RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

Benefits, Challenges, and Opportunities of Different Last-Mile Delivery Strategies

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16. Abstract

As online shopping nears its third decade, it is clear that its impacts on urban goods flow are profound. Increased freight traffic and related negative externalities such as greenhouse gas emissions and local air pollution can impede sustainability goals. In response, e-retailers are exploring innovative distribution strategies to enhance last-mile delivery sustainability and efficiency. They use urban consolidation centers with light-duty vehicles like electric vans and cargo bikes, establish alternative customer pickup points, and deploy crowdsourced delivery networks. Advanced technologies that may streamline deliveries, such as autonomous delivery robots and unmanned aerial vehicles, are being tested. University of California Davis and Irvine researchers have investigated these strategies under economic viability, environmental efficiency, and social equity frameworks. Different modeling approaches were implemented to evaluate last-mile network designs and the potential for decarbonizing delivery fleets by switching to electric vehicles. Key findings suggest that while these innovative strategies offer substantial environmental benefits and reduce operational costs, they also present challenges like higher initial investments and operational hurdles. The study emphasizes the need for ongoing innovation and careful strategy implementation to balance sustainability with urban delivery systems' economic and service reliability demands.

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The California Resilient and Innovative Mobility Initiative (RIMI) serves as a living laboratory – bringing together university experts from across the four UC ITS campuses, policymakers, public agencies, industry stakeholders, and community leaders – to inform the state transportation system's immediate COVID-19 response and recovery needs, while establishing a long-term vision and pathway for directing innovative mobility to develop sustainable and resilient transportation in California. RIMI is organized around three core research pillars: Carbon Neutral Transportation, Emerging Transportation Technology, and Public Transit and Shared Mobility. Equity and high-road jobs are cross-cutting themes integrated across the three pillars.

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Benefits, Challenges, and Opportunities of Different Last-Mile Delivery Strategies

Executive Summary

As online shopping marks nearly three decades of influencing consumer behavior, it has dramatically reshaped urban goods flow and distribution strategies. The changes have prompted significant development in distribution systems to provide convenience, reliability, and access to worldwide markets. At the same time, this evolution raises concerns regarding sustainability due to increased freight traffic, elevated distribution costs, and adverse environmental impacts such as greenhouse gas emissions and local air pollution. In response, E-retailers have adopted various innovative distribution strategies to enhance the sustainability and efficiency of last-mile deliveries. These strategies include:

Urban consolidation centers: Using distribution locations within the core market (e.g., micro-hubs, consolidation centers, staging areas) with light-duty vehicles like electric vans and cargo bikes to reduce local traffic and operational costs.

Alternative pickup points: Establishing collection points (e.g., cargo lockers) where customers pick up goods, reducing the burden of last-mile delivery.

Crowdsourced delivery: Engaging independent drivers to provide flexible and cost-effective delivery solutions (this strategy may have issues with reliability and equity).

Advanced technological solutions: Implementing autonomous delivery robots (ADRs) and unmanned aerial vehicles (UAVs) to streamline last-mile processes.

Alternative fuel vehicles: replacing fleets of conventional fuel vehicles with zero- or near-zero emissions vehicles to reduce the environmental burden generated by the distribution operation.

These strategies each have unique benefits and challenges for implementation. A performance evaluation can elucidate their qualities and support decision-making. University of California Davis and Irvine researchers have explored these distribution strategies to assess their economic viability, environmental efficiency, and social equity. The work leverages advanced modeling techniques developed by the teams and focuses on:

Last-mile network design (LMND): A complex routing problem solved using an adaptive extensive neighborhood search to evaluate various distribution strategies under a common setting and with the same assumptions.

Fleet transition to zero-emissions vehicles: Assessing cost implications, emissions reduction, and fleet efficiency.

Findings demonstrate that electric vehicles and alternative delivery strategies significantly reduce environmental impacts and enhance distribution efficiency. However, they also present challenges like higher upfront costs and operational limitations. Moreover, strategies including crowdsourcing and autonomous deliveries require careful consideration of reliability, security, and customer satisfaction.

The study highlights the need for continuous innovation in distribution strategies to meet growing consumer demands and address sustainability concerns effectively. Ongoing research is required to refine these strategies, reduce costs, increase operational reliability, and improve customer service in urban delivery systems.

This comprehensive analysis provides stakeholders with critical insights on how to navigate urban freight management. Applying strategies explored here can ensure economically viable, environmentally sustainable, and socially responsible goods distribution in metropolitan areas.

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Introduction

This year marks nearly three decades since online shopping began reshaping the consumer experience (Lewis, 1994). The increasing prevalence of internet marketplaces and the consequent transformation of individual shopping behaviors have focused academic interest on the sustainability of urban goods flow. As e-retailers compete by providing increasingly consumer-focused service, online shopping-induced personal travel to brick-and-mortar stores and a substantial increase in less-than-truckload freight traffic have affected urban road networks. This can increase freight distribution costs and negative externalities from urban goods flow. Externalities include greenhouse gas emissions affecting global climate change, criteria pollutant emissions impact local air quality, and traffic congestion resulting in noise pollution and accidents, as documented by Figliozzi (2007), Van Loon and others (2015), and Pahwa and Jaller (2022), among others. Thus, e-retailers deploy alternate distribution structures for last-mile delivery to sustainably compete with traditional retailers.

One alternate last-mile distribution strategy includes using urban consolidation facilities coupled with light-duty delivery vehicles such as electric vans, cargo bikes, autonomous delivery robots (ADRs), or unmanned aerial vehicles (UAVs). Adding this echelon to the distribution structure reduces the need for medium and heavy-duty delivery trucks in core commercial and residential parts of cities. This reduces the adverse effects of freight traffic and lowers operational costs for e-retailers (Estrada and Roca-Riu, 2017; Isa et al., 2021; Quak and Tavasszy, 2011). Delivery using such an alternate distribution strategy has logistical limitations. It requires adding a layer in the distribution system to transfer goods, thus affecting costs and the need for a physical location in core urban areas. It is, therefore, most feasible for expedited delivery in dense urban environments where service with conventional large-sized delivery trucks may be difficult or where delivery time is prioritized over costs (Browne et al., 2011; Lemardelé et al., 2021; Pahwa and Jaller, 2022).

Opportunities and challenges associated with another multi-echelon distribution strategy, with collection points for customer pickup, have been evaluated by several authors (Iwan et al. 2016, Hofer et al. 2020, van Duin et al. 2020). In effect, the e-retailer outsources the last few miles of travel to the customer, thereby enabling expedited delivery at low costs, as evident by the studies above. In addition, these studies have highlighted the potential for collection points to reduce the negative externalities associated with goods flow if the e-retailer could establish a dense network of such collection points located near customers' home, school, or workplace, thereby minimizing customer detours to collect packages.

Another option for e-retailers is to outsource the entire last mile, employing a fleet of crowdsourced drivers for low-cost door-to-door expedited delivery service (Arslan et al., 2019; Guo et al., 2019; Pourrahmani and Jaller, 2021). The literature has emphasized the potential for crowdsourced deliveries to reduce transportation-related externalities, assuming they do not induce vehicle use for crowdshipping alone. However, De Ruyter and others (2018) raised equity and welfare concerns that may be associated with gig work because of the independent contractor status of crowdsourced drivers.

The COVID-19 pandemic prompted e-retailers to develop additional delivery methods that are more disaster-resilient. These provide robust, redundant, resourceful, and rapid distribution structures capable of handling disruptions in the last mile (Pahwa and Jaller, 2023). One such strategy is anticipatory shipping. To minimize product shortages and reduce customer lead time, a delivery truck functions as a mobile warehouse by carrying high-demand products in anticipation of customer requests. When an order is placed, autonomous delivery robots and unmanned aerial vehicles move goods from the truck to the destination (Lee, 2017; Singh et al., 2021; Srinivas and Marathe, 2021).

These myriad distribution structures serve a variety of shopping behaviors and needs. Researchers at the University of California Davis and Irvine leveraged their complementary skills in sustainable transportation, modeling, and urban logistics to explore opportunities and challenges associated with emerging distribution strategies and related use of alternative fuel vehicles. The study analyses the research questions under economic viability, environmental efficiency, and social equity paradigms. The research team developed distribution models to understand relevant parameters better and then completed two case studies.

In the first case study, this work simulates the decision-making process for an e-retailer with a Monte-Carlo simulation framework encompassing the LMND problem formulated as a two-echelon capacitated location routing problem with time-windows addressed using the ALNS metaheuristic algorithm (Appendix a). This simulation framework begins with a strategic decision-making process wherein an e-retailer establishes the type, number, and location of primary and secondary distribution facilities and the size and composition of the associated delivery fleet required to meet anticipated customer demand over a 10-year planning horizon. The framework then simulates the tactical and operational decisions with the e-retailer, defining the order of customer visits for each day of a month sampled from the planning horizon to meet the daily stochastic customer demand, given the primary and secondary distribution facilities and the associated delivery vehicle fleet. This model allows benchmarking strategies under a common framework and common assumptions and considerations.

The second case study focuses on decarbonizing last-mile distribution by electrifying the delivery fleet. It considers the interrelationship between service region size, service region structure, and EV battery range in terms of the cost-minimizing fleet size and mix, vehicle miles traveled, and emissions. This case study models the underlying problem as a fleet-size-and-mix vehicle routing problem.

In the following sections, the authors introduce data and methodology, document case studies, and present empirical results. Ultimately, the authors discuss the opportunities and challenges associated with alternate last-mile distribution strategies and emphasize the managerial and policy implications for urban freight management stakeholders.

A Collaborative Effort

This project hinged on collaboration between research groups at Davis and Irvine. The groups held webinars, conference meetings, and offline communication to share research ideas, methods, data, and other materials to achieve research objectives. The webinar included presentations from primary investigators and graduate student researchers conducting and leading various research projects. The joint effort enabled knowledge sharing between the two institutions, leveraging previous and ongoing research. This crossover was especially valuable when defining the work plan and the focus areas of the research project in ways that complemented the research groups' skills and interests and assessing model availability to fulfill the project's objectives.

