

AI-Driven Optimization Techniques for Meal Delivery: Metropolitan Urban Logistics Approach

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Abstract

This chapter explores how integrating predictive modeling with route optimization can enhance the performance of urban meal delivery systems. Three routing strategies—Greedy, Vehicle Routing Problem (VRP), and VRP enhanced with LSTM-based predictive rebalancing—were evaluated across varying temporal periods throughout the day. Results show that while VRP reduces delivery durations compared to heuristic routing, the hybrid VRP+LSTM model achieves additional efficiency gains by anticipating spatial-temporal demand fluctuations. These improvements translate into lower delivery times, and greater operational stability. Policy implications emphasize the need for open urban data infrastructures, AI-driven optimization frameworks, and adaptive governance models to support sustainable last-mile logistics. The study demonstrates that hybrid predictive-optimization frameworks can significantly advance intelligent and sustainable urban delivery networks.

1. Introduction

Urban life is increasingly characterized by speed, convenience, and digital connectivity, with meal delivery emerging as a critical component of this transformation. However, managing efficient delivery operations in densely populated metropolitan areas presents significant challenges. Traffic congestion, fluctuating demand patterns, and intricate urban layouts often strain traditional logistics systems, leading to delayed deliveries, elevated operational costs, and heightened environmental impacts.

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In response, artificial intelligence (AI) has emerged as a transformative tool for urban logistics. By leveraging machine learning algorithms and predictive analytics, AI enables real-time, adaptive decision-making that can optimize delivery routes, forecast demand, allocate courier workloads efficiently, and mitigate emissions (Wang et al., 2023). These techniques shift meal delivery from a reactive to a proactive, data-driven process, capable of navigating complex urban environments with both efficiency and sustainability.

This chapter examines AI-driven optimization strategies for metropolitan meal delivery, emphasizing approaches that integrate urban dynamics, fleet management, and operational efficiency. Its originality lies in the integration of the Vehicle Routing Problem (VRP) framework with Long Short-Term Memory (LSTM)-based demand forecasting to analyze the impact of dynamic courier rebalancing on delivery efficiency. Unlike earlier studies that treated routing and forecasting separately, this chapter presents a unified model linking predictive demand analysis with real-time operational optimization. By analyzing how AI can reduce delays and improve resource allocation, the study provides practical insights for enhancing delivery performance in high-density cities. This work also offers a forward-looking perspective on the digital evolution of urban food delivery, highlighting the potential for AI to create smarter, faster, and more sustainable urban logistics systems.

The chapter is organized as follows: the next section reviews the literature on VRP and AI applications in urban logistics and food delivery; the methodology section presents the case study and introduces the VRP–LSTM integration and rebalancing framework; results and analyses are then presented; and finally, the discussion and conclusion reflect on implications for sustainable urban logistics and future research directions.

2. Literature Review

The rapid growth of urban populations, combined with the rising demand for on-demand services, has profoundly transformed the landscape of urban logistics. Among these services, meal delivery platforms have become a cornerstone of modern urban economies, offering convenience to consumers but also introducing new logistical challenges. The dense and dynamic nature of cities creates unique constraints—ranging from traffic congestion and variable demand patterns to narrow delivery windows—that traditional logistics frameworks often fail to address effectively (Savelsbergh & Van Woensel, 2016; Allen et al., 2018). Consequently, there is a growing need for intelligent, adaptive systems that can manage these complexities

efficiently. In this context, Artificial Intelligence (AI) has emerged as a transformative enabler, allowing the development of data-driven and self-learning logistics systems that optimize urban delivery operations (Goodchild & Toy, 2018).

A core challenge in meal delivery logistics lies in the optimization of delivery routes, commonly framed as the Vehicle Routing Problem (VRP). The VRP involves determining optimal routes for a fleet of vehicles to service a set of customers while respecting constraints such as delivery time windows, vehicle capacity, and service requirements (Toth & Vigo, 2014). In the specific case of meal delivery, these constraints are even more stringent due to the perishability of food and the high time sensitivity of customer expectations. Over the years, traditional VRP models have evolved into dynamic and time-dependent variants that incorporate real-time traffic data, stochastic travel times, and fluctuating customer demands (Psaraftis et al., 2016). More recently, AI and machine learning (ML) approaches have further advanced VRP solutions by enabling systems to predict and adapt to dynamic urban conditions. Reinforcement learning, deep neural networks, and hybrid optimization models have been applied to achieve faster, more responsive routing decisions (Nazari et al., 2018; Kool et al., 2019).

