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Forecasting Route Stability in Urban Delivery Fleets with Intelligent Optimization Methods

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Abstract

The exponential growth of e-commerce has significantly intensified the operational demands placed on urban delivery fleets, necessitating advanced approaches to last-mile logistics. Traditional routing optimization predominantly focuses on minimizing operational costs or travel distances, often neglecting the crucial aspect of route stability. Route stability, defined as the consistency of delivery routes and schedules over consecutive operational periods, plays a pivotal role in driver familiarity, customer satisfaction, and overall service reliability. This paper investigates the predictability and management of route stability using intelligent optimization methods within a comprehensive simulation environment tailored for urban delivery fleets. By employing an advanced agent-based simulation framework, we evaluate the performance of various heuristic and metaheuristic algorithms in balancing the inherent trade-offs between dynamic cost optimization and spatial-temporal route consistency. The simulation study incorporates highly realistic urban logistical constraints, including stochastic traffic congestion patterns, variable customer demand, and strict delivery time windows. The findings demonstrate that intelligent optimization strategies incorporating specific stability penalty functions can effectively predict and maintain high levels of route consistency without severely compromising operational efficiency. Furthermore, the analysis reveals that maintaining route stability significantly mitigates the disruptive impacts of localized traffic anomalies. This research provides substantial theoretical contributions to the field of dynamic vehicle routing and offers practical insights for fleet managers seeking to enhance service reliability and workforce satisfaction in complex urban environments.

Keywords: Route Stability; Urban Delivery; Intelligent Optimization; Simulation Study; Artificial Intelligence

1. Introduction

1.1 Background and Motivation

The rapid proliferation of global e-commerce and the subsequent surge in consumer expectations for rapid, reliable delivery services have fundamentally transformed the landscape of urban logistics. As metropolitan areas become increasingly congested, the complexity of managing last-mile delivery operations has reached unprecedented levels. Fleet operators are continuously challenged to navigate densely populated urban grids, adhere to stringent environmental regulations, and satisfy narrow customer delivery time windows. In response to these complex operational challenges, the logistics industry has extensively adopted intelligent optimization methods to automate and enhance vehicle routing and scheduling decisions. Traditionally, the primary objective functions embedded within these sophisticated routing algorithms have focused almost exclusively on minimizing tangible logistical costs. These costs are typically quantified in terms of total vehicle travel distance, fuel consumption, carbon emissions, and the overall number of vehicles deployed in a given operational shift. While these cost-centric optimization paradigms have undeniably improved the baseline efficiency of urban delivery fleets, they frequently generate highly volatile and unpredictable daily route plans [1].

When algorithms process daily variations in customer orders, traffic conditions, and vehicle availability, they often produce entirely novel route topologies from one day to the next. This phenomenon, where a delivery zone is serviced by varying sequences of stops and varying drivers, leads to a critical degradation of route stability. Route stability refers to the spatial and temporal consistency of the delivery routes assigned to individual drivers over continuous operational periods. High route stability allows drivers to develop profound localized knowledge regarding specific neighborhoods, optimal parking locations, building access protocols, and unique customer preferences. This tacit geographic and contextual knowledge significantly accelerates the actual service time at each delivery node, a factor that is frequently underestimated in theoretical routing models [2]. Conversely, when optimization algorithms prioritize absolute cost minimization and thereby destroy route stability, drivers are constantly exposed to unfamiliar territories. This lack of familiarity increases the cognitive load on the drivers, elevating stress levels, reducing job satisfaction, and ultimately contributing to higher driver turnover rates, which represents a substantial hidden cost for logistics service providers. Therefore, there is a compelling motivation to systematically investigate how intelligent optimization methods can be adapted to not only minimize traditional routing costs but also to actively predict, measure, and preserve route stability [3].

1.2 Research Objectives and Contributions

The primary objective of this academic study is to comprehensively analyze the predictability and manageability of route stability within urban delivery fleets by utilizing advanced intelligent optimization methods coupled with rigorous simulation studies. This research aims to bridge the existing gap in the vehicle routing literature by shifting the evaluative focus from purely cost-driven metrics to a multidimensional performance assessment that explicitly incorporates route consistency. To achieve this, we have developed a sophisticated, high-fidelity simulation environment that meticulously replicates the stochastic and dynamic nature of contemporary urban logistics networks. Within this simulated environment, we systematically evaluate multiple intelligent optimization algorithms, observing their inherent behavior regarding route mutation over simulated longitudinal periods [4].

