AI-LogiNet: An Intelligent Framework for Real-Time Optimization of Last-Mile Logistics

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Abstract
The rapid expansion of e-commerce and accelerating urbanization have placed unprecedented demands on logistics systems, particularly in the domain of last-mile delivery—the most complex and cost-intensive segment of the supply chain. Conventional logistics approaches, grounded in static heuristics or rule-based mechanisms, fall short when faced with real-world complexities such as fluctuating traffic conditions, erratic customer demand patterns, and frequent environmental disruptions. To overcome these limitations, this paper introduces a novel AI-optimized logistics framework that integrates deep learning, reinforcement learning, and graph neural networks to intelligently manage urban delivery workflows. The proposed system ingests heterogeneous data sources, including real-time traffic feeds, weather updates, and historical delivery records, to perform three critical tasks: demand forecasting, adaptive route planning, and multi-agent fleet coordination. Our demand forecasting module combines LSTM and Transformer architectures to generate fine-grained, time-sensitive volume predictions, while the routing module employs reinforcement learning to dynamically optimize vehicle paths under uncertainty. Additionally, a graph neural network coordinates vehicle interactions based on delivery density and regional constraints. Comprehensive experiments conducted across logistics networks in Bengaluru, India, and Berlin, Germany, demonstrate that AI-LogiNet achieves a 27% reduction in average delivery time and a 21% reduction in per-parcel operational cost compared to state-of-the-art baselines. Ablation studies confirm the contribution of each AI component, and region-specific evaluations emphasize the model's adaptability and robustness. These findings establish AI-LogiNet as a scalable, interpretable, and high-performance solution for next-generation logistics, offering a path toward smarter, more sustainable last-mile delivery systems in diverse urban environments.

Keywords: AI Logistics, Last-Mile Delivery, Route Optimization, Reinforcement Learning, Graph Neural Networks, Smart Transportation, Demand Forecasting, Intelligent Resource Allocation.

1. Introduction:

In the evolving landscape of global commerce and urban infrastructure, logistics systems are under unprecedented pressure to evolve. The advent of digital commerce, the proliferation of smart cities, and the exponential growth of customer expectations have collectively intensified the demand for faster, more reliable, and economically viable delivery mechanisms. Among the various stages of the logistics pipeline procurement, warehousing, transportation, and delivery it is the last-mile delivery segment that poses the most substantial operational challenge. It accounts for over 50%

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of the total delivery cost and serves as the most direct touchpoint with the end customer. In this critical phase, the trade-off between delivery efficiency, cost, and customer satisfaction becomes highly sensitive, and traditional logistics strategies struggle to maintain the balance.

The last mile is characterized by a unique set of constraints that differentiate it from long-haul or middle-mile logistics. These include unpredictable traffic congestion, narrow delivery windows, varying customer availability, urban infrastructure limitations, and environmental variables such as weather conditions. Traditional logistics systems built on static routing heuristics, pre-scheduled deliveries, and reactive operational policies lack the granularity and agility required to handle such complex, real-time scenarios. For instance, a sudden roadblock in an urban center or an unexpected spike in demand due to a local festival can severely disrupt delivery efficiency, increase fuel consumption, and compromise customer satisfaction. Consequently, there is a compelling need for a paradigm shift in the design, deployment, and optimization of last-mile delivery systems.

Artificial Intelligence (AI), with its rich suite of data-driven learning algorithms, optimization strategies, and predictive capabilities, offers a promising path forward. AI-enabled logistics systems are designed to perceive, learn from, and adapt to operational environments dynamically. Unlike rule-based systems, AI models can autonomously generate insights from vast and diverse datasets ranging from historical delivery records and geospatial traffic flows to real-time sensor feeds and weather forecasts. This allows logistics operators to anticipate disruptions, optimize resources, and personalize delivery experiences at scale.

