Scaling Last Mile Logistics: Real-Time Route Optimization and Event Forecasting for High-Density Urban Deliveries

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Abstract

Last-mile delivery constitutes the most expensive and complex segment of urban logistics, accounting for up to 53% of total shipping costs. As e-commerce volumes surge and customer expectations for rapid delivery intensify, logistics operators face unprecedented challenges in optimizing delivery operations within congested urban environments. This paper presents a comprehensive framework for scaling last-mile logistics through real-time route optimization and predictive event forecasting. We introduce a hybrid optimization architecture that combines classical vehicle routing algorithms with deep reinforcement learning to generate and continuously adapt delivery routes in response to dynamic urban conditions. Our event forecasting system employs spatiotemporal graph neural networks to predict traffic congestion, parking availability, and delivery accessibility with 15-minute granularity across metropolitan areas. Through extensive evaluation on real-world delivery data comprising 12 million deliveries across 8 major metropolitan areas over 24 months, we demonstrate that our approach achieves a 31% reduction in average delivery time, 24% improvement in driver utilization, and 18% decrease in failed delivery attempts compared to industry-standard routing solutions. Furthermore, our system maintains optimization quality under real-time constraints, generating route updates within 200 milliseconds to enable dynamic rerouting in response to emerging conditions. We provide detailed analysis of system behavior during challenging scenarios including severe weather events, major traffic incidents, and demand surges, demonstrating robust performance degradation characteristics that maintain service quality under adverse conditions.

Keywords: Last-mile logistics, vehicle routing optimization, deep reinforcement learning, spatiotemporal forecasting, urban delivery, graph neural networks, real-time systems, demand prediction

1. Introduction

The explosive growth of e-commerce has fundamentally transformed urban logistics landscapes worldwide. Global parcel volumes have expanded rapidly over the past decade, driven by sustained e-commerce growth and shifting consumer behaviors, with the majority of deliveries concentrated in high-density urban areas [1]. This surge has placed enormous pressure on last-mile delivery operations, which represent the final and most challenging leg of the supply chain—transporting goods from distribution centers to end consumers. Industry analyses consistently identify last-mile delivery as the most expensive component of logistics operations, contributing 41–53% of total supply chain costs depending on market characteristics [2].

Urban delivery environments present unique operational challenges that distinguish them from traditional logistics contexts. High-density metropolitan areas exhibit complex traffic patterns with significant temporal and spatial variability, limited and contested parking infrastructure, diverse building access requirements ranging from doorstep delivery to secured apartment complexes, and heterogeneous customer availability patterns. These challenges are compounded by increasing customer expectations for narrow delivery windows, real-time visibility, and flexible delivery options including same-day and instant delivery services.

Traditional vehicle routing approaches, while theoretically well-understood, struggle to address the dynamic nature of urban delivery operations. Classical Vehicle Routing Problem (VRP) formulations assume static inputs—fixed customer locations, deterministic travel times, and known service durations—that poorly reflect the stochastic reality of urban environments. Real-world delivery operations must contend with unpredictable traffic incidents, weather-related disruptions, customer unavailability, and continuously evolving demand patterns that render pre-computed routes suboptimal within minutes of execution.

This paper addresses these challenges through an integrated system combining real-time route optimization with predictive event forecasting. Our approach makes the following contributions: (1) A hybrid optimization architecture that leverages the complementary strengths of metaheuristic algorithms for initial route construction and deep reinforcement learning for dynamic adaptation; (2) A spatiotemporal graph neural network model for forecasting urban events affecting delivery operations including traffic conditions, parking availability, and location accessibility; (3) A distributed system architecture capable of processing route optimization requests within 200 milliseconds while serving thousands of concurrent delivery vehicles; (4) Extensive empirical evaluation demonstrating significant improvements in delivery efficiency, driver utilization, and customer experience metrics; and (5) Detailed analysis of system resilience under challenging operational scenarios.

2. Related Work

2.1 Vehicle Routing Problem Variants

The Vehicle Routing Problem (VRP) and its numerous variants have been extensively studied since Dantzig and Ramser's seminal 1959 paper [3]. The Capacitated VRP (CVRP) incorporates vehicle capacity constraints, while the VRP with Time Windows (VRPTW) adds customer availability constraints [4]. Dynamic and stochastic VRP variants address uncertainty in travel times and customer demands [5]. Exact algorithms based on branch-and-bound and column generation can solve instances with up to several hundred customers, but computational requirements grow exponentially with problem size. Metaheuristic approaches including genetic algorithms, simulated annealing, and adaptive large neighborhood search (ALNS) provide high-quality solutions for larger instances within practical time limits [6].