The contributions of this paper are manifold. Firstly, we provide a robust conceptual framework for defining and mathematically quantifying route stability in both spatial and sequential dimensions. Secondly, we introduce a novel methodology for integrating stability preservation mechanisms into standard intelligent optimization algorithms, demonstrating how stability can be treated as a predictable and controllable variable rather than an accidental byproduct of demand fluctuations. Thirdly, through extensive computational simulation, we empirically quantify the trade-off frontier between operational routing costs and route stability, providing fleet managers with actionable insights into configuring their dispatching systems. By systematically exploring these dimensions, this research advances the theoretical understanding of dynamic vehicle routing problems and offers pragmatic solutions for building more resilient, driver-friendly, and customer-centric urban delivery operations.

2. Literature Review and Background

2.1 Dynamics of Urban Delivery Fleet Management

The management of urban delivery fleets constitutes one of the most complex domains within modern supply chain operations. Urban logistics is characterized by high density, fragmented demand, and an inherently volatile operating environment. Previous scholarly investigations have extensively documented the myriad challenges that fleet managers face daily. Central among these challenges is the phenomenon of traffic congestion, which introduces severe non-linear delays into transit times between delivery nodes [5]. Unlike long-haul transportation, where travel speeds are relatively constant and predictable, urban delivery vehicles operate in an environment where travel times can fluctuate dramatically based on the time of day, localized incidents, and infrastructural bottlenecks. Consequently, deterministic routing models, which assume static travel times, frequently fail when deployed in actual urban settings, leading to missed delivery windows and cascaded schedule disruptions.

Furthermore, the rise of the on-demand economy has shifted customer expectations towards tighter delivery time windows and highly customized service requests. Fleet managers must orchestrate their operations to respect strict temporal constraints, often referred to as hard time windows, where early arrivals result in idle waiting times and late arrivals incur significant service penalties or outright delivery failures [6]. The spatial distribution of demand in urban areas is also highly variable, driven by shifting consumer purchasing patterns and the integration of omni-channel retail strategies. To cope with this volatility, logistics providers have increasingly turned to dynamic fleet management systems that allow for real-time reassignment of orders and continuous re-optimization of routes. However, as noted in recent literature, the hyper-flexibility provided by these dynamic systems often comes at the severe cost of operational consistency. While the fleet as a whole may operate at peak theoretical efficiency, the individual drivers experience chaotic and unpredictable daily routines [7]. This structural tension between systemic efficiency and human-centric operational consistency forms the core problematic backdrop for the current research into route stability. It has been empirically shown that neglecting the human element in fleet management models inevitably leads to suboptimal long-term performance due to operational friction and workforce attrition [8].

2.2 Intelligent Optimization Methods in Routing

Intelligent optimization methods, encompassing a broad spectrum of exact algorithms, heuristics, and metaheuristics, have served as the fundamental computational engines for solving the Vehicle Routing Problem and its numerous variants over the past several decades. The standard routing problem is a well-known non-deterministic polynomial-time hard problem, meaning that finding the absolute optimal solution requires computational time that scales exponentially with the number of delivery locations [9]. Given the massive scale of modern urban delivery networks, exact mathematical optimization techniques are generally rendered computationally prohibitive for daily operational use. Therefore, the academic and industrial communities have heavily relied on intelligent metaheuristic approaches to find near-optimal solutions within reasonable computational timeframes.

