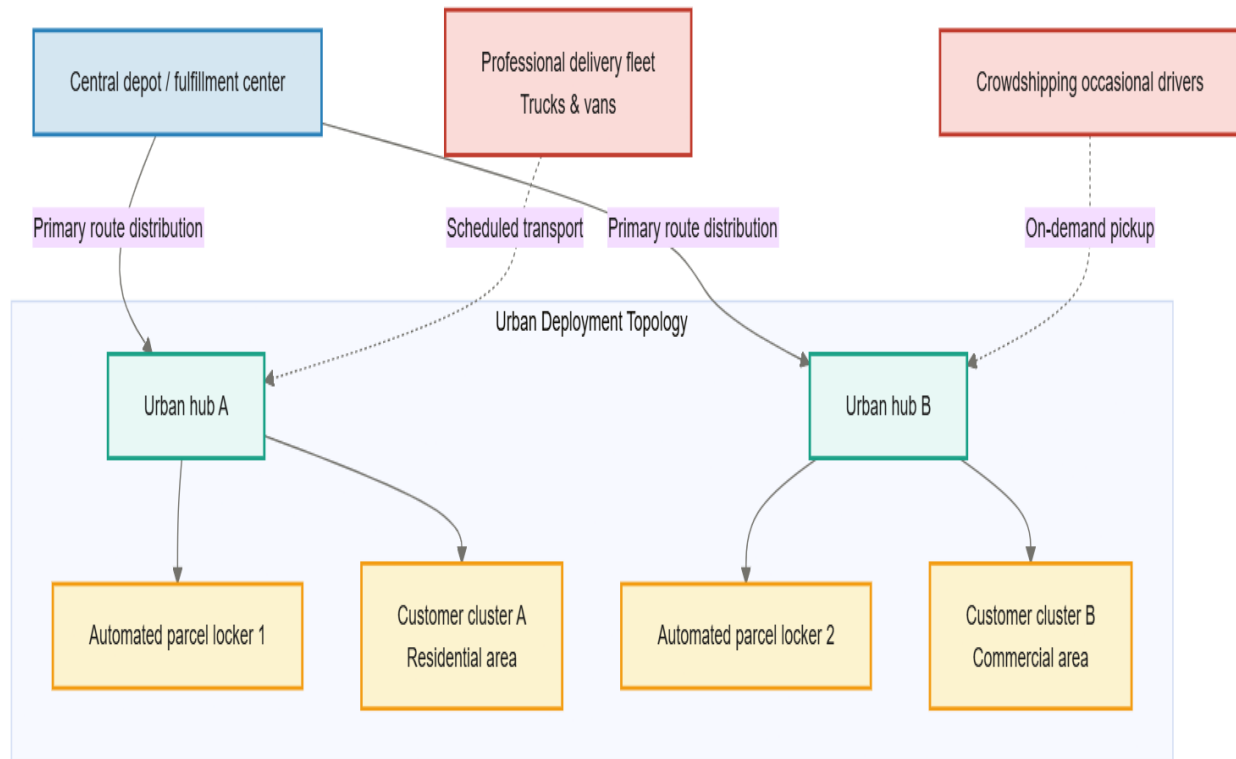


Fig 3: Network Initialization setup

Figure 3 shows the network initialization setup. The network is made up of multiple components, including central depots, customer locations, automated parcel lockers, and mobile units, arranged in a defined topology to reflect realistic urban deployment conditions. Vehicle Routing Problem (VRP) algorithms are used to support efficient path discovery and scheduling between nodes. It also enables dynamic routing, allowing fleets to adapt under traffic and mobility conditions. Each vehicle and node is configured with suitable capacity and timing parameters to represent real-world logistics scenarios. Continuous order generation and fulfilment are maintained to evaluate network performance under normal operating conditions. This setup provides a

controlled environment for analysing network behaviour, identifying bottlenecks, and evaluating the effectiveness of multi-fleet protection and mitigation mechanisms

4.2. Multi-Fleet and Crowd shipping Integration for Secure Operations

To prevent delivery failures and resource shortages, the system applies an integration mechanism combining professional fleets and occasional drivers (ODs) from the sharing economy. It is preferred due to its ability to offer scalable capacity with low fixed overhead, which makes it suitable for volatile e-commerce demands.