Equally crucial to efficient meal delivery is demand forecasting, which directly affects how resources are allocated and scheduled. Accurate prediction of customer demand enables platforms to plan for peak hours, allocate riders strategically, and minimize both idle time and delayed deliveries. AI-driven forecasting models leverage diverse data sources, including historical orders, customer profiles, weather conditions, and local events, to forecast demand at fine spatial and temporal resolutions. Machine learning techniques—such as regression models, ensemble methods, and neural networks like LSTMs and CNNs—have demonstrated superior performance in capturing non-linear relationships in demand data (Bandara et al., 2020). Integrating these forecasting models with routing algorithms creates a closed-loop decision system, where anticipated demand informs vehicle routing and resource distribution in real time.

Another essential component of adaptive logistics systems is rebalancing, which refers to the dynamic repositioning of couriers or delivery vehicles in response to fluctuating demand. Without effective rebalancing, meal delivery platforms face inefficiencies such as excessive idle time, underutilized capacity, and unbalanced workloads across the fleet. These AI-driven approaches continuously monitor real-time information—such as order density, traffic flow, and rider availability—to make autonomous relocation

decisions, thereby improving service reliability and reducing operational costs. By integrating rebalancing into the overall optimization framework, platforms can achieve smoother demand–supply alignment and enhanced customer satisfaction.

The integration of AI-driven optimization techniques across demand prediction, vehicle routing, and rebalancing creates the foundation for a cohesive, adaptive, and sustainable urban delivery system. Such integration allows real-time decision-making that jointly optimizes routing efficiency, resource allocation, and environmental sustainability. Moreover, the inherent adaptability of AI systems enables rapid responses to disruptions such as traffic incidents or sudden spikes in demand, maintaining high service levels and customer satisfaction even under uncertainty.

Building on this background, the present study explores AI-driven optimization for metropolitan meal delivery systems by integrating demand forecasting, vehicle routing, and rebalancing strategies into a unified system. Specifically, it examines whether cluster-level demand predictions generated by LSTM networks can improve delivery performance by pre-positioning couriers in high-demand zones before orders occur. This approach is compared against conventional greedy routing and standard VRP-based optimization. The study evaluates multiple operational metrics—including average delivery time, congestion impact, and fleet utilization—across various time slots. By combining predictive analytics with dynamic routing and proactive rebalancing, this research aims to demonstrate how AI can effectively reduce service delays, balance workloads, and improve overall system efficiency in complex metropolitan environments. Ultimately, it contributes to the development of a data-driven, adaptive, and sustainable framework for urban meal delivery logistics, illustrating the potential of AI to transform last-mile delivery into a smarter and greener system.

3. Methodology

The study focuses on a metropolitan meal delivery scenario inspired by the city of Amsterdam. A synthetic dataset of 1,000 delivery requests was generated, distributed across three representative urban clusters with varying spatial densities. Requests were assigned to 24 hourly time slots, reflecting realistic daily demand patterns, including lunch (10:00–13:00) and dinner (16:00–19:00) peaks (Figure 1). In this study, it is also assumed the riders can carry at most 10 packages in one ride.