Researchers identified common interests in sustainable operations, decarbonization, operational and vehicle technology-based improvement strategies, environmental and social justice, and equity. They discussed data analysis methods, techniques, and simulation and optimization modeling (e.g., vehicle routing problems). This document references relevant publications by members of the research teams, highlighting complementary areas of expertise. For example, teams identified commonalities in survey data (e.g., the American Time Use Survey) to develop behavioral modeling. This yielded insights about consumer decisions to shop through different channels and led to using spatial analyses to identify potential operational improvement areas.

The teams focused on two case studies to understand the benefits, challenges, and opportunities related to changes in consumer shopping and last-mile delivery. Case study 1 evaluated the economic and environmental performance of different last-mile delivery strategies to satisfy changes in consumer shopping (e.g., from single-channel to multi-channel) in the City of Los Angeles, California. Case study 2 analyzed the electrification of the last-mile delivery fleet by exploring the relationship between vehicle specifications and distribution network structure in Los Angeles and Orange counties, California, and in Manhattan, New York.

During the project, research teams published partial results in peer-reviewed journals. They presented at events such as the Transportation Research Board Annual Meeting and the Sustainable Transportation Energy Pathway Symposium. Unpublished results are under consideration by journal editors. The results of this project were also considered during the development of a white paper synthesizing improvement strategies for urban freight systems commissioned by the California Air Resources Board.

Case Study 1: Comparing Distribution Strategies Within a Region

Problem Description

This case study evaluates e-retail distribution strategies in Los Angeles, California, a city of 3.3 million residents. The authors model last-mile distribution operations for an e-retailer operating in this region with a 1% market share. The e-retailer offers expedited service with rush delivery by the end-of-day. The authors assume the distribution structure for this e-retailer encompasses a regional distribution facility located in San Bernardino, 50 miles east of downtown Los Angeles, along with strategically located primary and secondary distribution facilities (Figure 1).

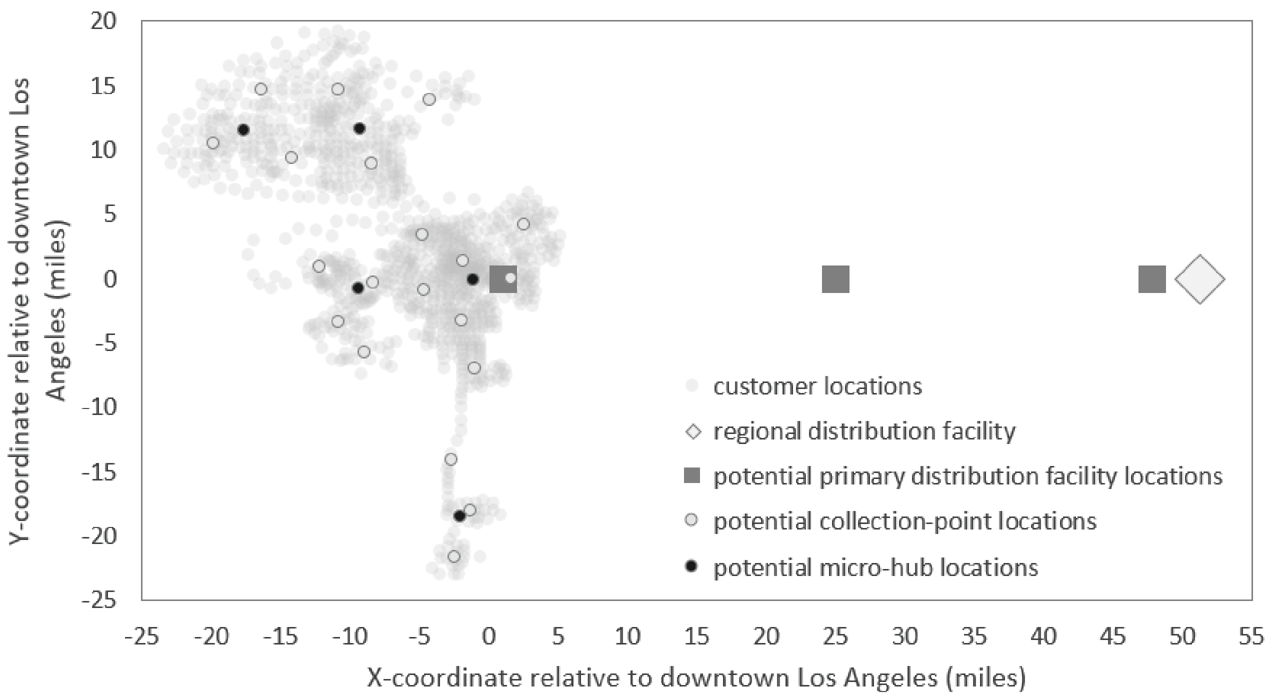

Figure 1. Last-mile distribution structure of the e-retailer.

The study considers a typical delivery process beginning at a regional distribution facility, where the e-retailer sorts packages for overnight (off-hours) delivery to specific primary distribution facilities using a fleet of heavy-duty delivery vehicles. Each primary distribution facility has a fleet of medium-duty delivery vehicles. Here, the e-retailer further sorts packages, some for direct delivery to the customer and others for delivery from one of the secondary distribution facilities by the end of the day. Secondary distribution facilities include micro-hubs with a fleet of light-duty delivery vehicles for last-mile delivery and collection points where customers traverse the last mile to collect packages.

Thus, considering the possible configurations of the distribution structure, the distribution strategy could encompass a single-echelon distribution structure with direct deliveries from the primary distribution facilities to the customer's doorstep with a fleet of medium-duty delivery vehicles such as class-5 diesel trucks (DD-C5DT), diesel vans (DD-DV), class-5 electric trucks (DD-C5ET), or electric vans (DD-EV); or a crowdsourced fleet of light-duty delivery trucks (DD-CSLT). Further, the distribution strategy could include a two-echelon distribution structure wherein the e-retailer delivers some packages directly, as described above, with other packages distributed via secondary distribution facilities. These may include micro-hubs coupled with light-duty delivery vehicles such as electric cargo bikes (MH-ECB) or collection points with customer pickup (CP-PC). In addition, the e-retailer can also deploy a hybrid strategy, using mobile micro-hubs, i.e., medium-duty delivery vehicles coupled with light-duty delivery vehicles such as autonomous delivery robots (MMH-ADR) or unmanned aerial vehicle (MMH-UAV). Refer to Table 1 for a review of the distribution structures modeled in this work incorporating the characteristics of heavy-, medium-, and light-duty vehicles.

Using a sample of sales and lease data for industrial facilities in the study region, the authors estimate facility fixed costs as $\$356.37(x^2+y^2)^{-0.115}$ per square foot for a distribution facility located at x, y miles relative to downtown Los Angeles (CoStar, 2020). Considering the need for reducing freight-related externalities in this region, this analysis accounts for carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter (PM) emissions from last-mile distribution operations, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively (Caltrans, 2017; Marten and Newbold, 2012), in operational cost.

To establish opportunities and challenges associated with last-mile distribution strategies, the authors optimized the configuration of last-mile distribution structures for an economically viable, environmentally efficient, and socially equitable (i.e., sustainable) last-mile delivery when formulating the LMND problem. The authors split the LMND problem into its constituent strategic, tactical, and operational decisions. These strategic decisions establish the type, number, and location of primary and secondary distribution facilities to meet anticipated customer demand for the e-retailer in a 10-year planning horizon. Years are allotted 330 working days with nine working hours every day. The tactical and operational decisions then establish the size and composition of the associated delivery fleet and the order of customer visits for the 30 sampled days of the planning horizon, respectively, to meet the daily stochastic customer demand observed by this e-retailer, given the primary and secondary distribution facilities and the associate delivery vehicle fleet.

When addressing the LMND problem, the authors employ the ALNS metaheuristic algorithm. Starting from an initial solution developed using a k-means clustering algorithm; the ALNS metaheuristic algorithm performs ten iterations, each in a batch of 250 segments. In each iteration, the algorithm selects one random, related, and worst removal operator and one type of insertion operator using a roulette wheel selection procedure. The selected removal operator removes specific customer nodes (ranging from a minimum of four to a maximum of sixty customer nodes) from the current solution. This renders a partial solution, and subsequently, the selected insertion operator re-inserts these customer nodes into the partial solution to develop a new solution. This final step reconfigures 10% to 40% of the original solution.

Table 1. Vehicle characteristics for select delivery vehicles used for last-mile distribution.