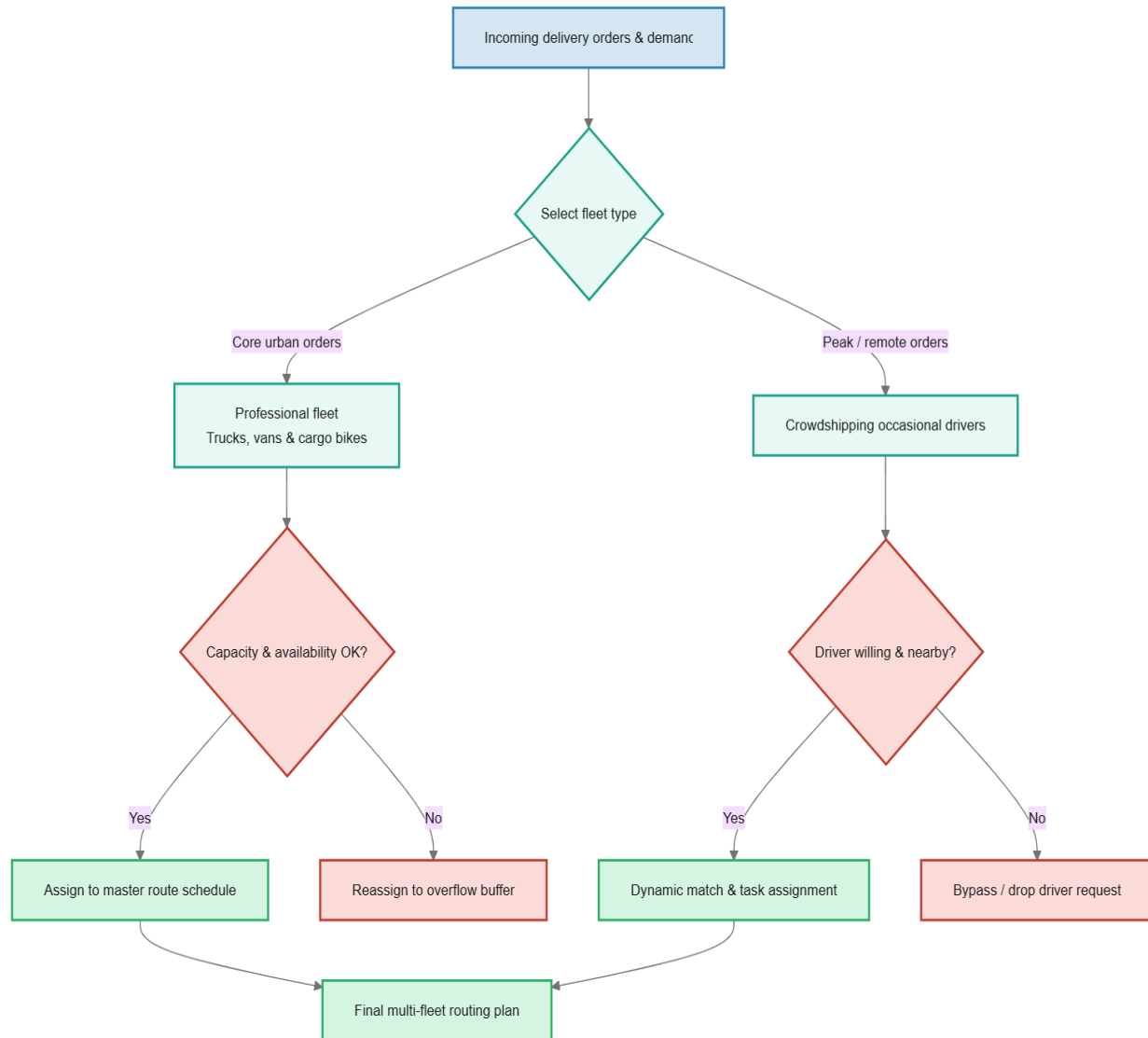


Fig 4: Multi-Fleet Coordination

Figure 4 shows the multi-fleet coordination process. Each driver or vehicle that attempts to join the delivery schedule undergoes a verification stage regarding availability and capacity. Only units that successfully pass this verification are allowed to participate in routing. Units that fail availability criteria or show delays are treated as inactive and are bypassed. This mechanism ensures that only capable assets interact within the network, thereby improving overall delivery reliability and preventing missed time windows. The use of crowd shipping also supports