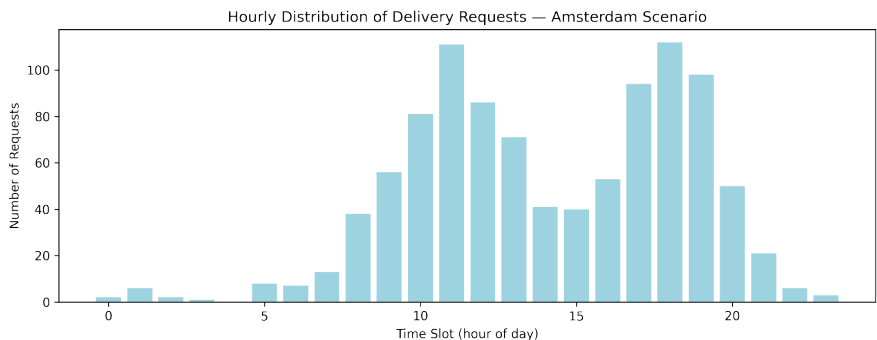


Figure 1. Temporal Distribution of Delivery Requests

Geographic coordinates were mapped onto the underlying street network using OSMnx and NetworkX, allowing shortest-path distance computations for all delivery locations and the central depot (Figure 2). This setup enables the simulation of delivery operations in a realistic urban environment, incorporating spatial clustering, demand variability, and network topology constraints.

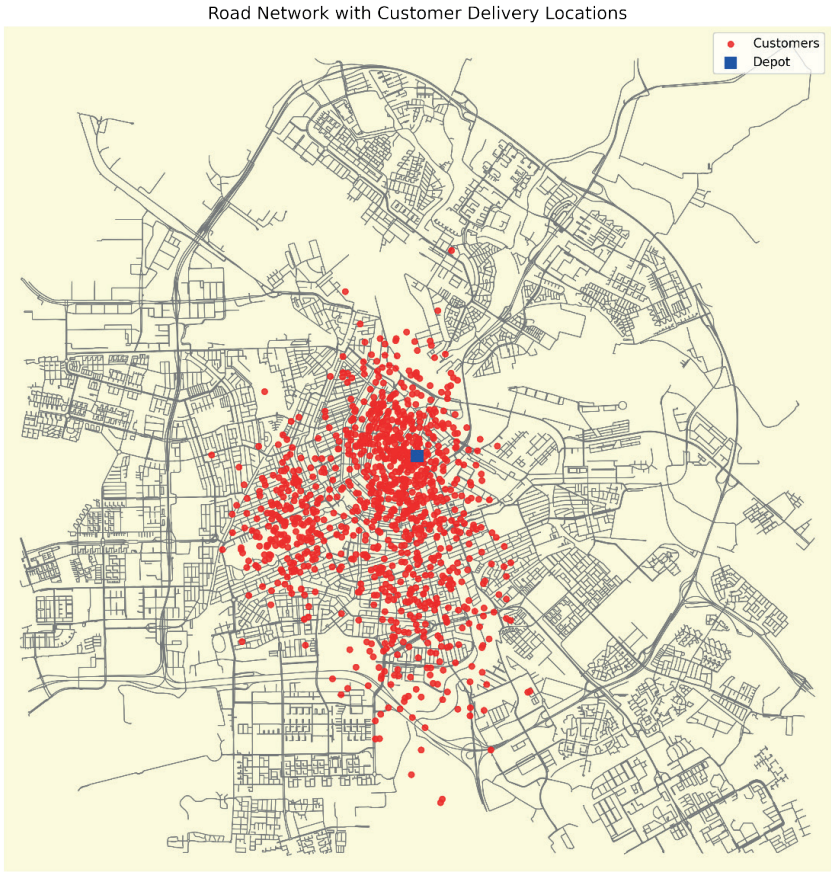


Figure 2. Road Network of Amsterdam Map with Customer Delivery Locations

At the first level, a greedy myopic routing algorithm was implemented as a baseline. In this approach, vehicles iteratively serve the nearest feasible request until their capacity constraints are reached, after which they return to the depot. While this method is computationally simple and fast, it does not incorporate global optimization, forecasted demand, or proactive resource allocation, making it a representative benchmark for reactive delivery strategies.

Building on this baseline, the study employs the Capacitated Vehicle Routing Problem (CVRP) framework, implemented using Google OR-Tools, to optimize delivery routes. In this framework, each vehicle departs from the depot, respects capacity constraints, and seeks to minimize total travel distance. Shortest-path distances derived from the street network are used as cost metrics. Solutions are obtained through a combination of path-

cheapest-arc first solution strategies and guided local search metaheuristics. Compared to the greedy baseline, this approach provides a globally optimized routing strategy, accounting for spatial clustering of requests and balanced load distribution across vehicles.