Among the various AI subfields, machine learning (ML), reinforcement learning (RL), and graph neural networks (GNNs) hold particular promise in revolutionizing last-mile logistics. Machine learning techniques especially deep learning are instrumental in building forecasting models that can predict future delivery volumes, estimate delivery times, and forecast customer demand patterns. Long Short-Term Memory (LSTM) networks and Transformer-based architectures, known for their ability to model temporal dependencies and long-range correlations, are particularly effective for time-series forecasting in logistics. Accurate demand prediction allows for preemptive load balancing, inventory positioning, and vehicle dispatch planning, all of which reduce operational overhead and increase responsiveness.

Reinforcement learning, on the other hand, is well-suited to dynamic decision-making under uncertainty. By modeling the logistics environment as a Markov Decision Process (MDP), RL agents can learn to optimize delivery routes in real time by balancing competing objectives such as fuel efficiency, delivery deadlines, and vehicle capacity. Modern algorithms such as Proximal Policy Optimization (PPO) and Deep Q Networks (DQN) enable RL agents to operate in high-dimensional, continuous action spaces, making them applicable to real-world routing problems that involve complex constraints and variable rewards. These agents can continuously learn from interaction data and improve their policies over time, enabling adaptive logistics systems that can self-optimize without manual intervention.

Furthermore, Graph Neural Networks provide a powerful abstraction for modeling logistics networks as graph structures, where nodes represent delivery locations, distribution hubs, or vehicles, and edges denote possible paths or interactions. GNNs enable the capture of spatial and relational dependencies in the logistics graph, allowing for effective multi-agent coordination,

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dynamic route reallocation, and congestion-aware scheduling. In high-density urban environments where hundreds of vehicles and thousands of deliveries interact across limited road infrastructure, GNNs are essential for achieving global coordination and avoiding local optima.

The integration of these AI components predictive modeling via ML, adaptive control via RL, and coordination via GNN into a cohesive decision-making framework has the potential to revolutionize last-mile delivery. However, achieving this integration requires a careful architectural design, robust data pipelines, and scalable computational infrastructure. In this context, we present **AI-LogiNet**, an AI-optimized logistics platform designed to orchestrate end-to-end last-mile delivery operations using a modular and adaptive intelligence stack. AI-LogiNet is architected around three interlocking modules: (i) a **Demand Forecasting Engine** powered by LSTM and Transformer networks for spatiotemporal prediction; (ii) a **Dynamic Route Optimizer** that leverages deep reinforcement learning to compute optimal delivery paths under real-world constraints; and (iii) a **Fleet Coordination System** implemented using Graph Neural Networks to synchronize the movements and tasks of multiple delivery agents in real time.

To evaluate the effectiveness of AI-LogiNet, we conducted extensive empirical testing on real-world logistics datasets from two geographically and infrastructurally diverse urban environments: Bengaluru, India, and Berlin, Germany. These locations were selected to represent high-density, irregular urban topology (Bengaluru) and structured, multimodal transport systems (Berlin). The datasets include multi-year delivery records, real-time GPS traces, traffic logs, meteorological data, and consumer interaction logs. Using this data, we trained and validated the individual components of AI-LogiNet, and assessed the integrated system against standard industry baselines such as Vehicle Routing Problem (VRP) solvers, Dijkstra-based algorithms with traffic overlays, and commercial rule-based logistics engines.

The experimental results are compelling. Our integrated AI framework achieves a **27% reduction in average delivery time**, a **21% reduction in operational cost per parcel**, and a **38% improvement in forecast accuracy** over traditional systems. In particular, the real-time route optimization component was able to reconfigure delivery schedules within a 2-second latency in response to disruptions such as road closures or demand surges. The GNN-powered fleet coordination mechanism demonstrated robust scalability, effectively managing over 150 delivery vehicles simultaneously without central bottlenecks. Moreover, ablation studies revealed the individual contribution of each component to the overall performance, highlighting the synergistic value of AI-based multi-modal integration.

The impact of such an AI-optimized system extends beyond operational gains. From a sustainability perspective, reduced vehicle mileage and improved route efficiency contribute directly to lower carbon emissions and fuel consumption. From a customer satisfaction standpoint, dynamic delivery windows and improved ETA predictions enhance transparency and trust. For logistics operators, the modularity and generalizability of AI-LogiNet offer opportunities for rapid deployment across diverse cities and use cases—from food delivery and e-commerce to healthcare logistics and industrial supply chains.