Vehicle characteristics	Vehicle type	
Heavy-duty vehicles		
	Class-8 DT	Class-8 ET
Purchase cost [a] ($)	120k	200k*
Capacity (customers per tour)	1800	1800
Range (mi)	1000	500
Speed on rural network (mph)	50	50
Speed on urban network (mph)	15	15
Delivery time at customer (hour)	-	-
Loading time at facility (hour)	1	1
Refueling time at station (hour)	0.208	0.9
Refueling time at facility (hour)	0.06	0.9
Driver cost [b] ($/hour)	35	35
Maintenance cost [a] ($/mi)	0.190	0.140
Fuel cost [c] ($/gal, $/kWh)	3.86	0.12
Fuel con. rate [a] (gal/mi, kWh/mi)	0.125	1.800
CO_2 emission rate [d] (g/mi)	1592	0
CO emission rate [d] (g/mi)	0.81	0
NO_x emission rate [d] (g/mi)	5.55	0
PM emission rate [d] (g/mi)	0.09	0

Vehicle characteristics	Vehicle type			
Medium-duty vehicles				
	Class-5 DT	DV	Class-5 ET	EV
Purchase cost [a] ($)	80k	45k	150k*	70k*
Capacity (customers per tour)	360	360	360	360
Range (mi)	500	350	150	150
Speed on rural network (mph)	55	55	55	55
Speed on urban network (mph)	20	20	20	20
Delivery time at customer (hour)	0.017	0.017	0.017	0.017
Loading time at facility (hour)	1.8	1.8	1.8	1.8
Refueling time at station (hour)	0.083	0.039	0.800	0.534
Refueling time at facility hour)	0.025	0.011	0.800	0.534
Driver cost [b] ($/hour)	35	35	35	35
Maintenance cost [a] ($/mi)	0.200	0.250	0.150	0.175
Fuel cost [c] ($/gal, $/kWh)	3.86	3.86	0.12	0.12
Fuel con. rate [a] (gal/mi, kWh/mi)	0.100	0.067	0.800	0.534

CO_2 emission rate [d] (g/mi)		1049	549	0	0
CO emission rate [d] (g/mi)		0.77	0.50	0	0
NO_x emission rate [d] (g/mi)		4.10	2.42	0	0
PM emission rate [d] (g/mi)		0.130	0.021	0	0
Vehicle characteristics	**Vehicle type**				
Light-duty vehicles					
	LT	ECB	ADR	UAV	PC
Purchase cost [a] ($)	-	6.5k*	4k*	4k*	-
Capacity (customers per tour)	30	30	1	1	20
Range (mi)	500	30	30	6	500
Speed on rural network (mph)	60	10	1.5	15	60
Speed on urban network (mph)	25	10	1.5	15	25
Delivery time at customer (hour)	0.008	0.008	0.050	0.008	0.008
Loading time at facility (hour)	0.250	0.150	0.008	0.008	0.167
Refueling time at station (hour)	0.050	0.121	-	-	0.020
Refueling time at facility (hour)	0.050	0.604	0.875	0.493	0.020
Driver cost [b] ($/hour)	20	30	15	15	20
Maintenance cost [a] ($/mi)	-	0.02	0.164	0.265	-
Fuel cost [c] ($/gal, $/kWh)	-	0.12	0.12	0.12	-
Fuel con. rate [a] (gal/mi, kWh/mi)	-	0.029	0.042	0.118	-
CO_2 emission rate [d] (g/mi)	386	0	0	0	303
CO emission rate [d] (g/mi)	1.77	0	0	0	1.09
NO_x emission rate [d] (g/mi)	0.17	0	0	0	0.08
PM emission rate [d] (g/mi)	0.003	0	0	0	0.002

DT: Diesel Truck, ET: Electric Truck, DV: Diesel Van, EV: Electric Van, LT: Light-duty Truck, PC: Passenger Car

DT refueling rate is 10gal/min at the refueling station and 35gal/min at the facility (Environmental Protection Agency, 1993).

Battery recharging infrastructure - Level 3 DC for electric heavy- and medium-duty vehicles (Nicholas, 2019).

Battery recharging infrastructure - Level 1 charger for electric light-duty vehicles (Nicholas, 2019).

[a] Burke and Miller (2020) [b] Caltrans (2016) [c] AAA (2019) [d] California Air Resource Board (2018)

*Charging infrastructure cost excluded

Tantamount to the uniqueness and quality of this new solution in comparison to the current and the best solution, the algorithm updates these scores for the selected removal and insertion operators by 15 if the new solution is unique and better than the best solution; 10 if the new solution is still unique but only better than the current solution; and three if the new unique solution is worse (e.g., underperforms) than the current solution yet accepted as the current solution.

The algorithm accepts a worse new solution than the current one using a simulated annealing procedure to explore the search space comprehensively. An initial temperature is set such that the algorithm could accept a solution 5% worse than the initial solution with a probability of 0.5, cooled off by a factor of 0.9975 with every iteration of the algorithm. At the end of the segment, the ALNS metaheuristic algorithm updates the operator weights using operator scores accumulated in the segment. The weights are normalized by operator count and adjusted by a reaction factor of 0.1 while accounting for scores accumulated through the previous segments of the algorithm, adjusted by a factor of 0.9. After every 125 segments, the algorithm employs local search operators, including 2-opt, move, and swap local search. Each search runs for, at most, 20 iterations, stopping at the first improvement. Finally, after 2,500 iterations, the algorithm terminates and returns the best-found solution.

This study employs Julia v1.7.2 (Bezanson et al., 2017) on an Intel Core i7-11800H @ 2.30GHz CPU with 64GB RAM to model the LMND problem and develop the encompassing the ALNS metaheuristic for LRP. For a comprehensive description of the algorithms and the corresponding Julia code, refer to the GitHub release LML v1.0 (Pahwa, 2022).

Empirical Results

In this section, the authors present empirical results assessing the sustainability of e-commerce last-mile distribution for an e-retailer with a 1% market share, operating in Los Angeles County, and offering expedited service with rush delivery by the end of the day (same-day delivery). The work analyzed opportunities and challenges associated with last-mile distribution strategies to serve daily stochastic customer demand.

Distribution strategy: Direct Delivery with Class-5 Diesel Trucks (DD-C5DT)

In this strategy, the e-retailer establishes a single-echelon distribution structure with direct delivery using a fleet of Class-5 diesel trucks operating from a primary distribution facility fulfilled by a regional distribution facility located in San Bernardino with a fleet of Class-8 diesel trucks (Figure 2). The strategic decision-making process guides the e-retailer to deploy a fleet of 19 Class-5 diesel trucks operating from a primary distribution facility close to downtown Los Angeles to cater to the anticipated customer demand over the planning horizon. With this, the e-retailer can meet daily customer demand at $3.87 per package (total cost), with fixed and operational costs of $0.90 and $2.97 per package, respectively. Note, in such a distribution structure, goods flow from the regional distribution facility to the customers' doorstep with 0.6 miles of distance traveled per package, on average, resulting in 656g of CO_2, 0.46g of CO, 2.53g of NO_x, and 0.08g of PM emissions, thus accruing $0.29 in emissions cost per package.

Table 2. Vehicle characteristics assumed for select delivery vehicles.

Distribution strategy	Fixed Cost	Operational Cost	Total Cost	VMT *	Emissions Cost
DD-C5DT	$0.896	$2.969	$3.865	0.598	$0.288
DD-DV	$0.806	$2.801	$3.607	0.598	$0.160
DD-C5ET	$1.131	$2.524	$3.655	0.596	$0.031
DD-EV	$0.926	$2.523	$3.449	0.598	$0.031
DD-CSLT	$0.687	$1.988	$2.675	1.437	$0.087

Distribution strategy	Fixed Cost	Operational Cost	Total Cost	VMT *	Emissions Cost
MH-ECB	$1.228	$2.851	$4.079	0.698	$0.138
CP-PC	$1.170	$2.000	$3.170	2.130	$0.388
MMH-ADR	$1.171	$5.663	$6.834	0.857	$0.410
MMH-UAV	$0.891	$2.753	$3.644	0.550	$0.265

*Vehicle miles traveled (VMT)

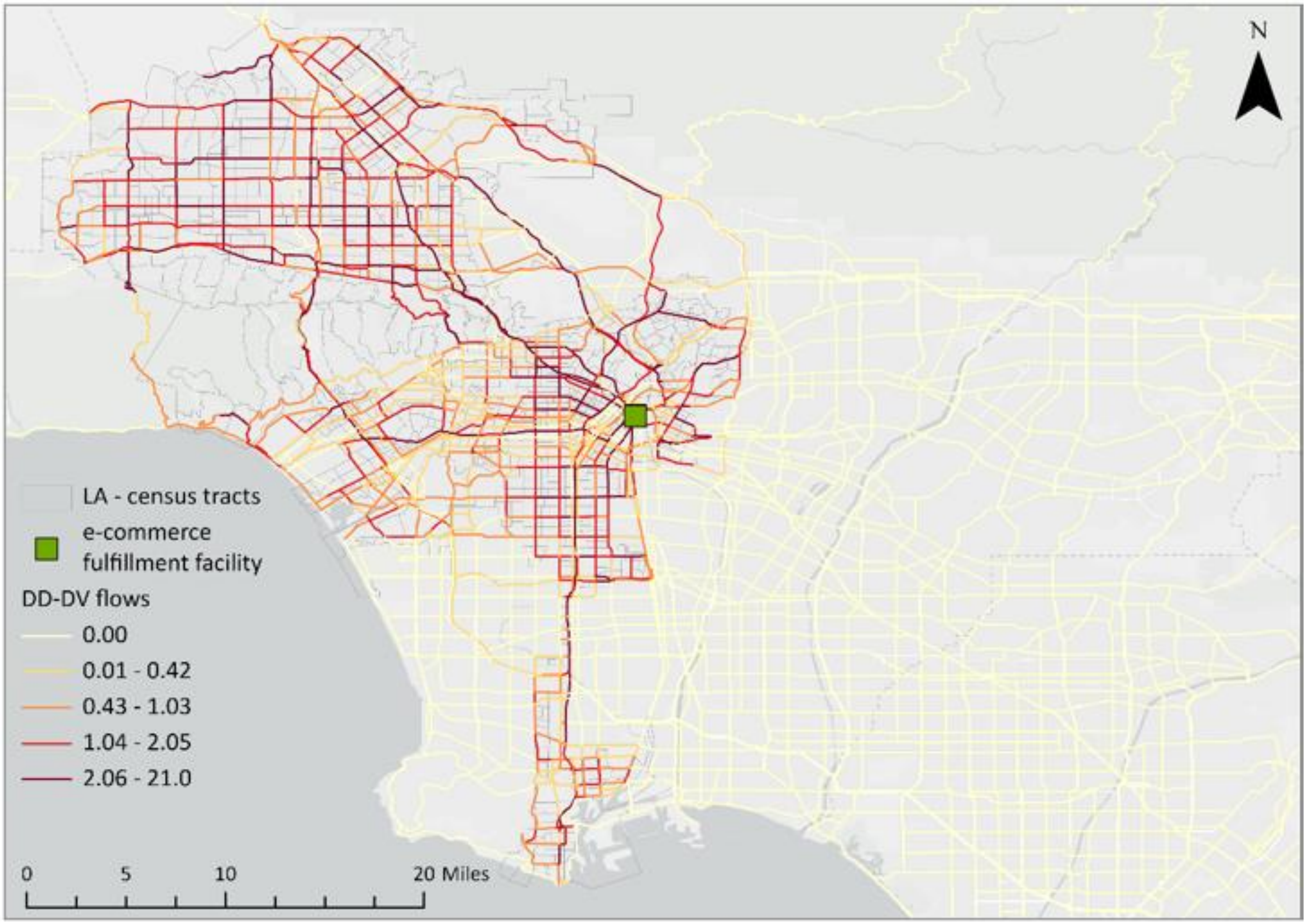

Figure 2. Freight flows with direct delivery using a fleet of Class 5 diesel trucks (DD-C5DT).