To anticipate future delivery demand, a cluster-level LSTM model was trained on historical request patterns. The model predicts demand for each urban cluster in the next time slot using a sliding window of previous hourly demands. These predictions inform pre-positioning strategies, allowing vehicles to be proactively allocated to anticipated “hotspot” clusters. The LSTM is trained on normalized cluster-level demand series, using mean squared error as the loss function, and is updated continuously over the 24-hour simulation horizon.

Rebalancing leverages these LSTM forecasts by allocating a fraction of vehicles to predicted high-demand clusters before each time slot begins. Vehicles assigned to rebalance nodes are incorporated into the VRP as starting points with zero demand, allowing the optimization to simultaneously consider both pre-positioned and depot-based vehicles. This proactive strategy enhances fleet management, reduces service delays, and mitigates congestion during peak periods.

Delivery performance is evaluated by calculating average delivery times per request across 24 time slots. Three strategies are compared: (i) greedy myopic routing, (ii) VRP without rebalancing, and (iii) VRP with LSTM-based rebalancing. Congestion effects are approximated based on the load ratios observed in each time slot, providing insights into the effectiveness of proactive versus reactive routing strategies.

4. Results

Table 1 summarizes the average delivery durations obtained from three optimization strategies—Greedy routing, VRP (Vehicle Routing Problem), and VRP with LSTM-based Rebalancing—across 24 hourly time slots. During low-demand periods (Time Slots 0–3 and 21–23), all methods exhibit similar performance due to limited routing complexity. Notably, in Slot 23, the VRP+LSTM approach reduces delivery time from 20.38 minutes (VRP and Greedy) to 16.06 minutes, illustrating the model’s ability to anticipate and adapt to spatial-temporal demand fluctuations.

Table 1. Performance Comparison of Delivery Durations Across Optimization Strategies

Time Slot	Requests	Avg Time Greedy (min)	Avg Time VRP (min)	Avg Time VRP+LSTM Rebalancing (min)
0	2	27.34	25.61	25.27
1	6	12.29	11.45	11.45
2	2	24.99	24.99	25.01
3	1	25.11	25.11	25.11
4	0	0.00	0.00	0.00
5	8	9.88	8.47	8.47
6	7	11.20	10.17	10.17
7	13	13.61	11.39	11.22
8	38	7.78	6.76	6.65
9	56	7.21	6.53	6.48
10	81	7.40	5.75	5.80
11	111	7.13	6.10	6.06
12	86	7.12	6.15	6.07
13	71	6.64	5.60	5.47
14	41	8.01	6.26	6.11
15	40	8.99	7.86	7.81
16	53	9.23	7.30	7.31
17	94	7.11	6.13	6.19
18	112	7.12	5.97	5.99
19	98	7.27	6.03	6.11
20	50	7.80	6.41	5.68
21	21	12.12	8.47	7.33
22	6	10.23	8.38	8.38
23	3	20.38	20.38	16.06

During medium- to high-demand periods (Slots 8–19), the Greedy algorithm consistently yields longer delivery times, highlighting its suboptimal performance under dense request conditions. The VRP approach achieves up to a 15% reduction in delivery duration relative to the Greedy method, demonstrating the effectiveness of global route optimization. The VRP+LSTM Rebalancing model further enhances performance, providing marginal but consistent improvements across most active time slots. Overall, these results indicate that integrating LSTM-based demand forecasting with VRP improves delivery efficiency and system stability, combining spatial optimization with temporal prediction for the most balanced and robust performance among the evaluated strategies.

Table 2 further quantifies the relative improvements achieved by the VRP and VRP+LSTM Rebalancing models compared to the Greedy baseline. The “VRP vs Greedy (%)” column reflects the percentage reduction in

delivery duration achieved by the VRP method, while the “Rebalancing vs VRP (%)” column indicates the additional effect of the LSTM-based rebalancing mechanism. Across most active hours (Slots 5–20), the VRP model consistently outperforms the Greedy algorithm, with reductions ranging from 6% to 22%. The most pronounced improvement occurs at Slot 21, with a 30.12% reduction, demonstrating VRP’s robustness under variable and late-hour demand conditions. In contrast, performance differences during low-demand periods remain minimal, reflecting the limited impact of routing optimization when demand is sparse.