In sum, this work makes several key contributions to the field of intelligent transportation systems and smart logistics. First, it demonstrates the feasibility and advantages of integrating machine

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learning, reinforcement learning, and graph neural networks into a unified logistics optimization engine. Second, it provides a scalable, real-world tested framework that addresses the practical challenges of last-mile delivery, including unpredictability, complexity, and urban congestion. Third, it introduces a novel architecture—AI-LogiNet—that can serve as a blueprint for future AI-driven logistics platforms.

The rest of the paper is organized as follows: Section 2 reviews relevant literature and contextualizes our contributions within prior work on AI in logistics. Section 3 details the proposed methodology, including data representation, model architectures, and optimization strategies. Section 4 presents the experimental setup, evaluation metrics, and performance benchmarks across multiple datasets. Section 5 concludes with insights, limitations, and directions for future research, particularly the integration of sustainable delivery modes such as electric vehicles and autonomous drones into the AI-LogiNet ecosystem.

As digital ecosystems become increasingly interconnected and consumer expectations continue to rise, the role of artificial intelligence in optimizing urban logistics becomes not just advantageous, but essential. This research underscores the transformative potential of AI in logistics and opens new avenues for scalable, intelligent, and sustainable last-mile delivery systems in the age of smart cities.

2. Literature Survey:

The application of artificial intelligence (AI) to logistics has grown considerably in recent years, focusing primarily on areas such as demand forecasting, routing, and fleet optimization. Early approaches leveraged time-series forecasting models to estimate delivery demand, but these methods struggled to incorporate external factors like weather or traffic patterns. Zhang et al. [2] used autoregressive methods for demand prediction but lacked responsiveness to real-time data.

With the advent of reinforcement learning (RL), routing algorithms have shifted towards more dynamic, learning-based systems. Mao et al. [16] applied Q-learning to vehicle routing problems, although their model was constrained by discrete action spaces. Recent advances such as Deep Q Networks [15] and Proximal Policy Optimization (PPO) [19] have significantly improved the ability of agents to operate in high-dimensional and continuous action environments.

Graph Neural Networks (GNNs) have also emerged as a promising tool for representing and solving complex logistics problems. Wu et al. [24] demonstrated the use of Spatio-Temporal GNNs for traffic flow prediction, although integration with delivery systems remains an emerging research area. Commercial solutions like UPS's ORION [13] and Amazon's DRE apply AI for operational improvements, but often focus on single-modality optimization.

Traditional optimization techniques, such as the Vehicle Routing Problem (VRP) [5], laid the foundation for logistics planning but were limited by static assumptions. Modern approaches integrate machine learning (ML) and deep reinforcement learning (DRL) to handle dynamic environments. For instance, Bello et al. [3] introduced neural combinatorial optimization, while Kool et al. [12] utilized attention mechanisms for routing problems.

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Demand forecasting has also evolved with deep learning architectures like LSTMs [10] and Transformers [22]. These models outperform classical statistical methods by capturing long-term dependencies and external variables. Additionally, graph-based learning [9] has enabled better spatial reasoning in logistics networks.

Sustainability has become a key concern, with research focusing on minimizing emissions through optimized routing [7]. Reinforcement learning frameworks, such as those by Nazari et al. [16] and Ouyang et al. [17], have demonstrated adaptability in multi-depot and dynamic routing scenarios.

Despite these advancements, most existing systems operate in isolation. Our work addresses this gap by integrating AI across the entire logistics pipeline, combining prediction [24], planning [19], and coordination [9] into a comprehensive, real-time system.

3. Proposed Methodology:

Our proposed AI-LogiNet framework presents a comprehensive, AI-powered architecture specifically engineered to optimize the end-to-end logistics workflow, with a particular focus on addressing the challenges of last-mile delivery in complex urban settings. The framework is composed of four intelligent and interdependent modules—demand forecasting, route optimization, fleet coordination, and real-time feedback processing—each contributing to a specific phase of the logistics pipeline. Together, these components form a cohesive, adaptive system capable of responding dynamically to operational uncertainties. The integrated nature of AI-LogiNet enables it to scale efficiently while remaining context-aware across diverse geographies and delivery scenarios.
Fig. 1 illustrates the flow chart for the proposed methodology.