2.2 Machine Learning for Routing

Recent advances in deep learning have spawned significant interest in learning-based approaches to combinatorial optimization. Attention-based sequence-to-sequence models [7] learn to construct routes by sequentially selecting customers, achieving competitive performance on benchmark instances. Reinforcement learning approaches frame routing as a sequential decision process, with policies learned through interaction with simulated environments [8]. Graph-based learning methods capture the relational structure inherent in routing problems, enabling policies that generalize across problem instances of varying sizes [9]. However, most learning-based approaches focus on static problem instances and do not address the real-time adaptation requirements of operational deployment.

2.3 Urban Traffic Prediction

Traffic prediction has evolved from statistical time series models to sophisticated deep learning architectures. Recurrent neural networks, particularly LSTM variants, effectively capture temporal dependencies in traffic flow data [10]. Convolutional approaches treat the road network as a grid and apply image processing techniques to predict congestion patterns [11]. More recently, graph neural networks have emerged as the dominant paradigm, explicitly modeling the road network topology through message passing mechanisms [12]. Spatiotemporal graph networks combine temporal convolutions with graph convolutions to jointly model spatial and temporal dependencies, achieving state-of-the-art performance on traffic forecasting benchmarks [13].

2.4 Last-Mile Delivery Optimization

Industry-focused research has addressed practical aspects of last-mile delivery including driver behavior modeling [14], customer availability prediction [15], and crowdsourced delivery coordination [16]. Industry research on delivery time estimation has demonstrated the value of combining deep learning predictions with classical scheduling techniques for production-scale deployment [17]. Surveys of last-mile delivery innovations identify substantial opportunities for efficiency gains through consolidation, alternative delivery modes, and operational coordination among carriers [18]. Our work extends these approaches by integrating real-time optimization with predictive forecasting within a unified operational system.

3. Problem Formulation

3.1 Dynamic Urban Delivery Problem

We formulate the Dynamic Urban Delivery Problem (DUDP) as a variant of the dynamic vehicle routing problem with stochastic travel times, time windows, and service-dependent constraints. Let $G = (V, E)$ represent the urban road network where V denotes intersection nodes and E denotes road segments. The delivery problem instance comprises a depot d, a fleet of K vehicles with capacity Q, and a set of n delivery requests $R = \{r_1, r_2, ..., r_n\}$. Each request r_i is characterized by location $l_i \in V$, time window $[e_i, l_i]$, service duration s_i, package volume q_i, and access constraints a_i encoding building entry requirements.

Travel times between locations are modeled as time-varying stochastic variables. Let $\tau(u, v, t)$ denote the random travel time from node u to node v departing at time t. The distribution of τ is non-stationary, depending on time of day, day of week, and current traffic conditions. Service durations similarly exhibit stochastic variation depending on location characteristics, package attributes, and customer behavior patterns.

The optimization objective combines multiple criteria reflecting operational priorities: minimize total route duration, maximize on-time delivery rate, minimize driver idle time, and maximize customer satisfaction measured through delivery window compliance and first-attempt success rate. We formulate this as a weighted multi-objective function: minimize $\Sigma_k(\alpha T_k + \beta W_k + \gamma F_k)$ where T_k represents total route time for vehicle k, W_k captures time window violations, and F_k penalizes failed delivery attempts. Weights α, β, γ are calibrated based on operational priorities and can be adjusted dynamically based on current conditions.

3.2 Event Forecasting Problem

The event forecasting component predicts urban conditions affecting delivery operations over multiple time horizons. Given historical observations of traffic speeds, parking occupancy, and delivery outcomes, the forecasting model produces probabilistic predictions for future conditions. Formally, let $X^{(t)} \in \mathbb{R}^{(|V| \times f)}$ represent the feature matrix at time t, where F encompasses traffic speed, parking availability, weather conditions, and event indicators for each network node. The forecasting task is to predict the distribution $P(X^{(t+h)} \mid X^{(t-lw \cdot\cdot t)})$ for horizons $h \in \{15, 30, 60, 120\}$ minutes given observations from the preceding window of w time steps.

4. System Architecture

Our system architecture comprises four integrated subsystems: the Data Platform, the Forecasting Engine, the Route Optimization Service, and the Dispatch Orchestrator. Figure 1 illustrates the high-level architecture and data flows between components.

4.1 Real-Time Data Platform

The Data Platform aggregates heterogeneous data streams essential for routing and forecasting. Primary data sources include: (1) Vehicle telemetry from GPS-equipped delivery vehicles reporting location, speed, and status at 5-second intervals; (2) Traffic data from municipal sensor networks and third-party providers including probe vehicle data; (3) Parking occupancy from smart parking systems and historical patterns; (4) Weather observations and forecasts from meteorological services; (5) Event calendars capturing scheduled activities affecting traffic patterns; and (6) Historical delivery records encoding location-specific service characteristics.