Table 2. Comparative Performance Gains of Optimization Strategies

Time Slot	Requests	Avg Time Greedy (min)	Avg Time VRP (min)	Avg Time VRP+LSTM Rebalancing (min)	VRP vs Greedy (%)	Rebalancing vs VRP (%)
0	2	27.34	25.61	25.27	6.33	1.33
1	6	12.29	11.45	11.45	6.83	0.00
2	2	24.99	24.99	25.01	0.00	-0.08
3	1	25.11	25.11	25.11	0.00	0.00
4	0	0.00	0.00	0.00	0.00	0.00
5	8	9.88	8.47	8.47	14.27	0.00
6	7	11.20	10.17	10.17	9.20	0.00
7	13	13.61	11.39	11.22	16.31	1.49
8	38	7.78	6.76	6.65	13.11	1.63
9	56	7.21	6.53	6.48	9.43	0.77
10	81	7.40	5.75	5.80	22.30	-0.87
11	111	7.13	6.10	6.06	14.45	0.66
12	86	7.12	6.15	6.07	13.62	1.30
13	71	6.64	5.60	5.47	15.66	2.32
14	41	8.01	6.26	6.11	21.85	2.40
15	40	8.99	7.86	7.81	12.57	0.64
16	53	9.23	7.30	7.31	20.91	-0.14
17	94	7.11	6.13	6.19	13.78	-0.98
18	112	7.12	5.97	5.99	16.15	-0.34
19	98	7.27	6.03	6.11	17.06	-1.33
20	50	7.80	6.41	5.68	17.82	11.39
21	21	12.12	8.47	7.33	30.12	13.46
22	6	10.23	8.38	8.38	18.08	0.00
23	3	20.38	20.38	16.06	0.00	21.2

The LSTM-based rebalancing mechanism contributes additional improvements over the VRP baseline in several key intervals, including Slots 7–15, 20–21, and 23, with the largest enhancement reaching 21.2% at Slot

23. This indicates that predictive rebalancing effectively anticipates demand imbalances and reallocates couriers to maintain efficient service, particularly during transition or off-peak periods. Negative values observed in Slots 10 and 16–19 suggest minor over-adjustments by the predictive model, likely due to discrepancies between forecasted and actual demand. However, these fluctuations are small (below 1.5%) and do not compromise overall system efficiency. Collectively, these results confirm that combining LSTM-based predictive rebalancing with VRP enhances delivery stability and efficiency across varying demand levels.

Figure 3 illustrates the temporal variation of average delivery durations and relative improvements for the three strategies, highlighting lunch (10:00–13:00) and dinner (16:00–19:00) peak periods. The Greedy algorithm consistently produces longer delivery times, particularly during peaks, whereas the VRP method maintains lower and more stable durations throughout the day. The addition of LSTM-based rebalancing further refines performance, particularly during transitional periods such as early afternoon and late evening, by preemptively redistributing couriers based on predicted demand.

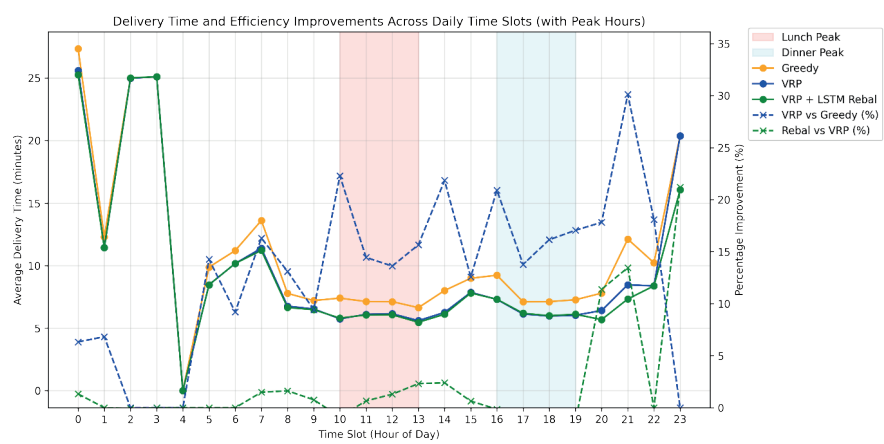


Figure 3. Temporal Comparison of Delivery Duration and Relative Performance Across Routing Strategies