Distribution Strategy: Direct Delivery with Diesel Vans (DD-DV)

In this strategy, the e-retailer meets the daily customer demand with direct delivery from the downtown Los Angeles primary distribution facility using a fleet of diesel vans (Figure 3). This incurs a total cost of only $3.61 per package, with operational costs rendering the most savings of all strategies due to the lower operational cost of a diesel van compared to a Class-5 diesel truck. Diesel vans have lower emissions rates than Class-5 diesel trucks, resulting in last-mile distribution with direct delivery emissions of 384g of CO_2, 0.32g of CO, 1.62g of NO_x, and 0.02g of PM emissions per package. Each package incurs only $0.16 in emissions cost despite requiring a similar 0.6 miles of vehicle travel as the DD-C5DT strategy.

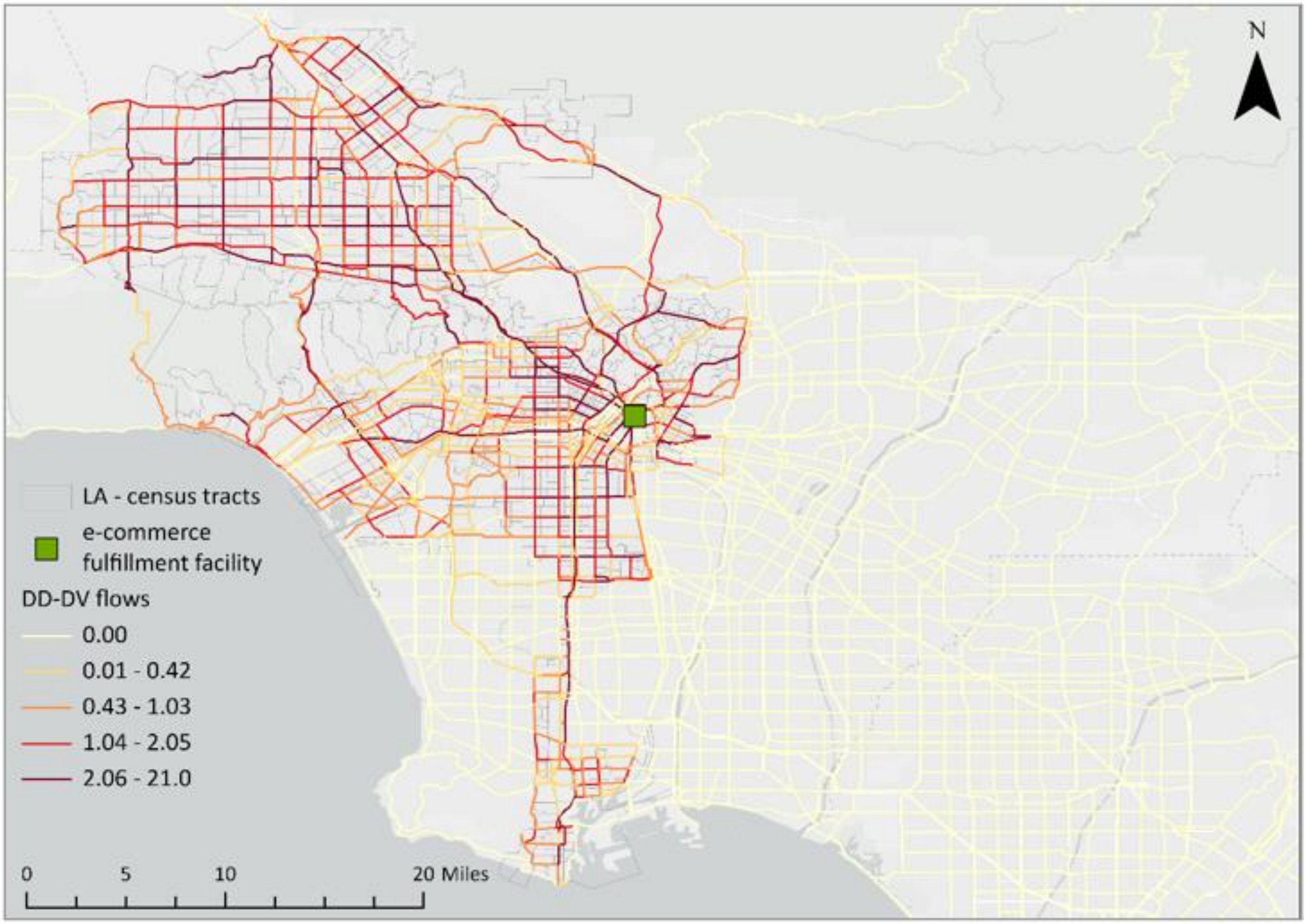

Figure 3. Freight flows with direct delivery using a diesel vans (DD-DV) fleet.

Distribution Strategy: Direct Delivery with Class-5 Electric Trucks (DD-C5ET)

In this strategy, the e-retailer provides direct delivery using a fleet of class-5 electric trucks with an operating range of 150 miles. The e-trucks operate from a primary distribution facility fulfilled by a regional distribution facility with a fleet of Class-8 diesel trucks (Figure 4). As with the DD-C5DT strategy, the e-retailer establishes a primary distribution facility next to downtown Los Angeles. They deploy 19 Class-5 e-trucks to meet anticipated customer demand. With this electric delivery vehicle fleet, the e-retailer can serve the daily customer demand at a total cost of $3.66 per package with fixed costs as high as $1.13 per package, while operational costs only amount to $2.524 per package, including $0.03 in tailpipe emissions. These results demonstrate the potential for electric trucks to render operational improvements in last-mile delivery despite their higher fixed cost.

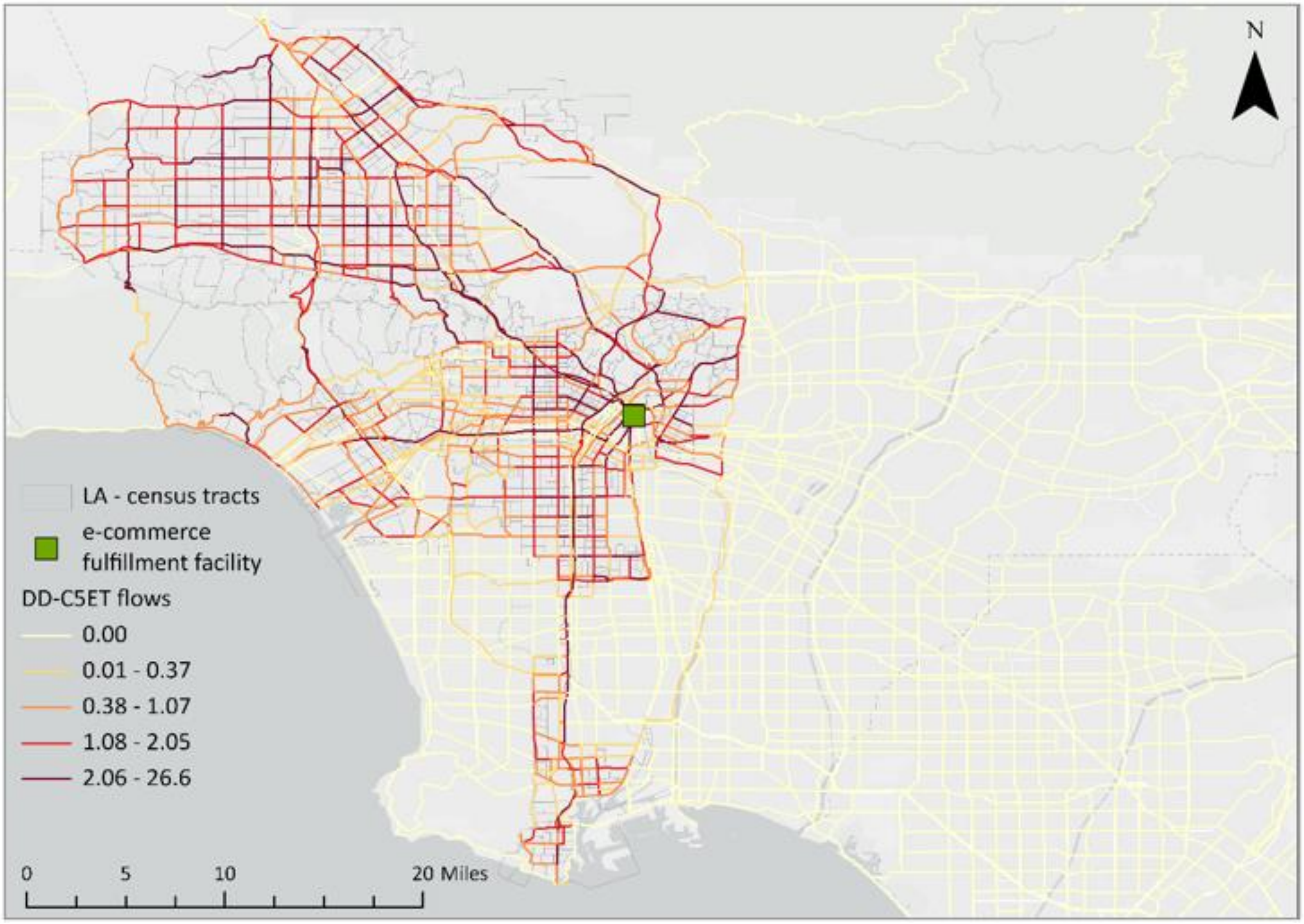

Figure 4. Freight flows with direct delivery using a fleet of Class-5 electric trucks (D-C5ET).