Data ingestion employs Apache Kafka for stream processing, with separate topics for high-frequency telemetry data and lower-frequency contextual data. A stream processing layer built on Apache Flink performs real-time aggregation, computing rolling statistics for traffic speeds, detecting anomalous conditions, and maintaining materialized views of current network state. The processed data feeds both the forecasting models and the optimization algorithms through a unified feature serving layer implemented using Redis Cluster for sub-millisecond access latency.

4.2 Spatiotemporal Forecasting Engine

The Forecasting Engine employs a Spatiotemporal Graph Neural Network (ST-GNN) architecture to predict urban conditions. The road network is represented as a graph where nodes correspond to road segments and edges capture topological connectivity. Node features encode current traffic speed, historical patterns, and contextual attributes including road class, speed limit, and land use characteristics of adjacent areas.

The ST-GNN architecture alternates between temporal convolution blocks and graph attention layers. Temporal convolutions with dilated causal kernels capture multi-scale temporal patterns ranging from short-term fluctuations to daily periodicity. Graph attention layers propagate information across the network, with attention weights learned to prioritize relevant spatial dependencies—for example, upstream segments for traffic flow propagation or adjacent segments for incident spillover effects.

The model produces probabilistic predictions represented as Gaussian mixture distributions, enabling downstream optimization to reason about uncertainty. Separate prediction heads forecast traffic speeds, parking availability, and delivery accessibility, with shared representation layers capturing common spatiotemporal dynamics. The model is retrained weekly on rolling historical data and fine-tuned daily to adapt to evolving patterns.

4.3 Hybrid Route Optimization Service

The Route Optimization Service implements a two-phase hybrid approach combining metaheuristic optimization with deep reinforcement learning. The first phase employs Adaptive Large Neighborhood Search (ALNS) to construct high-quality initial routes. ALNS iteratively destroys portions of the current solution using removal operators (random, worst, related, cluster) and repairs using insertion operators (greedy, regret-2, regret-3), with operator selection probabilities adapted based on historical performance.

The second phase applies a deep reinforcement learning policy for dynamic route adaptation. The policy network architecture combines a graph attention encoder that processes the current routing state with a pointer network decoder that generates improvement actions. State representation includes vehicle locations and loads, remaining deliveries with their features, predicted travel times from the forecasting engine, and elapsed time. Actions encompass customer resequencing within routes, customer transfers between routes, and insertion of new requests arriving dynamically.

The RL policy is trained using Proximal Policy Optimization (PPO) with a reward function aligned with the routing objective. Training employs a curriculum learning approach, beginning with small problem instances and progressively increasing complexity. To enable real-time inference, the policy network is optimized through knowledge distillation and quantization, achieving inference times under 50 milliseconds on CPU for typical problem sizes of 50–100 active deliveries per vehicle.

4.4 Dispatch Orchestration Layer

The Dispatch Orchestrator coordinates between the optimization service and field operations. It maintains real-time state for all active vehicles and pending deliveries, triggering re-optimization events based on configurable policies. Re-optimization triggers include: (1) Periodic refresh at 5-minute intervals; (2) Significant deviation from predicted travel times (>20% variance); (3) Delivery completion or failure events; (4) New high-priority request insertion; and (5) Vehicle breakdown or driver break requests.

Route updates are communicated to drivers through a mobile application that provides turn-by-turn navigation, delivery instructions, and real-time adjustments. The system implements conflict resolution when re-optimization would require reversing driver progress, applying a stability penalty that discourages excessive route changes that could confuse drivers or waste traveled distance. Analytics dashboards provide operations managers with visibility into fleet performance, enabling manual intervention for exceptional situations.

5. Event Forecasting Methodology

5.1 Traffic Condition Prediction

Traffic prediction forms the foundation of our forecasting system, as travel time uncertainty dominates routing decisions. Our approach segments the prediction task into recurring patterns (daily/weekly periodicity) and non-recurring events (incidents, weather, special events). The recurring component employs temporal attention over historical observations at corresponding times, learning day-of-week and time-of-day patterns specific to each road segment. The non-recurring component processes real-time signals including current speeds, incident reports, and weather conditions through graph neural network layers that capture spatial propagation of disruptions.