The relative improvement curves reinforce these observations. The VRP vs Greedy curve shows consistent gains of 10–25% during peak hours, demonstrating the efficiency advantage of route optimization under dense demand. The Rebalancing vs VRP curve exhibits frequent positive contributions, with localized improvements exceeding 10% in off-peak hours (21:00–23:00), where predictive rebalancing effectively reduces courier

idle time. Overall, the figure highlights that the VRP+LSTM Rebalancing strategy delivers the most balanced and resilient performance across daily operational cycles.

Figure 4 depicts average delivery durations overlaid with hourly request volumes, providing a visual link between demand intensity and algorithmic performance. The Greedy method shows high delivery times during periods of elevated demand, emphasizing its limited scalability. The VRP approach demonstrates lower and more stable durations, confirming its system-level routing efficiency. VRP+LSTM Rebalancing further improves performance during high-demand intervals (approximately 10:00–19:00) by dynamically reallocating couriers according to short-term forecasts, thereby maintaining service efficiency under rapidly shifting demand patterns. During off-peak hours, all strategies converge, reflecting minimal optimization impact when demand is sparse.

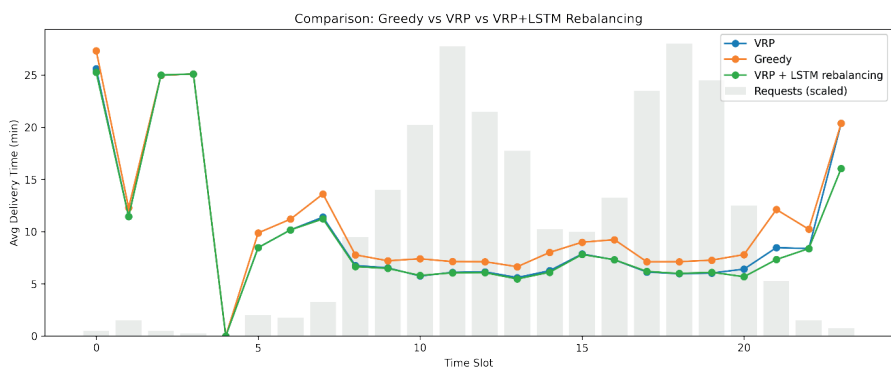


Figure 4. Temporal Comparison of Delivery Duration and Request Volume

Finally, Figure 5 presents a comparative visualization of average delivery durations for all three methods across 24 hourly time slots. The Greedy algorithm consistently shows the highest durations, particularly during peak demand, while the VRP-based approach achieves shorter and more stable times throughout the day. The VRP+LSTM Rebalancing model enhances efficiency further, particularly during midday and evening peaks, with the most substantial reductions (up to 20%) observed in late hours (21:00–23:00). These results demonstrate that integrating predictive demand modeling with route optimization yields a more adaptive, resilient, and time-efficient delivery process, highlighting the hybrid method’s applicability

for urban micro-delivery systems characterized by dynamic and temporally heterogeneous demand.