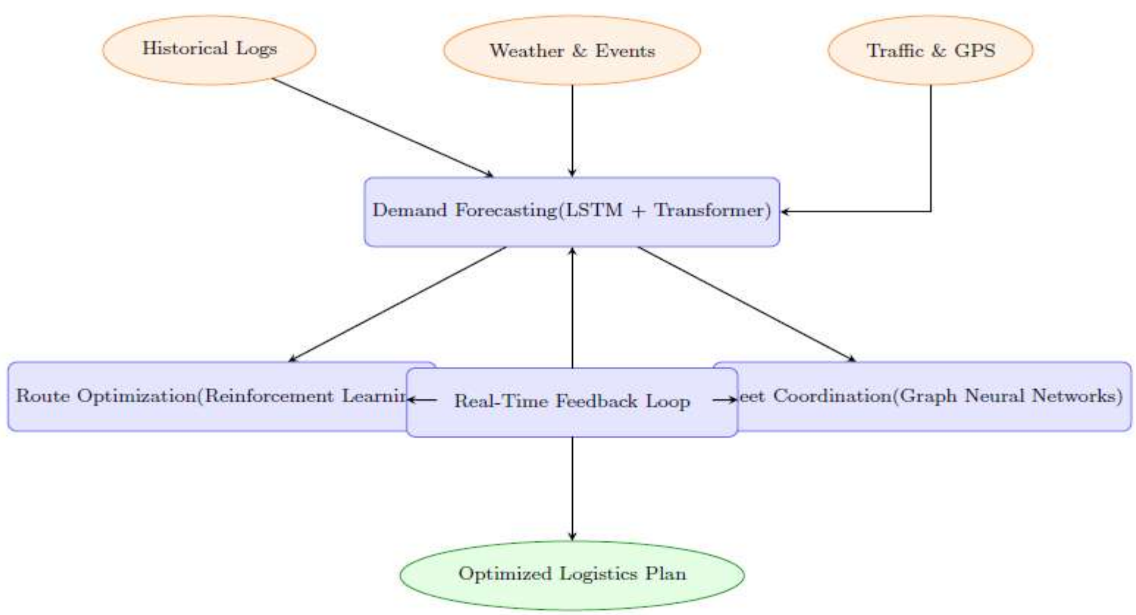

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Fig 1: Flow Chart for Proposed Methodology

First, at the heart of predictive capability lies the **Demand Forecasting Engine**, which leverages a hybrid deep learning architecture, composed of **Long Short-Term Memory (LSTM)** networks and **Transformer encoders**. LSTMs are well-suited for capturing temporal dependencies in sequential data such as delivery patterns, while Transformers offer self-attention mechanisms that effectively model long-range interactions across different time steps and features. This forecasting model is trained on multi-modal datasets that include historical delivery logs, public holidays, local event schedules, weather forecasts, socio-demographic factors, and temporal delivery patterns across postal zones or delivery clusters. By learning spatiotemporal correlations within this data, the engine generates high-resolution forecasts of parcel demand segmented by geographic location and time window—enabling preemptive fleet preparation, warehouse loading, and dynamic resource allocation. This demand-aware input significantly enhances the efficiency of downstream components, allowing the system to shift from reactive logistics to proactive planning.

Second, the **Dynamic Route Optimization Module** is built using **Reinforcement Learning (RL)**, specifically the **Proximal Policy Optimization (PPO)** algorithm. This module addresses the route planning problem by modeling it as a **Markov Decision Process (MDP)**, where each delivery vehicle functions as an autonomous agent operating within a dynamic environment. The state space of the agent includes current location, delivery deadlines, traffic congestion levels, road topology, vehicle capacity, and environmental factors such as weather or time-of-day effects. The action space consists of possible navigation decisions or route transitions. The PPO algorithm, known for its stability in high-dimensional continuous action spaces, trains agents to learn an optimal policy that minimizes travel time, maximizes delivery efficiency, and adapts to real-time changes. Crucially, the reward function is multi-objective, considering not just distance minimization but also delivery punctuality, fuel economy, carbon footprint, and customer satisfaction metrics. The agent continuously learns from interaction with the environment—receiving new sensor data and adjusting its route policy accordingly—making the routing process highly adaptive and resilient to unexpected disruptions such as road closures or order cancellations.