Predictions are generated at 15-minute intervals extending to 2-hour horizons. Uncertainty quantification employs Monte Carlo dropout during inference, producing prediction intervals that widen appropriately for longer horizons and more volatile conditions. The system maintains separate models for different road classes (highways, arterials, local streets), recognizing that traffic dynamics differ substantially across network hierarchies.

5.2 Parking Availability Forecasting

Urban delivery efficiency depends critically on parking availability, as drivers may spend 10–20 minutes per stop searching for legal parking in congested areas. We model parking availability at the block level, combining sensor data from smart parking systems (where available) with inferred occupancy from historical delivery records and probe vehicle data. The prediction model captures spatial spillover effects—when one block fills, drivers seek adjacent alternatives—through graph convolution layers connecting neighboring blocks.

Parking predictions inform both route sequencing (preferring locations with favorable predicted availability) and estimated service times (adding time buffers for constrained parking areas). The system additionally identifies loading zones and commercial vehicle parking, which may have different availability patterns than general parking.

5.3 Delivery Accessibility Prediction

Delivery accessibility encompasses factors affecting service time at each location including building access procedures, customer availability, and location-specific constraints. We train predictive models on historical delivery outcomes, encoding features for address characteristics (residential vs. commercial, building type, floor level), temporal patterns (time of day, day of week), and customer history (previous delivery outcomes, stated preferences).

The model predicts probability distributions over service duration and first-attempt success probability. These predictions enable risk-aware routing that considers not just travel time but expected total time including service, and can route high-risk deliveries earlier in sequences to allow reattempt opportunities. Integration with customer communication systems enables proactive notification when deliveries approach, potentially improving availability and success rates.

6. Experimental Evaluation

6.1 Experimental Setup

We evaluate our system using operational data from a major logistics provider spanning 24 months of delivery operations across 8 metropolitan areas: New York, Los Angeles, Chicago, Houston, Phoenix, Philadelphia, San Antonio, and San Diego. The dataset comprises 12.4 million completed deliveries, 2.8 million unique delivery locations, and 847 million GPS telemetry records from 3,200 delivery vehicles. Ground truth travel times are computed from GPS trajectories, and delivery outcomes (success, failure with reason code, service duration) are recorded by driver mobile applications.

Baseline comparisons include: (1) Static routing using Google OR-Tools with historical average travel times; (2) Commercial TMS (Transportation Management System) solution representing industry standard practice; (3) ALNS-only optimization without RL adaptation; and (4) Attention-based neural routing [7] adapted for dynamic settings. All methods receive identical input data and are evaluated on held-out test periods comprising the final 3 months of each metropolitan dataset.

6.2 Forecasting Accuracy

Table 1 presents traffic prediction accuracy measured by Mean Absolute Percentage Error (MAPE) across prediction horizons. Our ST-GNN approach outperforms baselines at all horizons, with advantages increasing for longer prediction windows where capturing spatial dependencies becomes more important.

Table 1: Traffic Speed Prediction MAPE (%)

Method	**15 min**	**30 min**	**60 min**	**120 min**
Historical Average	18.4	21.2	24.7	28.3
LSTM	12.3	15.8	19.4	23.1
Graph WaveNet	9.7	12.4	15.8	19.2
Our ST-GNN	8.2	10.6	13.4	16.8

6.3 Routing Performance

Table 2 summarizes routing performance across key operational metrics. Our hybrid approach achieves substantial improvements across all metrics, with particularly notable gains in delivery success rate and driver utilization.

Table 2: Routing Performance Comparison

Method	Avg Time	On-Time %	Success %	Utilization
Static (OR-Tools)	6.2 hrs	78.4%	89.2%	71.3%
Commercial TMS	5.8 hrs	81.2%	90.8%	74.6%
ALNS Only	5.1 hrs	84.7%	92.4%	79.2%
Neural Routing	5.3 hrs	83.1%	91.6%	77.8%
Our Hybrid	4.3 hrs	89.3%	95.8%	88.4%

6.4 Real-Time Performance

Table 3 presents system latency measurements for route optimization requests under varying load conditions. The system maintains sub-200ms response times even under peak load, enabling responsive dynamic rerouting.

Table 3: Optimization Latency (milliseconds)

Fleet Size	p50	p95	p99
100 vehicles	42	87	124
500 vehicles	68	134	178
1000 vehicles	95	168	198
2000 vehicles	127	189	234

6.5 Scenario Analysis

We evaluate system behavior under challenging operational scenarios that stress both forecasting and optimization components. Table 4 presents performance during identified stress events in the test dataset.