Distribution Strategy: Direct Delivery with Electric Vans (DD-EV)

An e-retailer can cater to the daily customer demand with direct delivery from the downtown Los Angeles primary distribution facility using a fleet of electric vans at a total cost of only $3.45 per package with $0.93 in fixed costs and $2.52 in operational costs, including $0.03 in tailpipe emissions (Figure 5). These results further bolster the case for using electric delivery vehicles, especially electric delivery vans, for last-mile delivery.

Distribution Strategy: Direct Delivery with Crowdsourced Light-Duty Truck Drivers (DD-CSLT)

Here, the e-retailer establishes direct delivery with a fleet of crowdsourced drivers using light-duty trucks to perform last-mile distribution operations from a primary distribution facility (Figure 6). Like DD-C5DT and DD-C5ET, the e-retailer fulfills this primary distribution facility using a fleet of Class-8 diesel trucks from a regional distribution facility 50 miles east of downtown Los Angeles. However, unlike in DD-C5DT and DD-C5ET, the e-retailer does not own the fleet of delivery vehicles working from the primary distribution facility. Therefore, the e-retailer remunerates these crowdsourced drivers only for their labor at $20/hour while avoiding vehicle maintenance and fuel costs. Considering the incentive structure, the authors assume that crowdsourced drivers only perform, at most, two delivery tours per day for the e-retailer. Thus, to meet daily customer demand, the e-retailer requires 63 crowdsourced drivers servicing the primary distribution facility a mile from downtown Los Angeles. This results in a total cost of $2.68 per package, with fixed costs accounting for $0.69 per package and operational costs amounting to $1.99 per package. This cost is lower than last-mile delivery with an e-retailer-owned fleet. Nonetheless, owing to the limitations of this light-duty truck fleet, crowdsourcing delivery renders an inefficient flow of goods, with every package necessitating 1.44 miles of vehicle travel, resulting in 618g of CO_2 emissions.

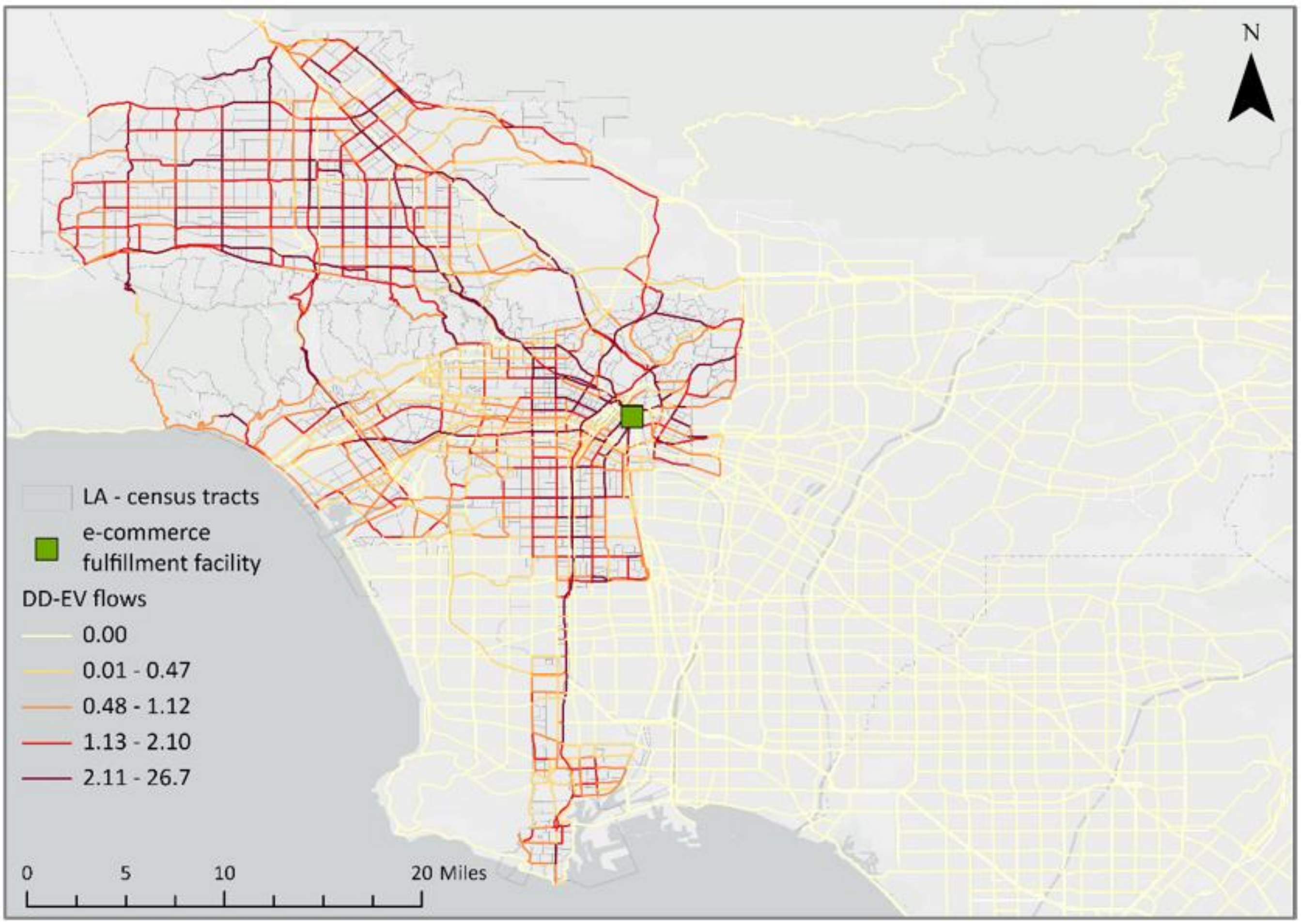

Figure 5. Freight flows with direct delivery using a fleet of electric vans (DD-EV).

Distribution Strategy: Delivery via Micro-hubs and Electric Cargo Bikes (MH-ECB)

In this strategy, an e-retailer establishes a two-echelon distribution structure. The first echelon has five micro-hubs, and the second is a fleet of 49 cargo bikes, with 5-15 bikes serving at each hub (Figure 7). The regional distribution facility fulfills the primary distribution facility using Class-8 diesel trucks, and the primary distribution facility, in turn, uses Class-5 diesel trucks to fulfill micro-hub facilities strategically located in the region. The e-retailer estimates customer demand by location and installs five micro-hub facilities accordingly.

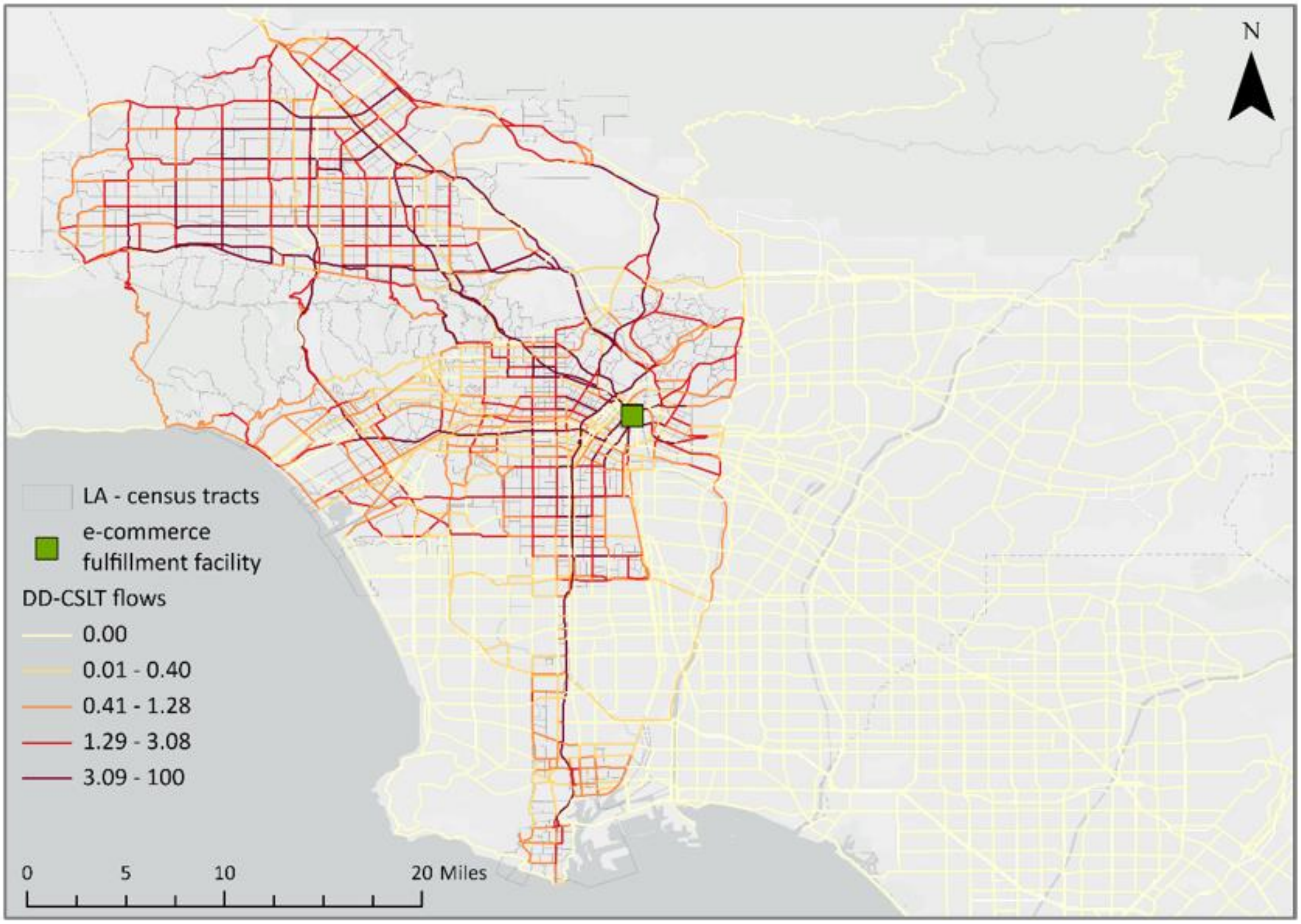

Figure 6. Freight flows with direct delivery using a crowdsourced fleet of light-duty trucks (DD-CSLT).