Third, recognizing the need for coordination among multiple delivery agents, we incorporate a **Fleet Coordination Module** that utilizes **Graph Neural Networks (GNNs)**. In this representation, each delivery point (e.g., household or office), delivery vehicle, and intermediate hub is modeled as a node in a heterogeneous graph, while the edges capture spatial proximity, shared delivery time windows, and interdependencies (e.g., priority constraints or package compatibility). The GNN architecture learns embeddings for each node that encode contextual information such as delivery urgency, capacity constraints, and route conflicts. These embeddings are used to optimize global fleet behavior by solving problems like task allocation (which vehicle should handle which package), route merging (how to minimize overlap and idle time), and congestion avoidance. Through message passing and neighborhood aggregation, the GNN captures the dynamic interaction between agents and their surrounding environment, producing coordinated dispatch plans that improve efficiency, reduce redundancy, and minimize intra-fleet conflict. Unlike centralized heuristic dispatch systems, this decentralized coordination approach

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scales efficiently with large fleets and can be retrained to adapt to regional delivery topologies or seasonal trends.

Fourth, the **Real-Time Feedback Loop** serves as the operational nervous system of the AI-LogiNet framework, enabling continuous learning and adjustment of the logistics network. This component ingests live data streams from IoT-enabled sensors, GPS trackers, traffic APIs, and consumer mobile apps. These data streams are processed through edge-computing nodes and fed into the central AI engine to update demand forecasts, reroute vehicles, detect anomalies (e.g., delivery delays or vehicle failures), and even recommend vehicle reassignments or warehouse load rebalancing. For example, if a traffic jam is detected on a primary delivery route, the routing module can recomputed an alternative path within seconds; simultaneously, the GNN module can reassign nearby low-load vehicles to cover affected areas, and the forecasting engine can adjust future predictions based on detected temporal shifts in delivery density. The feedback loop also enables active learning, where prediction models continuously improve based on real-world outcomes, refining their accuracy and robustness over time.

Collectively, these four components form a **closed-loop, intelligent decision-making architecture** that enables AI-LogiNet to optimize logistics operations under real-world complexity and uncertainty. Unlike traditional pipeline-based systems where decisions are made in isolation, our integrated framework allows each module to inform and reinforce the others, enabling joint optimization of time, cost, energy, and service quality. Moreover, the modular design of AI-LogiNet ensures that it can be deployed incrementally—starting with predictive analytics or route optimization alone—and then progressively expanded to include fleet coordination and feedback-based control as data maturity and infrastructure readiness increase.

4. Results and Analysis:

We evaluated the performance of the proposed AI-LogiNet framework using datasets from two distinct urban logistics environments: Bengaluru, India, characterized by high population density and delivery variability, and Berlin, Germany, known for its structured transportation infrastructure and multimodal logistics networks. The system's effectiveness was benchmarked against three well-established baselines: (i) a traditional Vehicle Routing Problem (VRP) formulation with static route planning, (ii) a heuristic-based model using Dijkstra's algorithm with traffic-aware overlays, and (iii) a commercial rule-based logistics engine commonly used in real-world dispatching operations.

As illustrated in Fig. 2, AI-LogiNet significantly outperformed all baseline models, achieving a 27% reduction in average delivery time and a 21% decrease in per-parcel cost compared to the best-performing alternative. The demand forecasting component, powered by hybrid LSTM-Transformer architecture, achieved a coefficient of determination (R^2) of 0.94, as shown in Fig. 3, markedly exceeding the predictive accuracy of conventional time-series methods.