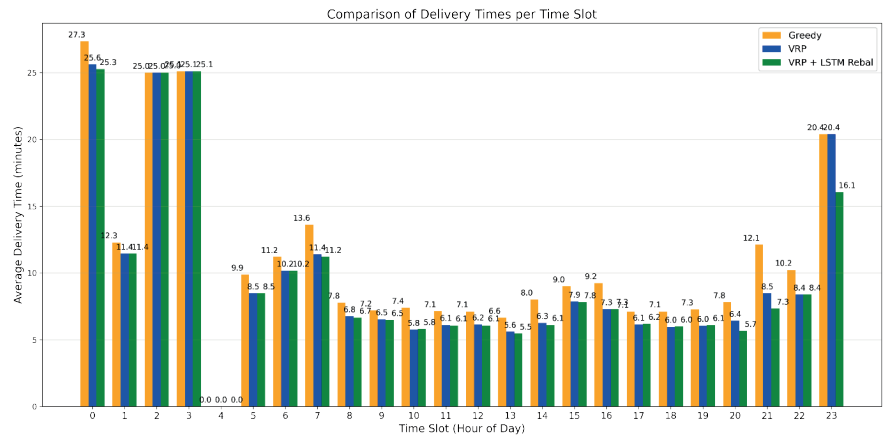


Figure 5. Performance Comparison per Time Slot

5. Discussion

The comparative analysis of the three routing strategies—Greedy, VRP, and VRP combined with LSTM-based Rebalancing—reveals distinct operational advantages and limitations across varying demand intensities. Consistent with expectations, the Greedy approach performs adequately under sparse request conditions but exhibits significant inefficiencies as demand density increases. This outcome reflects the algorithm’s local optimization behavior, which lacks the capacity to account for global spatial relationships and temporal fluctuations in delivery requests (Savelsbergh & Van Woensel, 2016). In contrast, the VRP method demonstrates a clear performance advantage, achieving substantial reductions in delivery durations during medium to high-demand periods. This improvement underscores the importance of global optimization in coordinating courier assignments and route sequencing, especially within dense urban environments where real-time spatial efficiency is critical (Toth & Vigo, 2014).

The integration of LSTM-based predictive rebalancing into the VRP framework further enhances overall system robustness and adaptability. The hybrid VRP+LSTM approach consistently outperforms the baseline methods, particularly during transitional and off-peak periods, by proactively repositioning couriers based on anticipated demand shifts. This result highlights the potential of combining data-driven forecasting with optimization algorithms to achieve spatio-temporal equilibrium in dynamic

delivery systems. The observed improvement of up to 21.2% in certain time slots illustrates that predictive intelligence can effectively mitigate temporal mismatches between supply and demand, reducing idle time and improving service continuity.

Nevertheless, the minor negative improvements observed in a few intervals suggest that predictive rebalancing is sensitive to forecast accuracy. Small deviations between predicted and actual demand can lead to over-adjustments in courier distribution, especially when temporal variability is high. These findings point to a key challenge in predictive optimization which is achieving reliable real-time demand estimation under stochastic and rapidly evolving urban conditions (Goodfellow et al., 2016). Despite these fluctuations, the overall gains in efficiency demonstrate that incorporating LSTM-based demand anticipation enhances delivery system resilience without introducing instability or excessive computational cost.

From a broader perspective, these results emphasize the strategic value of integrating machine learning with classical optimization in urban logistics. The VRP+LSTM framework not only improves operational performance but also aligns with sustainability goals by reducing redundant travel and optimizing resource utilization (Klumpp, 2021). Shorter and more stable delivery times translate to reduced energy consumption, fewer emissions, and improved customer satisfaction. These factors are increasingly critical in the design of sustainable meal delivery systems. Moreover, the system's adaptability during both peak and off-peak hours reflects a capacity for continuous performance balancing, an essential feature for modern on-demand platforms operating under volatile demand conditions (Savelsbergh & Van Woensel, 2016).

Therefore, the findings validate that a hybrid predictive–optimization approach offers a superior balance between efficiency and robustness compared to purely heuristic or static optimization methods. By anticipating demand trends and integrating them into routing decisions, urban delivery systems can achieve more intelligent resource deployment, enhanced temporal stability, and greater responsiveness to consumer needs. These insights contribute to the ongoing discourse on sustainable and adaptive logistics systems, underscoring the transformative role of AI-driven predictive modeling in the evolution of urban mobility and last-mile delivery operations (Cattaruzza et al., 2017; Ghiani et al., 2022).

The findings of this study carry several important implications for policymakers, urban mobility planners, and researchers aiming to develop more efficient and sustainable last-mile meal delivery systems.

The demonstrated efficiency gains from integrating predictive demand modeling into routing operations suggest that public authorities should actively promote the adoption of intelligent logistics systems. This can be achieved through well-designed incentives and regulatory frameworks that facilitate data sharing and encourage the use of AI-driven optimization tools (European Commission, 2020; McKinnon, 2021). Establishing open urban data infrastructures, such as platforms providing real-time information on traffic flow and delivery demand, would further enhance coordination between private operators and municipal authorities, hence reducing congestion and environmental impact (Taniguchi & Thompson, 2014).