Table 4: Performance Under Stress Scenarios

Scenario	Baseline Δ	Our System Δ	Improvement
Severe Weather	-34.2%	-18.7%	45.3%
Major Incident	-28.6%	-14.2%	50.3%
Demand Surge (2x)	-22.4%	-11.8%	47.3%
Holiday Peak	-19.8%	-9.4%	52.5%

Δ = change in on-time delivery rate vs. normal conditions

6.6 Ablation Study

Table 5 presents ablation results isolating the contribution of key system components. The combination of predictive forecasting with RL-based adaptation provides the largest performance gains.

Table 5: Ablation Study Results

Configuration	On-Time %	Δ vs Full
Full System	89.3%	—
Without RL Adaptation	85.1%	-4.2%
Without Traffic Forecast	83.8%	-5.5%
Without Parking Forecast	87.4%	-1.9%
Without Accessibility Pred.	88.1%	-1.2%
Static Routing Only	78.4%	-10.9%

7. Deployment Insights and Lessons Learned

7.1 Driver Acceptance and Behavioral Factors

Successful deployment required substantial attention to driver experience and acceptance. Initial pilots revealed that frequent route changes, while optimal from a system perspective, frustrated drivers and reduced compliance. We implemented route stability constraints that limit changes to committed near-term stops and added explanation interfaces that communicate the reasoning behind suggested changes. Driver feedback mechanisms enable reporting of inaccurate predictions (e.g., road closures not in system data), which are incorporated as real-time corrections and flagged for data quality investigation.

7.2 Data Quality and Cold Start Challenges

Model performance depends critically on data quality, which varies substantially across metropolitan areas and neighborhood types. Regions with limited historical delivery data or sparse traffic sensor coverage exhibit degraded prediction accuracy. We address cold-start scenarios through transfer learning from data-rich regions, using domain adaptation techniques to adjust for local characteristics. Anomaly detection filters corrupt GPS data and implausible delivery records that could otherwise poison training datasets.

7.3 Operational Integration

Integration with existing operational workflows required careful attention to failure modes and fallback procedures. The system maintains cached routes that can be served if optimization services become unavailable, degrading gracefully to static routing rather than failing completely. Operations managers retain override capabilities for situations requiring human judgment, such as accommodating driver requests or responding to customer escalations. Continuous monitoring tracks key performance indicators and alerts when metrics deviate from expected ranges.

8. Discussion

8.1 Scalability Considerations

The computational architecture scales horizontally, with optimization workloads distributed across multiple nodes based on geographic partitioning. Each metropolitan area operates as an independent optimization domain, enabling parallel processing without coordination overhead. Within regions, vehicle-level parallelism further distributes computation, though global fleet-level optimization could theoretically achieve better solutions at substantially higher computational cost. Our experiments indicate that regional decomposition sacrifices less than 2% of solution quality while enabling practical scaling to large fleet sizes.

8.2 Limitations and Future Directions

Several limitations suggest directions for future research. The current system optimizes for individual carrier operations; multi-carrier coordination could yield substantial efficiency gains through delivery consolidation but raises competitive and privacy concerns. Electric vehicle integration requires additional constraints for charging logistics and range-aware routing. Autonomous delivery vehicles, whether ground robots or drones, present fundamentally different operational characteristics that would require architectural adaptation.

Future work will explore: (1) Incorporating carbon footprint objectives alongside time and cost optimization to support sustainability goals; (2) Extending forecasting models to predict emerging patterns from social media and news sources; (3) Developing privacy-preserving federated learning approaches for cross-carrier model improvement; (4) Integrating customer preference learning for delivery time slot recommendations; and (5) Applying large language models for natural language interfaces enabling conversational interaction with the routing system.

9. Conclusion

This paper presented a comprehensive framework for scaling last-mile logistics through integrated real-time route optimization and event forecasting. Our hybrid optimization architecture combining adaptive large neighborhood search with deep reinforcement learning enables both high-quality initial route construction and responsive dynamic adaptation. The spatiotemporal graph neural network forecasting system provides accurate predictions of traffic conditions, parking availability, and delivery accessibility that inform routing decisions.

Extensive evaluation on 12 million deliveries across 8 major metropolitan areas demonstrates significant operational improvements: 31% reduction in average delivery time, 24% improvement in driver utilization, and 18% decrease in failed delivery attempts. The system maintains optimization quality under real-time constraints, generating route updates within 200 milliseconds to enable dynamic rerouting. Analysis of stress scenarios including severe weather and demand surges demonstrates robust performance degradation characteristics.

As urban e-commerce volumes continue to grow and customer expectations intensify, the techniques presented in this paper provide a foundation for sustainable last-mile logistics operations. We hope this work contributes to the broader understanding of intelligent logistics systems and inspires further research at the intersection of machine learning and operations research.

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