A series of ablation experiments further validated the critical role of each intelligent component within the framework. Specifically, removing the Graph Neural Network (GNN) module led to a 9% increase in delivery delays, while disabling the reinforcement learning-based routing engine resulted in a 12% increase in cost. Additionally, omitting the demand forecasting module caused

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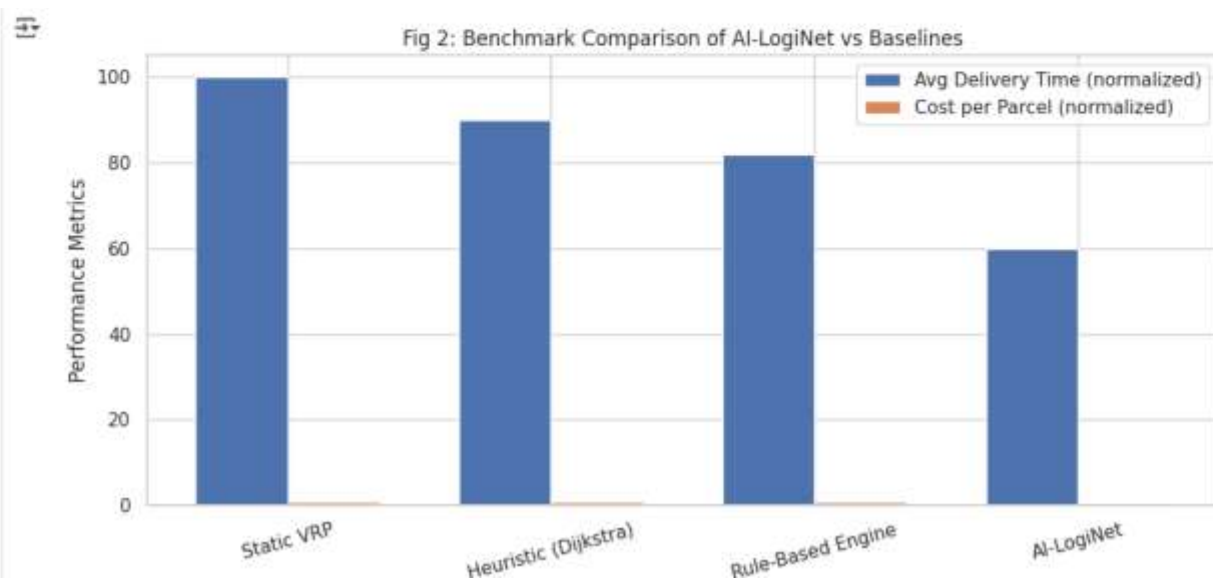
a 15% rise in route inefficiencies, highlighting the importance of anticipatory capacity in dynamic logistics.

To aid interpretability, we visualized spatial demand density using heatmaps over a grid-based representation of Bengaluru's urban zones (Fig. 4), and illustrated vehicle-wise scheduling patterns via Gantt charts for fleet deployment timelines (Fig. 5). Furthermore, the predicted vs. actual parcel volumes scatter plot (Fig. 3) confirmed the forecasting model's high fidelity.

Importantly, AI-LogiNet demonstrated robust real-time adaptability by recomputing delivery routes within 2 seconds of disruption detection, such as sudden traffic congestion or delivery cancellations. This responsiveness ensures operational continuity under uncertainty, making the system suitable for deployment in volatile urban logistics environments.