With this distribution structure, some customers receive packages via a Class-5 diesel truck delivering directly from the primary distribution facility located a mile east of downtown Los Angeles. In contrast, other customers receive packages from micro-hubs via a cargo bike.

These last-mile delivery operations result in a distribution cost of $4.08 per package with $1.23 in fixed costs and $2.85 in operational costs. This is a significantly higher cost than the conventional distribution strategy (DD-C5DT), owing to the costs of the additional echelon. Further, owing to the multi-echelon nature of the distribution structure, each package generates 0.7 vehicle miles traveled, substantially higher than a single-echelon distribution structure—nonetheless, tailpipe emissions amount to $0.14 per package when using cargo bikes for last-mile delivery.

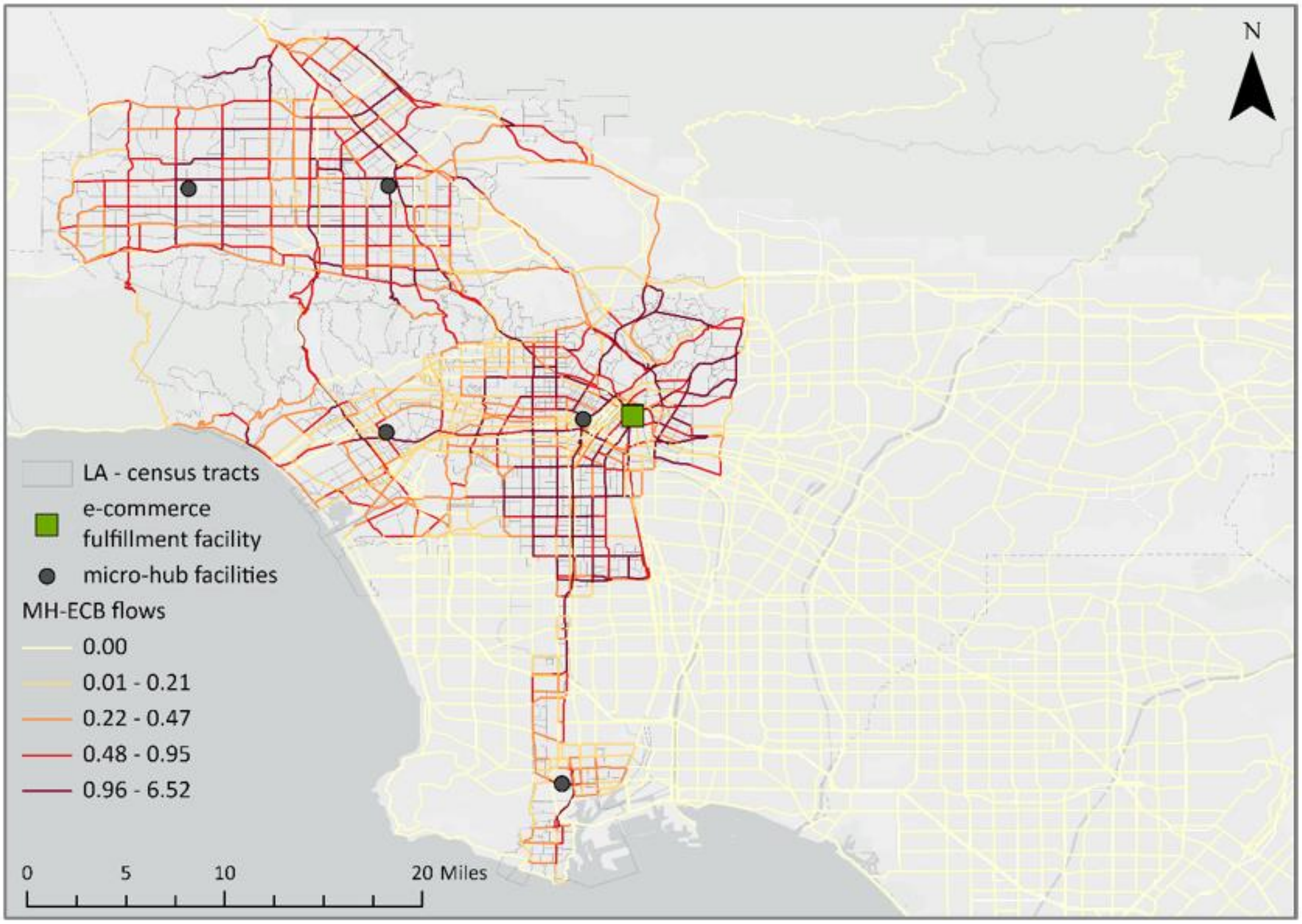

Figure 7. Freight flows with delivery via micro-hubs using electric cargo-bikes (MH-ECB).

Distribution Strategy: Collection Points with Pickup by Customers (CP-PC)

Again, the e-retailer establishes a two-echelon distribution structure, with the first echelon consisting of the primary distribution facility and the collection points acting as the second echelon. Some packages travel directly to customer doorsteps via one of nine Class-5 diesel trucks operating from the primary distribution facility near downtown Los Angeles. Alternatively, customers travel to one of 15 collection points to retrieve packages. The e-retailer strategically locates collection-point facilities according to estimates of customer demand. The regional distribution facility fulfills the collection points via the primary distribution facility (Figure 8). The author assumes customers must travel, at most, five miles to collect packages. With this arrangement, the e-retailer effectively outsources a segment of the last mile to the customer. The delivery cost is just \$3.17 per package, with fixed costs amounting to \$1.17 per package and operational costs accounting for \$2.00 per package. Nonetheless, considering that individuals travel in their cars to collect packages, collection-point pickup renders an inefficient flow of goods, with each package traveling 2.13 miles and, consequently, generating 1,218g of CO_2, 2.09g of CO, 3.18g of NO_x, and 0.1g of PM tailpipe emissions that amount to a cost of \$0.39 per package.

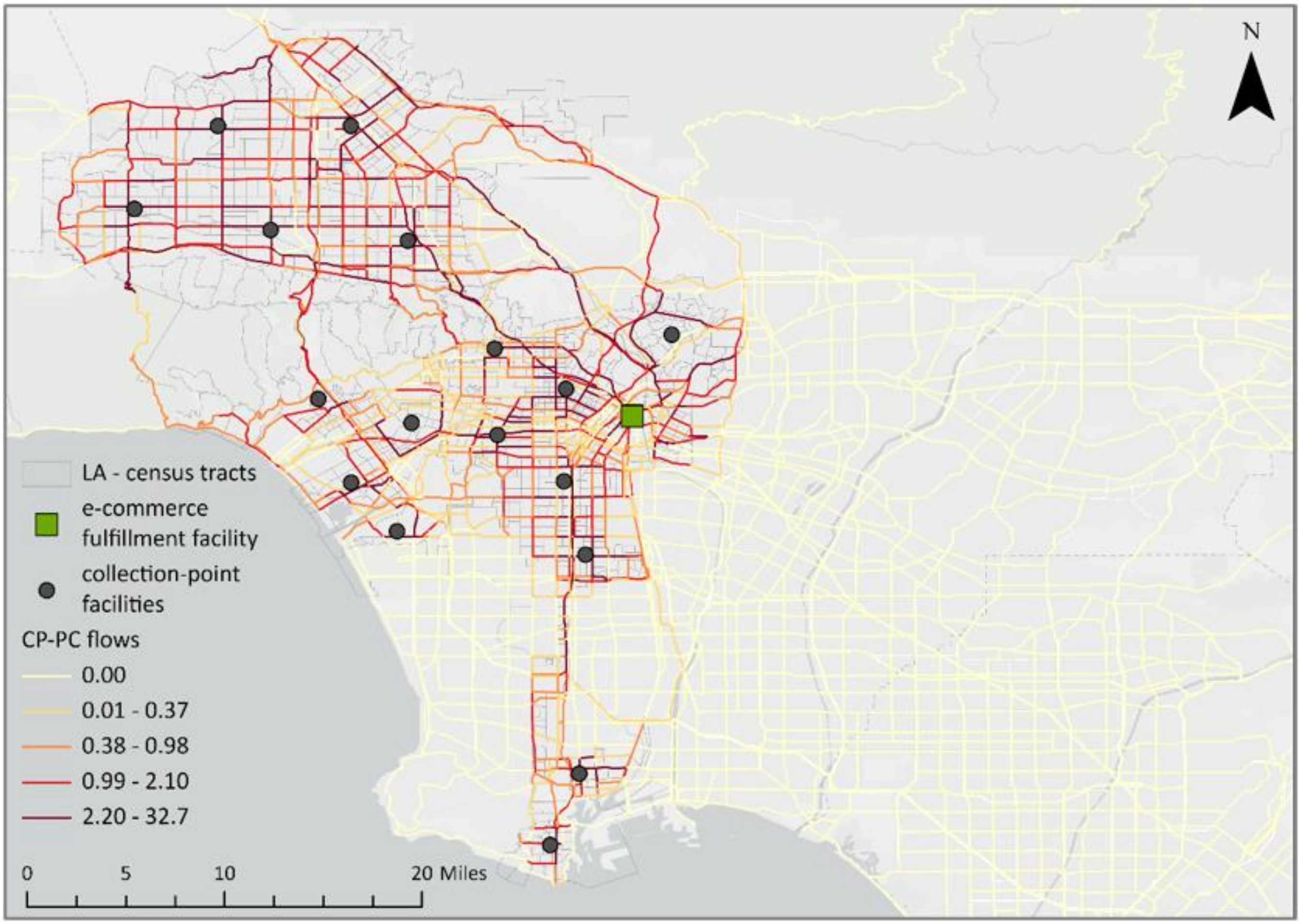

Figure 8. Freight flows with delivery via collection points with customer pickup (CP-PC).