The observed improvements in delivery stability and reduced courier idle times also highlight opportunities to better align meal delivery logistics with broader sustainability and decarbonization goals. Cities committed to promoting low-emission transportation can leverage predictive routing technologies to optimize the use of bicycle couriers and other eco-friendly modes, ensuring efficient service delivery without expanding vehicle fleets. Integrating these intelligent routing mechanisms into municipal logistics zones or urban consolidation centers could support more equitable, energy-efficient, and resilient delivery networks that contribute to long-term climate and mobility objectives.

Furthermore, the robustness of the hybrid VRP+LSTM framework across varying demand levels offers valuable insights for designing adaptive urban logistics policies. This adaptability is especially relevant for cities experiencing dynamic retail and e-commerce demand cycles, where conventional static routing regulations often fall short. Embedding predictive analytics into smart-city governance frameworks can therefore enhance strategic decision-making in areas such as transport planning and dynamic pricing for delivery operations (European Commission, 2021). By aligning predictive intelligence with policy innovation, municipalities can create more responsive and sustainable delivery systems capable of adapting to fluctuating urban conditions.

Despite the demonstrated potential of the hybrid VRP+LSTM model, several avenues remain open for future research and practical development. One key direction involves integrating richer, real-time data streams—such as live courier positions, weather conditions, and traffic dynamics—to further enhance predictive accuracy and adaptability. Strengthening collaboration between urban authorities, logistics providers, and technology developers will also be essential for implementing and testing these predictive routing systems in real-world environments. Such pilot projects can provide valuable

empirical insights into operational feasibility, human–AI coordination, and data governance challenges, bridging the gap between simulation and deployment.

Beyond the technical and operational dimensions, future investigations should also address the social and ethical implications of predictive logistics. Ensuring fairness in task allocation, transparency in algorithmic decision-making, and protection of courier autonomy will be vital for building equitable and trustworthy AI-driven delivery systems. Addressing these aspects will not only strengthen public acceptance but also ensure that technological innovation supports the overarching goals of sustainable, inclusive, and human-centered urban development.

6. Conclusion

In conclusion, the integration of LSTM-based predictive rebalancing with VRP optimization represents a promising pathway toward sustainable, adaptive, and intelligent urban delivery systems. By combining spatial optimization with temporal foresight, cities and logistics operators can achieve greater efficiency, lower environmental impact, and improved service reliability which are key pillars for advancing sustainable urban logistics in the age of digitization.

In addition, this research makes a distinctive contribution to the existing body of knowledge by establishing a comprehensive model that synthesizes temporal demand forecasting with spatial route optimization, hence illustrating how data-driven predictive mechanisms can substantially enhance the efficiency, responsiveness, and resilience of meal delivery logistics operations.

The case study analysis demonstrates substantial performance gains over greedy and conventional VRP approaches, particularly in terms of delivery duration. Notably, the implementation of predictive rebalancing resulted in an average 2.29% decrease in average delivery duration comparing traditional VRP approach, thereby providing quantitative evidence of the model's operational efficacy and scalability in dynamic urban contexts.

From a policy perspective, these findings emphasize the importance of integrating predictive analytics into urban logistics governance. Policymakers should promote the adoption of intelligent logistics systems through incentives and regulatory frameworks that support data sharing and AI-based optimization. Developing open urban data infrastructures and providing real-time information on traffic, and delivery demand can further strengthen coordination between municipalities and private operators while

advancing sustainability and decarbonization goals through greater use of low-emission transport modes.

Future research should extend this study by incorporating richer real-time data sources, such as courier locations, weather, and traffic dynamics, to improve predictive accuracy and adaptability. Collaborative pilot projects between city authorities, logistics providers, and technology developers are essential to assess real-world feasibility and governance challenges. Furthermore, addressing ethical concerns such as fairness in task allocation, transparency in algorithmic decisions, and courier autonomy will be crucial for ensuring that AI-driven delivery systems remain inclusive, equitable, and aligned with the broader goals of sustainable urban development. Lastly, by integrating spatial optimization with temporal foresight, this study presents a pathway toward efficient, low-impact, and reliable delivery solutions which are key areas of sustainable urban logistics in the digital age.

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