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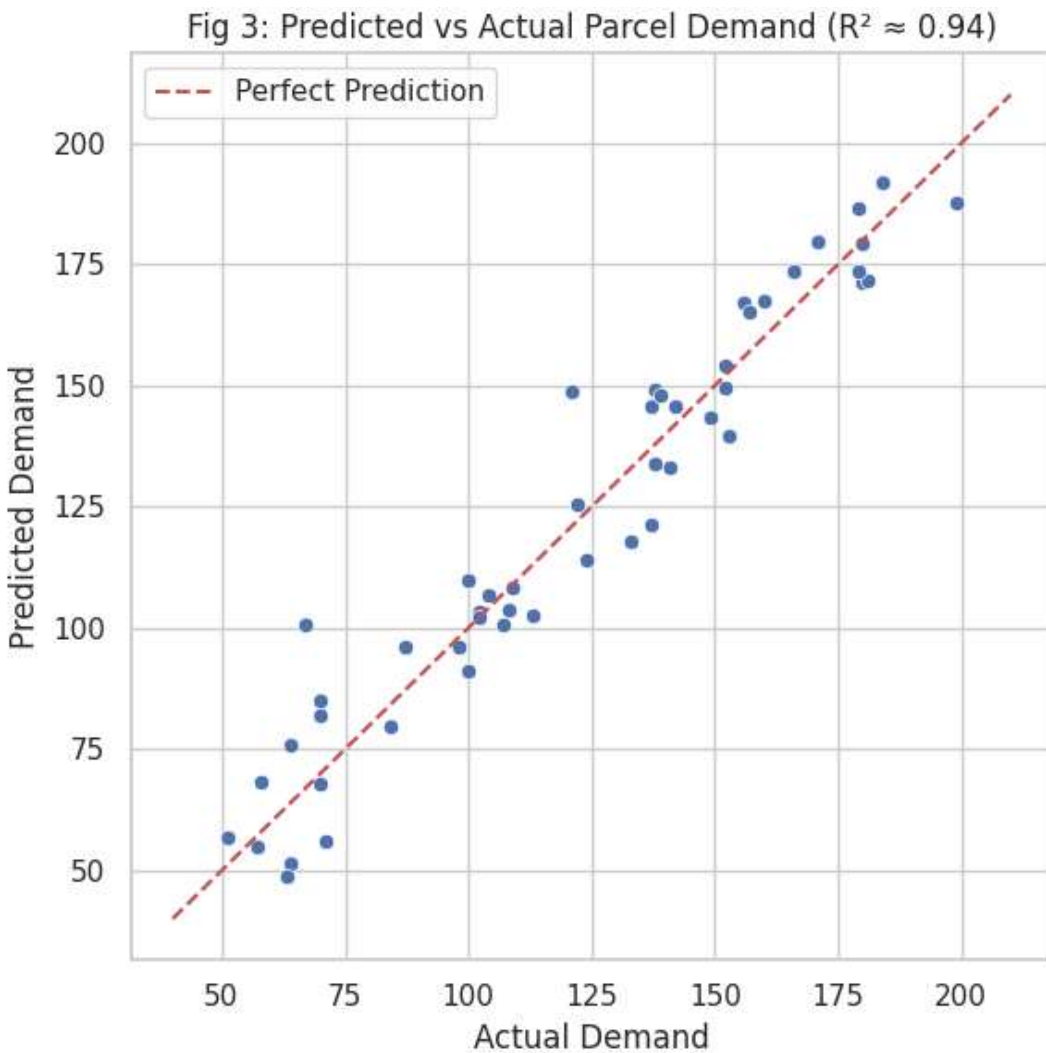