Distribution Strategy: Mobile Micro-hubs with Autonomous Delivery Robots (MMH-ADR)

In this hybrid distribution strategy, an e-retailer deploys mobile micro-hubs comprising delivery vans and autonomous delivery robots (Figure 9). Delivery vans stop at predetermined locations, and delivery robots carry out the last leg of travel. Here, due to the low operational speed of a delivery robot, the e-retailer employs as many as 29 delivery vans and 87 delivery robots to meet daily customer demand. This results in a total cost of \$6.83 per package, with a fixed cost of \$1.17 per package and an operational cost of \$5.66 per package. A large share of the distribution emissions result from the last-mile travel performed by diesel delivery vans. An e-retailer could, instead, deploy electric delivery vans and stop at predetermined locations equipped with appropriate charging infrastructure to use the idle time and recharge the delivery van while delivery robots traverse the last foot. This would reduce the van-related emissions, though not modeled in this study, and will require analyzing the optimal location of such charging infrastructure.

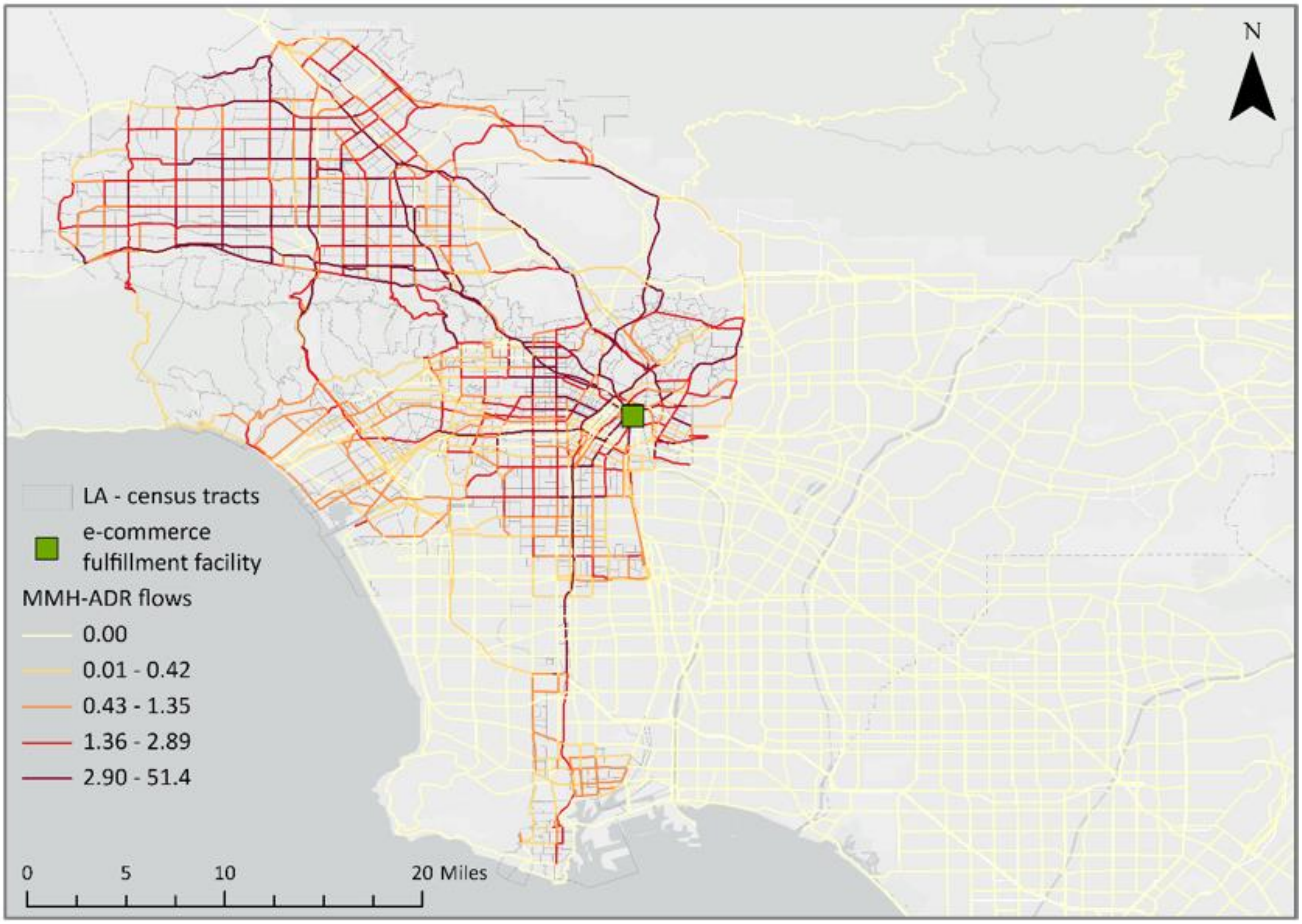

Figure 9. Freight flows for delivery via mobile micro-hubs using autonomous delivery robots (MMH-ADR).

Distribution Strategy: Mobile Micro-hubs with Unmanned Aerial Vehicles (MMH-UAV)

Much like the MMH-ADR strategy, the e-retailer performs hybrid distribution with delivery vans stopping at predetermined locations while three unmanned aerial vehicles per van traverse the last foot (Figure 10). However, unlike delivery robots, aerial delivery vehicles allow for rapid last-leg delivery operations. Therefore, the e-retailer employs 12 delivery vans and 36 aerial vehicles to meet daily customer demand. This incurs a total cost of $3.64 per package, with fixed and operational costs accounting for $0.89 and $2.75 per package, respectively. A significant portion of distribution-related emissions stems from the last-mile travel executed by the diesel delivery vans. As discussed earlier, to address this issue, the e-retailer could opt to utilize electric delivery vans, which can recharge at predetermined stops with suitable charging infrastructure during their idle time, as aerial vehicles cover the last leg of the journey. Follow-up research could evaluate this alternative, acknowledging the need to select locations for deployment and charging optimally.

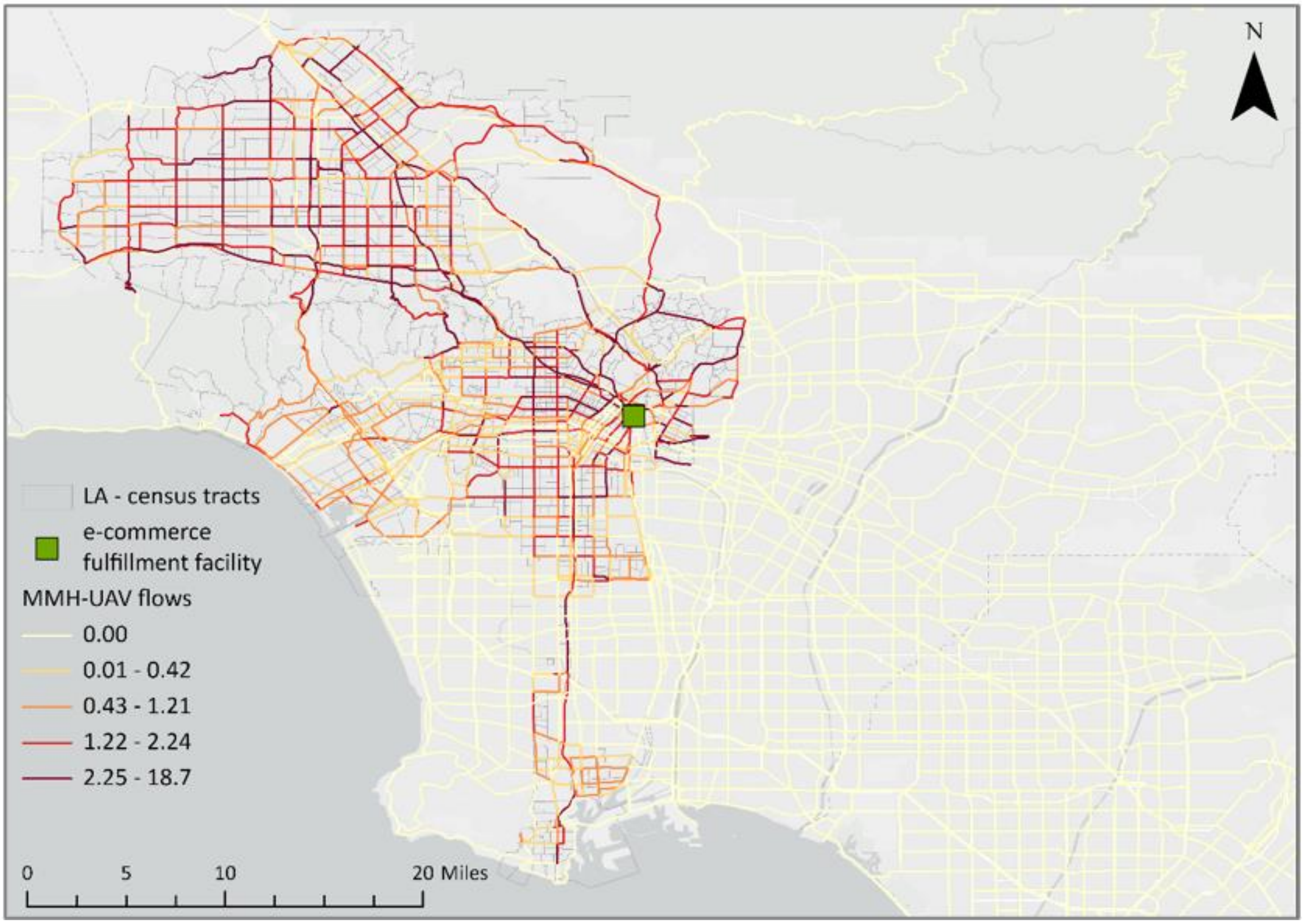

Figure 10. Freight flows for delivery via mobile micro-hubs using unmanned aerial vehicles (MMH-UAV).