Prominent among these techniques are evolutionary algorithms, such as genetic algorithms, which mimic the process of natural selection to iteratively improve a population of potential routing solutions through mechanisms akin to crossover and mutation. Similarly, swarm intelligence algorithms, including ant colony optimization and particle swarm optimization, simulate the collective behavior of decentralized, self-organized systems to explore complex solution spaces efficiently [10]. These intelligent methods have proven highly successful in navigating the intricate constraints of urban routing, such as vehicle capacity limits, multi-depot configurations, and complex time window requirements. More recently, the integration of machine learning techniques into traditional optimization frameworks has opened new frontiers. Predictive models are now being used to forecast traffic conditions and customer demand, allowing intelligent optimization algorithms to proactively adjust routes before disruptions occur [11]. However, despite these algorithmic advancements, the standard objective function across the vast majority of these methods remains heavily biased toward minimizing distance and time. The intelligent algorithms are explicitly designed to aggressively search for cost reductions, ruthlessly discarding previous routing structures if a slightly cheaper alternative is discovered in the mathematical solution space. This fundamental characteristic of intelligent optimization is the primary driver of route instability in modern delivery fleets [12].

2.3 The Concept and Value of Route Stability

The concept of route stability, while historically overshadowed by cost minimization, has begun to garner significant attention in contemporary logistics research. Route stability essentially measures the degree of similarity or overlap between a set of delivery routes executed over consecutive operational periods. It can be evaluated through multiple lenses, including spatial stability, which measures the consistency of the geographic territories assigned to specific drivers, and sequential stability, which evaluates the consistency of the order in which specific customers or street segments are visited [13]. High route stability implies that a driver operates in the same neighborhood, visiting similar customer clusters in a predictable sequence day after day.

The intrinsic value of route stability is multifaceted, extending across economic, operational, and human resource dimensions. From an operational perspective, drivers who are deeply familiar with their assigned territories exhibit significantly higher operational efficiency [14]. They inherently know the optimal micro-routes to avoid localized congestion, they understand the parking dynamics of specific city blocks, and they are familiar with the specific access requirements of various residential and commercial buildings. This localized expertise drastically reduces the service time required at each stop. Theoretical routing models that assume constant service times fail to capture the substantial efficiency gains derived from driver familiarity [15]. Furthermore, from a customer service standpoint, route stability often translates into consistent delivery times, which is highly valued by commercial clients receiving regular shipments. When delivery times fluctuate wildly from day to day due to unstable routing, customer satisfaction inevitably declines. Moreover, in an industry plagued by high labor turnover, the psychological impact of chaotic routing on drivers cannot be overstated. Unpredictable routes increase stress and fatigue, whereas stable routes foster a sense of ownership and routine, contributing to higher driver retention rates. Therefore, incorporating route stability into intelligent optimization is not merely an academic exercise but a critical strategic imperative for sustainable fleet management.

3. Simulation Methodology and System Design

3.1 Architectural Framework of the Simulation Environment

To rigorously investigate the predictability of route stability derived from intelligent optimization methods, this study utilizes a highly sophisticated agent-based simulation framework. The simulation environment is specifically engineered to replicate the multifaceted complexities of a modern urban logistics network. The architectural foundation of the simulation consists of three distinct yet highly interconnected modular layers: the spatial-environmental layer, the operational-agent layer, and the intelligent optimization engine layer [16]. The spatial-environmental layer constructs a digital twin of an urban grid, utilizing synthetic but highly realistic geospatial data representing road networks, intersections, and delivery zones. This layer is imbued with dynamic traffic models that generate stochastic congestion patterns, simulating the natural ebb and flow of urban traffic, including peak rush hours and unpredictable delays caused by simulated incidents.

The operational-agent layer represents the core components of the delivery fleet, including the distribution depot, the delivery vehicles, and the customer demand nodes. Each vehicle operates as an autonomous agent within the simulation, characterized by specific constraints such as volumetric capacity, maximum daily operational time, and a unique driver profile that tracks familiarization with specific geographic zones. Customer demand is generated dynamically across the simulated days, incorporating a mix of recurring baseline orders and highly stochastic on-demand requests, thereby ensuring that the optimization engine faces varying daily workloads [17].