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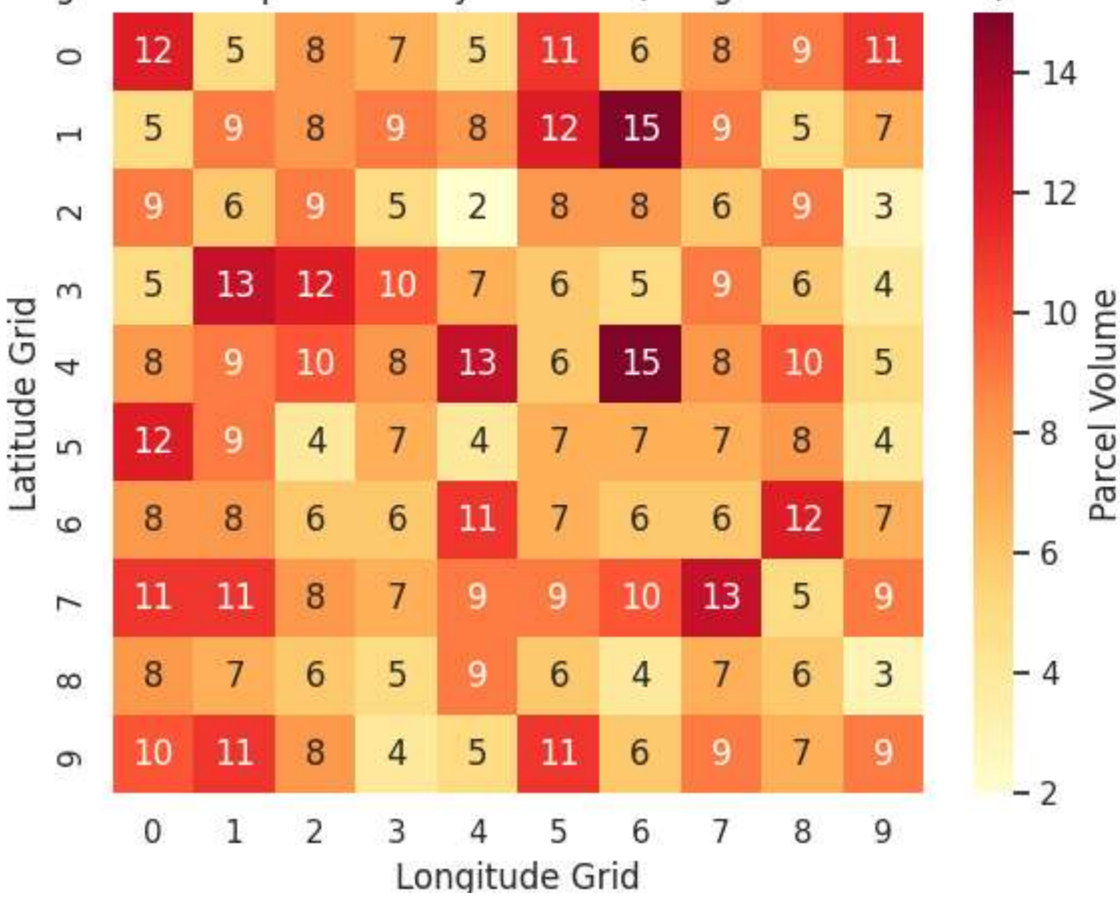

Fig 4: Heatmap of Delivery Demand (Bengaluru Zone Grid)

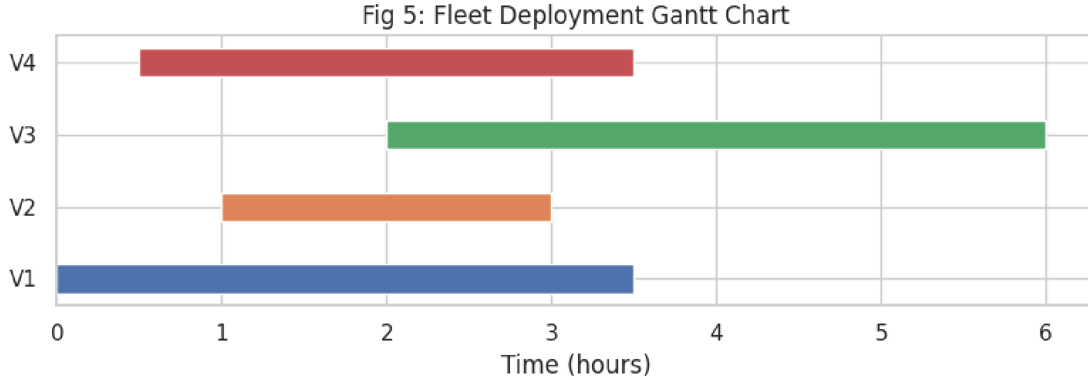

Fig 5: Fleet Deployment Gantt Chart

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5. Conclusion:

This paper presents an integrated AI framework for optimizing logistics and last-mile delivery operations through intelligent demand forecasting, dynamic route optimization, and multi-agent coordination. Our system, AI-LogiNet, leverages state-of-the-art machine learning techniques including LSTM-Transformer forecasting, PPO-based reinforcement learning, and GNN-driven fleet management—to address key inefficiencies in urban delivery networks. Empirical evaluations conducted in diverse geographical settings confirm significant performance gains in terms of delivery speed, cost savings, and system robustness. The modular and scalable nature of the framework allows for easy integration into existing logistics infrastructures, paving the way for smarter, more sustainable urban logistics. Future work will explore the inclusion of electric vehicle management, drone-based last-mile delivery, and carbon footprint optimization to align with global sustainability objectives.

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