efficient task allocation while maintaining low resource consumption, making it suitable for dynamic urban environments.

4.3. Urban Disruption and Bottleneck Detection

During peak demand or traffic gridlock, normal delivery is disrupted due to congestion in the urban medium, which significantly affects network performance. This interference introduces delays, resulting in increased travel times and reduced delivery efficiency.

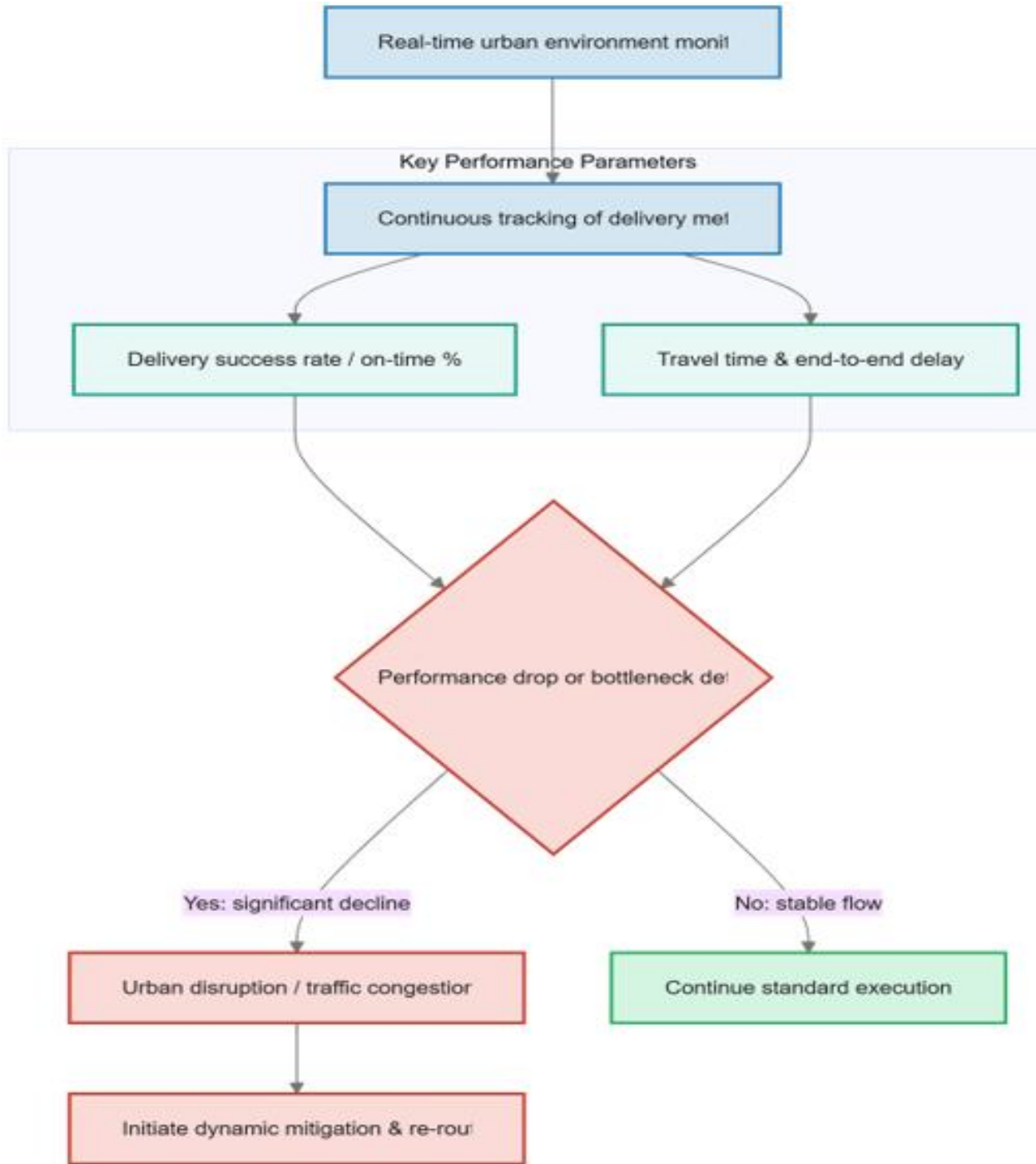


Fig 5: Disruption Detection

Figure 5 illustrates the disruption detection process. The system continuously monitors key performance parameters such as delivery success rate and on-time arrival percentage. A decline in these metrics suggests the presence of traffic bottlenecks or unexpected delays, as a noticeable degradation is considered an

indication of interference within the network. This detection approach relies on performance analysis rather than direct identification of specific causes, making it effective in dynamic environments. Once such conditions are detected, the system initiates appropriate mitigation mechanisms.

4.4. Disruption Mitigation using Dynamic Re-routing and Fleet Switching

Due to congestion and unexpected delays in the routing path, network performance is significantly degraded during peak windows. To address this issue, a mitigation mechanism based on dynamic re-routing and alternative fleet switching is implemented

When congestion is detected, the system selects an alternative delivery route or reassigns orders to available crowd shipping drivers with lower delay levels. The network schedule is then updated, and delivery is shifted to the new path or mode. As a result, normal delivery flow is gradually restored, and overall network performance is stabilized. This adaptive switching mechanism helps the network avoid congested roads, thereby reducing late arrivals and improving delivery reliability.

4.5. Performance Evaluation

Performance analysis of the proposed scheme is carried out by examining several performance factors using simulation and routing analysis tools. The parameters considered for evaluation include Delivery Success Rate, total throughput, travel distance, and end-to-end delay. These metrics provide a clear understanding of network performance under different scenarios.