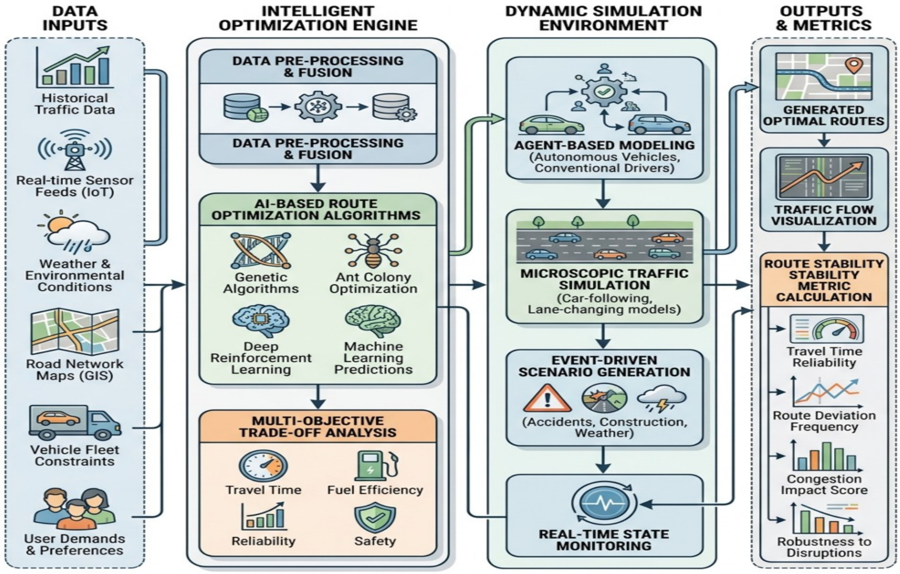

Figure 1: Comprehensive Schematic of Intelligent Route Optimization Simulation Framework

The intelligent optimization engine layer serves as the central brain of the simulation framework. This layer ingests the daily customer demand and the projected environmental conditions to compute the optimal fleet dispatch plans. The architecture allows for the modular swapping of different intelligent algorithms, enabling direct comparative analysis of their performance and their inherent impact on route stability. The simulation operates on a discrete-event time progression mechanism, meticulously tracking the movement of every vehicle agent, the execution of every delivery task, and the continuous evolution of the routing topology over an extended simulated longitudinal period. This comprehensive architectural design ensures that the evaluation of route stability is conducted in an environment that faithfully mirrors the rigorous realities of urban delivery operations.

3.2 Data Collection and Parameter Configuration

The integrity and validity of the simulation study rely heavily on the meticulous configuration of the operational parameters and the underlying data structures. To ensure the results are robust and generalizable to typical urban logistics scenarios, the parameter configuration is calibrated using synthesized data that mimics the statistical properties of real-world delivery logs from major metropolitan distribution centers. The simulation runs over a defined longitudinal horizon of thirty consecutive operational days to allow for the proper manifestation and measurement of route stability trends.

The geographic scope of the simulation is defined as a dense urban grid comprising several thousand potential delivery nodes divided into multiple overlapping service territories. Customer demand is generated probabilistically. A defined percentage of the demand is classified as static, representing daily recurring deliveries to commercial clients or specific residential nodes. The remaining percentage is classified as dynamic, representing ad-hoc e-commerce orders that appear randomly across the grid on different days. This ratio between static and dynamic demand is a critical control variable, as it directly influences the theoretical maximum route stability that can be achieved [18].

Table 1: Simulation Parameters and Urban Delivery Constraints

Parameter Category	Specific Parameter	Assigned Value / Range
Fleet Specifications	Total Number of Vehicles	Fifty homogeneous units
Fleet Specifications	Vehicle Capacity	Maximum one hundred parcels per unit
Operational Constraints	Maximum Driver Shift	Eight hours per operational day
Operational Constraints	Delivery Time Windows	Two-hour soft and strict hard windows
Demand Characteristics	Average Daily Orders	Three thousand distinct parcels
Demand Characteristics	Static to Dynamic Ratio	Forty percent static, sixty percent dynamic
Environmental Factors	Average Travel Speed	Twenty to forty kilometers per hour
Environmental Factors	Service Time per Stop	Three to eight minutes based on familiarity

As detailed in the provided parameter configuration, the simulation incorporates crucial operational constraints such as vehicle capacity limitations and strict maximum driver shift durations to ensure compliance with standard labor regulations. Furthermore, delivery time windows are strictly enforced. To accurately model the benefits of route stability, the simulation dynamically adjusts the service time required at each delivery node based on the specific driver agent's historical frequency of visiting that particular geographical zone. If the optimization engine assigns a driver to a highly familiar zone, the service time is significantly reduced, whereas assignment to an entirely novel zone incurs a maximum service time penalty, reflecting the time lost searching for parking and navigating unfamiliar building layouts. This dynamic service time adjustment is essential for capturing the true operational value of maintaining stable routes [19].