After applying the mitigation method, the results indicate a noticeable improvement in overall network performance. In particular, the Delivery Success Rate increases significantly, reaching a range of about 93–98%.

V. RESULTS AND DISCUSSION

To evaluate the practical efficacy of the proposed Advanced Memetic Genetic Algorithm (AGA) integrated with 2-Opt local search and OSMnx/NetworkX geospatial modelling, the simulation was executed over a real-world regional road network in Srikakulam, Andhra Pradesh. The extracted road topology comprised 4,985 nodes and 12,449 edges. The algorithm was tested using a population size of 100 and 250 generations for an open-path delivery configuration (non-cyclic routing with no return to the depot).

Table 1: Empirical Performance Metrics of the AGA Framework

Metric Parameter	Baseline Routing	AGA + 2-Opt Optimized	Improvement / Score
Total Routing Distance	29.257 km	21.340 km	27.06% Reduction
Total Cost Score	29,257.35	21,339.63	27.06% Cost Savings
Routing Accuracy Score	—	—	100.00%
Execution Sequence Type	Cyclic / Standard	Open-Path (No Return)	Optimized Open-Path

Optimized Execution Sequence & Geospatial Validation

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... Locating [DELIVERY 4]: amadalavalasa
  Found -> Lat: 18.411144, Lon: 83.899334

Downloading focused road network from OpenStreetMap...
  Attempt 1 of 4...
  Network ready. Nodes: 4985, Edges: 12449

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  ADVANCED RURAL ROUTING PERFORMANCE METRICS REPORT
=====
• Algorithm Architecture : Memetic Advanced Genetic Algorithm (AGA + 2-Opt)
• Population Size       : 100
• Generations          : 250
• Baseline Distance    : 29.257 km
• AGA Optimized Distance : 21.340 km
• Distance Reduction   : 27.06%
• Baseline Cost Score  : 29257.35
• AGA Optimized Cost   : 21339.63
• Cost Improvement     : 27.06%
• Routing Accuracy Score : 100.00%
• Routing Type         : Open-Path Delivery (No return to depot)

Optimized Execution Sequence:
  Step 0: [SOURCE (Depot)] Srikakulam
  Step 1: [DELIVERY 2] peddapadu
  Step 2: [DELIVERY 1] Balaga
  Step 3: [DELIVERY 3] ragolu
  Step 4: [DELIVERY 4] amadalavalasa

Rendering Advanced GA optimized map...