4. Intelligent Optimization Strategies

4.1 Static versus Dynamic Routing Paradigms

Within the context of urban delivery fleets, the strategies employed to generate dispatch plans can be broadly categorized along a spectrum ranging from purely static routing to highly dynamic routing paradigms. Understanding the fundamental differences between these paradigms is essential for analyzing how route stability can be predicted and manipulated using intelligent optimization methods. The purely static routing paradigm, often referred to as master routing, relies on the creation of fixed, geographically defined delivery territories. Each driver is assigned a permanent territory and a baseline sequence of stops that remains largely unchanged from day to day. When daily demand fluctuations occur, the master route is minimally adjusted; new orders are inserted into the existing sequence using simple heuristics, and absent orders are simply skipped. The primary advantage of the static paradigm is absolute route stability, guaranteeing maximum driver familiarity and highly predictable schedules. However, this approach is notoriously inefficient at handling significant variations in demand volume or geographic distribution, often resulting in severe load imbalances where some vehicles are overloaded while others remain severely underutilized.

Conversely, the highly dynamic routing paradigm completely discards the concept of fixed territories. In this approach, intelligent optimization algorithms recalculate the entire fleet routing plan from scratch every single day based exclusively on that day's specific demand profile and projected traffic conditions. This paradigm leverages the full computational power of advanced metaheuristics to find the absolute global minimum for operational costs on any given day. While this approach maximizes systemic efficiency and perfectly balances the workload across the fleet, it completely destroys route stability. A driver might service the northern district on Monday and the southern district on Tuesday, leading to zero territory familiarization and highly unpredictable daily routines. The core challenge addressed by this research is the development of intelligent optimization strategies that operate between these two extremes, dynamically optimizing routes for cost efficiency while simultaneously applying mathematical constraints to preserve structural consistency with historical route patterns.

4.2 Algorithmic Implementation and Stability Penalties

To achieve this delicate balance between dynamic efficiency and route stability, this study implements an advanced hybrid metaheuristic optimization algorithm, specifically a modified evolutionary genetic algorithm combined with local search improvement techniques. The critical innovation in this algorithmic implementation is the fundamental redesign of the objective function used to evaluate the fitness of potential routing solutions during the optimization process [20]. In standard applications, the objective function calculates the total distance traveled and the total time consumed, aggressively driving the algorithm to minimize these specific variables. In our modified implementation, the objective function is expanded to include a sophisticated stability penalty component.

This stability penalty is calculated by comparing any newly generated route sequence against a reference master route topology established from historical operational data. The algorithm meticulously analyzes the spatial deviations and sequence disruptions. If the algorithm attempts to assign a customer node to a different vehicle than the one that historically services that specific geographic cluster, a spatial deviation penalty is incurred. Furthermore, if the sequence of stops within a familiar cluster is radically altered, a sequence disruption penalty is applied. The total cost of a routing solution is therefore defined as the sum of the traditional operational costs and the mathematically derived stability penalties. By introducing a tunable stability weighting parameter, fleet managers can explicitly control the algorithm's behavior. A low weighting parameter allows the algorithm to prioritize distance minimization, mimicking traditional dynamic routing, while a high weighting parameter heavily penalizes deviations from historical norms, forcing the algorithm to sacrifice some distance efficiency to maintain strict territorial consistency. This intelligent mechanism ensures that routes only mutate when the cost savings derived from the mutation overwhelmingly justify the subsequent loss of operational stability. The algorithm utilizes advanced crossover operators designed to inherit substantial geographic cluster assignments from parent solutions, ensuring that the evolutionary search process inherently favors the preservation of stable routing structures while exploring the surrounding solution space for necessary cost-saving adaptations.