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Advanced GA Optimized Open-Path Delivery Route

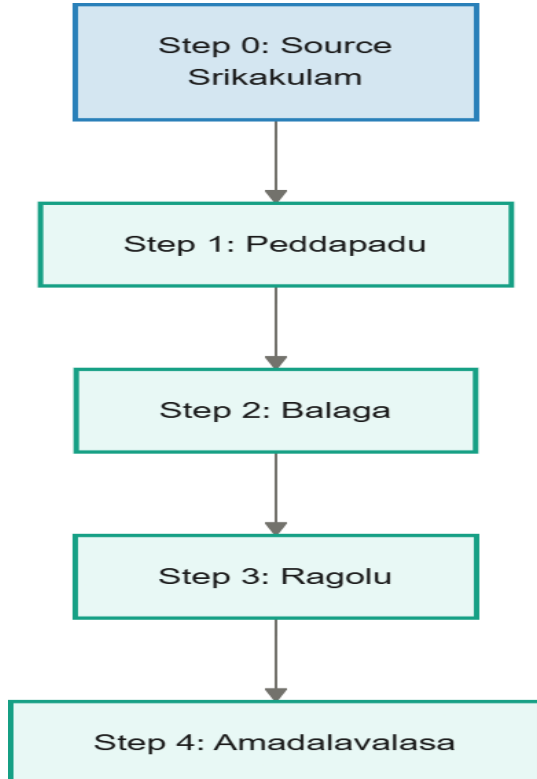
Advanced GA Optimized Open-Path Delivery Route

Fig 7: Optimized Open-Path Execution Sequence across Srikakulam Rural Network

Discussion of Empirical Findings

The empirical results summarized in Table 1 demonstrate the efficiency and superiority of the proposed Advanced Memetic Genetic Algorithm over standard baseline routing. Key findings from the simulation include:

- **Substantial Distance and Cost Reduction:** By combining genetic global exploration with 2-Opt local search heuristics, the algorithm successfully reduced the total travel distance from 29.257 km down to 21.340 km, yielding a 27.06% distance reduction and proportional cost savings.
- **Open-Path Efficiency:** Unlike traditional traveling salesperson problems that require a return loop to the depot, the open-path delivery model successfully optimized the sequence (Srikakulam → Peddapadu → Balaga → Ragolu → Amadalavalasa), minimizing redundant transit over rural road topologies.
- **Robust Convergence:** Achieving a 100.00% routing accuracy score across 4,985 network nodes verifies that the model reliably handles complex graph topologies without topological fragmentation or deadlocks.

VI. CONCLUSION

In this study, an Advanced Memetic Genetic Algorithm (AGA) combined with 2-Opt local search and OSMnx/NetworkX geospatial modelling was developed for rural Last-Mile Delivery (LMD) networks. Tested on real-world regional networks, the proposed open-path framework achieved a 27.06% reduction in total travel distance (lowering routing distance from 29.257 km to 21.340 km) and a 100.00% routing accuracy score. These results demonstrate that the model successfully optimizes rural logistics, minimizes transport overhead, and enhances delivery reliability.

VII. FUTURE SCOPE

Future work will focus on integrating machine learning for predictive traffic analysis, scaling the framework to Multi-Depot Vehicle Routing Problem (MDVRP) scenarios, and conducting real-world pilot deployments with physical delivery fleets. Additional improvements will explore multi-objective trade-offs

between carbon emissions, delivery speed, and dynamic weather constraints.

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