5. Results and Discussion

5.1 Analysis of Route Stability Metrics

The extensive simulation study yielded a highly robust dataset, allowing for a comprehensive analysis of the performance trade-offs inherent in balancing dynamic optimization with route stability preservation. The simulation continuously tracked multiple key performance indicators across the thirty-day longitudinal horizon, evaluating the proposed stability-aware intelligent optimization algorithm against traditional cost-centric dynamic routing approaches. To quantify the results, we analyzed spatial consistency, which measures the percentage of daily delivery nodes that were serviced by their historically assigned driver agent, and total operational cost, which aggregates distance traveled and total labor hours consumed.

The results clearly demonstrate that intelligent optimization methods can predictably control and maintain high levels of route stability without suffering catastrophic losses in operational efficiency. As detailed in the comparative performance data, the standard dynamic algorithm, operating without any stability penalties, achieved the lowest absolute theoretical operational cost. However, this came at the severe expense of spatial consistency, which plummeted to critically low levels, indicating highly chaotic daily driver assignments. In stark contrast, the intelligent stability-aware algorithms, utilizing moderate to high penalty weighting factors, successfully maintained spatial consistency levels significantly higher than the baseline dynamic approach [21].

Table 2: Performance Metrics Across Optimization Algorithms

Algorithm Configuration	Spatial Consistency Percentage	Relative Operational Cost Increase
Standard Dynamic Routing	Twenty-two percent	Baseline reference zero percent
Stability-Aware Low Penalty	Fifty-eight percent	Two point four percent increase
Stability-Aware Medium Penalty	Seventy-nine percent	Four point seven percent increase
Stability-Aware High Penalty	Ninety-one percent	Eight point two percent increase
Pure Static Master Routing	Ninety-eight percent	Fifteen point six percent increase

The data presented in the performance metrics table reveals a distinct, non-linear trade-off frontier. By implementing a medium penalty configuration within the intelligent optimization engine, the fleet achieved a massive improvement in spatial consistency, reaching highly acceptable levels for driver familiarization, while incurring an exceedingly modest increase in daily operational costs relative to the absolute theoretical minimum. This slight increase in raw distance-based cost is frequently offset in actual operations by the reduction in service times resulting from driver familiarity, a dynamic that the simulation accurately captured. The pure static routing approach, while maximizing consistency, proved to be highly inefficient, struggling to accommodate the dynamic demand portion and leading to severe vehicle capacity violations and extensive overtime costs. Therefore, the stability-aware intelligent optimization method proved to be the vastly superior predictive and operational strategy.

5.2 Impact of Dynamic Disruptions on Fleet Performance

Beyond the baseline analysis of route consistency and operational costs, the simulation study profoundly illuminated the critical role that route stability plays in buffering urban delivery fleets against dynamic environmental disruptions. Urban logistics networks are inherently fragile, subject to sudden localized traffic gridlocks, severe weather events, or unexpected infrastructural failures. To evaluate the resilience of the different routing strategies, severe localized traffic anomalies were stochastically injected into the simulation environment during the operational shifts.

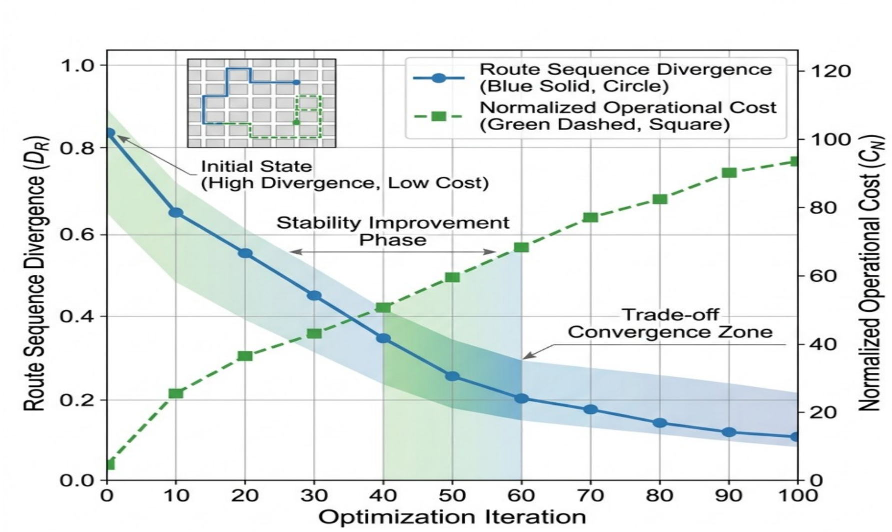

Figure 2: Analytical Line Chart of Route Sequence Divergence and Cost Trade

When massive localized delays were introduced, the fleets operating under the standard, highly volatile dynamic routing paradigm experienced severe cascading failures. Because drivers were operating in unfamiliar territories with optimized routes that possessed absolutely zero temporal slack, a significant delay at one intersection resulted in massive time window violations across the remainder of the daily sequence. The intelligent optimization engine, when attempting to dynamically re-route these highly volatile plans mid-shift, often generated further confusion and inefficiency. Conversely, the fleets operating under the stability-aware intelligent optimization paradigm demonstrated remarkable resilience. Because the drivers possessed deep contextual familiarity with their assigned geographic zones, they dynamically utilized alternative micro-routes and localized knowledge of parking and access shortcuts to mitigate the impact of the injected delays [22]. The preservation of route stability effectively created an operational buffer, transforming brittle, theoretically optimal mathematical plans into robust, human-executable operations. This finding strongly suggests that predicting and maintaining route stability through intelligent algorithmic design is not merely a mechanism for improving driver satisfaction, but a fundamental prerequisite for building resilient delivery networks capable of surviving the chaotic realities of modern urban environments. The strategic implication for fleet managers is clear: algorithms must be calibrated to value structural consistency, recognizing that mathematical perfection on paper often shatters when exposed to urban friction.

6. Conclusion and Future Work

6.1 Summary of Findings

This comprehensive academic study has systematically investigated the crucial, yet frequently overlooked, dimension of route stability within the context of urban delivery fleets utilizing intelligent optimization methods. Driven by the relentless pressures of modern e-commerce and complex urban logistical constraints, industry practices have historically heavily favored dynamic routing paradigms that aggressively minimize operational distances while simultaneously destroying the temporal and spatial consistency of daily driver routines. Through the deployment of a sophisticated, high-fidelity agent-based simulation framework, this research has conclusively demonstrated that intelligent optimization algorithms can be successfully re-engineered to accurately predict, manage, and preserve route stability. By integrating mathematically robust stability penalty functions directly into the evaluative objective function of advanced metaheuristic algorithms, fleet managers can predictably control the inherent trade-off between absolute computational cost efficiency and critical structural consistency. The empirical simulation results clearly indicate that immense gains in driver territorial familiarity and spatial consistency can be achieved with only marginal sacrifices in theoretical optimal travel distances. Furthermore, the analysis reveals that fleets operating with highly stable route architectures exhibit vastly superior operational resilience when confronted with stochastic urban traffic disruptions, thereby ensuring higher compliance with strict customer delivery time windows.

6.2 Limitations and Future Research Directions

While this study provides substantial theoretical and practical advancements in the field of dynamic vehicle routing, several limitations must be acknowledged, which subsequently open avenues for future scholarly research. Primarily, although the simulation environment utilized synthetic data meticulously designed to mirror real-world urban logistics networks, simulations inherently rely on simplified abstractions of highly complex human behaviors. The dynamic modeling of driver familiarization and its precise quantitative impact on node service times remains a mathematical estimation within this study. Future research should prioritize conducting extensive empirical pilot studies in active, real-world urban delivery operations to validate the simulated trade-off frontiers against actual longitudinal fleet performance data. Additionally, the computational demands of calculating complex stability penalties within large-scale metaheuristic algorithms represent a potential bottleneck for massive, real-time fleet operations. Future algorithmic development must focus on enhancing the computational efficiency of these stability-aware models. Finally, the integration of real-time Internet of Things data, predictive machine learning models for localized traffic forecasting, and dynamic weather tracking into the stability optimization framework represents a highly promising frontier. By fusing predictive analytics with stability-preserving intelligent optimization, researchers can develop next-generation routing systems that are not only mathematically efficient and operationally stable but also deeply resilient and continuously adaptive to the rapidly evolving challenges of the urban logistics ecosystem.

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