Case Study: Comparing Distribution Strategies Between Regions[1]

Our second case study provides insights into potential roles for electric vans and trucks in urban delivery fleets. Regions in California and New York, United States, are evaluated. Implications include fleet size, vehicle miles traveled (VMT), costs, and tailpipe emissions. Fleet managers make purchasing decisions to support delivery services, and they may choose electric vehicles (EVs) or conventionally fueled vehicles (CFVs). Our study models the decision problem as a fleet-size-and-mix vehicle routing problem and assumes fleet managers seek to minimize overall costs from vehicle purchasing and operation. The authors solve the problem using Google OR[2] tools (Google, 2024).

The model captures operational decisions, such as vehicle routes, and tactical decisions, such as vehicle fleet size and mix. Based on vehicle routes, we determine VMT by vehicle type and estimate tailpipe emissions of harmful local pollutants. Yang and Hyland (2024) analyzed the impact of EV subsidies and range on fleet performance. The research extends previous analyses by Hyland and Yang (2022) by considering the size and structure of service regions wherein EVs may operate when providing delivery services. For complete details on model formulation, service region design, and solution algorithms, please refer to Yang and Hyland (2024) and Hyland and Yang (2022).

Study Areas

This numerical case study focuses on two regions to provide insights into the impacts of (1) EV range, (2) service region size and structure (i.e., the number of depots) on the cost-optimal fleet mix, (3) VMT, (4) operational costs, and (5) tailpipe emissions.

The first region includes Los Angeles County and Orange County in California. The service area is about 2,850 mi^2. The study uses the California statewide travel demand model as the road network base. The case study randomly chooses 69 nodes representing package delivery locations, each including multiple delivery destinations. The total number of delivery orders for the 69 nodes is 1,500, so, on average, each node in the network is associated with 21.7 delivery stops. Google Map Direction Tool helps calculate the least-cost path between nodes to estimate travel distance and time. Google travel distance and time values represent conditions at noon on a typical Tuesday (Figure 11).

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[1] Material from this chapter was recently published and is available at:
Yang, Dingtong, and Michael F. Hyland. "Electric vehicles in urban delivery fleets: How far can they go?." *Transportation Research Part D: Transport and Environment* 129 (2024): 104127.

[2]https://developers.google.com/optimization

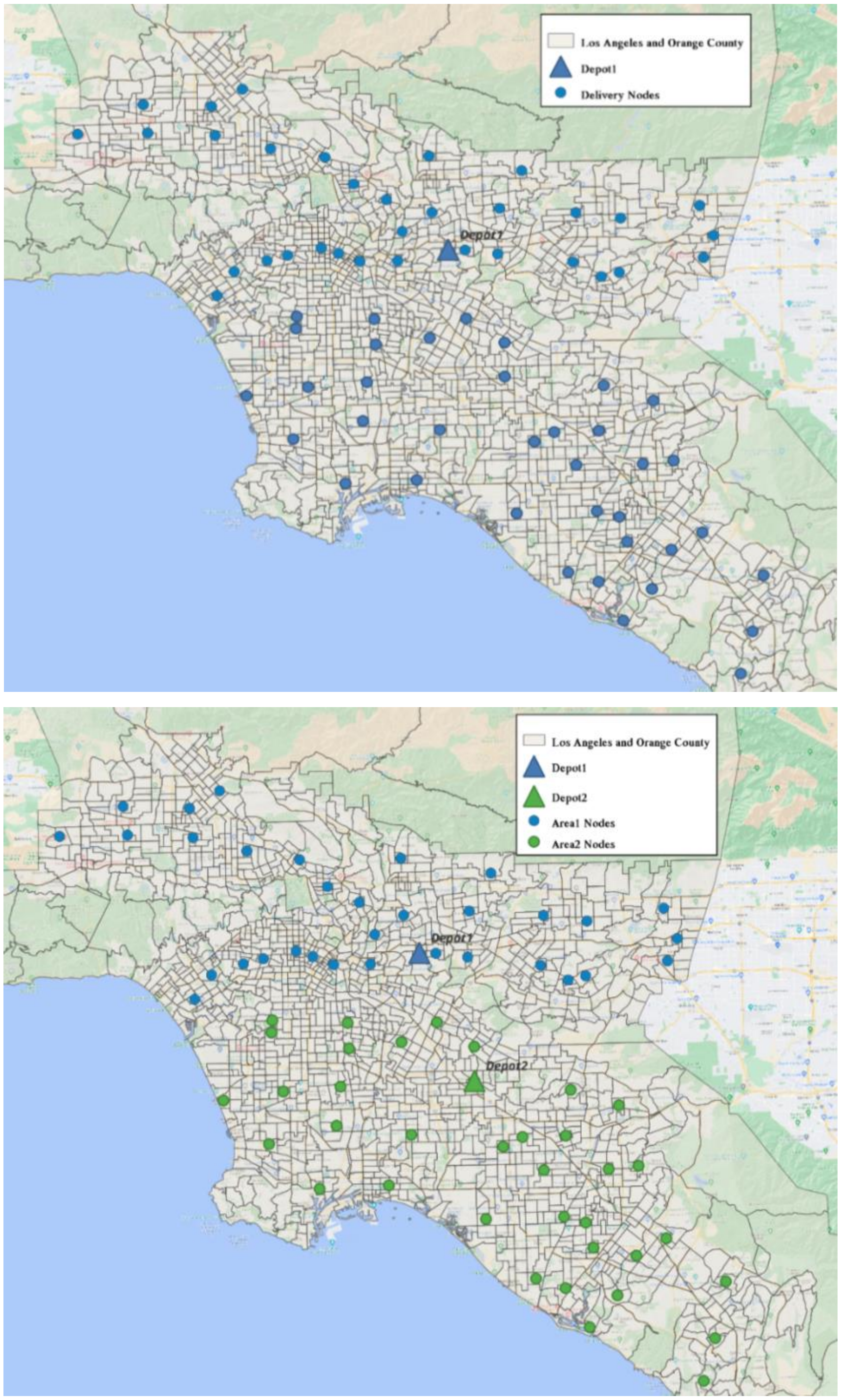

Figure 11. Depot(s) and delivery locations in the Los Angeles County and Orange County area for a one-depot case (top) and two-depot case (bottom). In the top map, one depot in East Los Angeles (blue triangle) serves 69 nodes. In the bottom map, the blue depot in East Los Angeles serves 33 nodes (blue dots), and the green depot in Anaheim serves 36 nodes (green dots).

Our second service region of interest is Manhattan, New York (Figure 12). This region covers 22.8 mi^2. Compared to Los Angeles, Manhattan has a much higher population density, a road network structure characterized by a grid pattern, and traffic conditions that vary significantly throughout the city. The total demand is the same for comparison purposes as the Los Angeles-Orange county analyses, with 1,500 delivery tasks for Manhattan. The analyses divided the Manhattan service region into 63 subregions, each with a node, and located the depot in a lower-density region in the northernmost part of the service region (only one depot is assumed in this case study considering the significant difference in the service areas, 2,850 mi^2 vs. 22.8 mi^2).

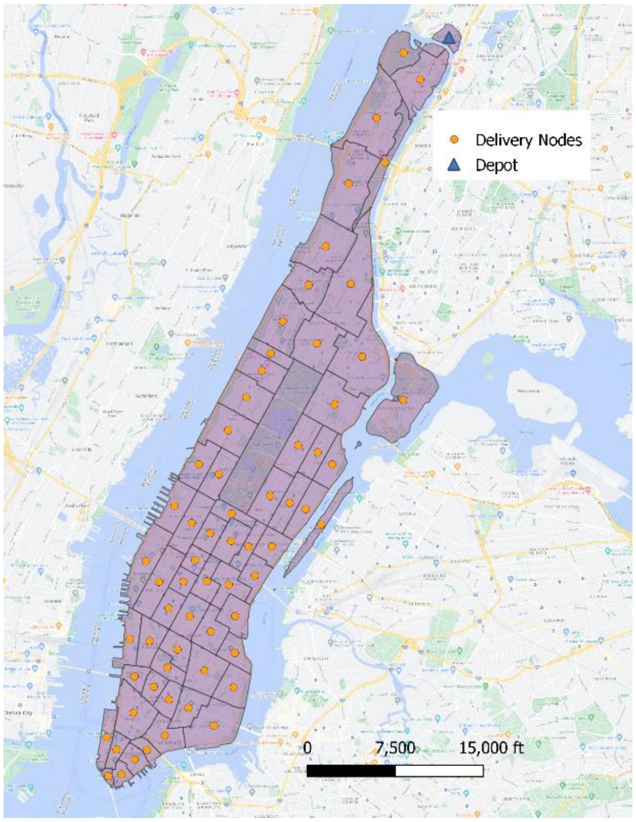

Figure 12. Sixty-three Manhattan service regions, nodes, and depot locations.

Scenario Parameters

The Los Angeles and Manhattan case studies build on a set of scenario parameters discussed here.

The EV range parameter varies from 80 to 200 miles, with different values in each scenario. We chose to introduce this variety because battery technology is improving rapidly, there is significant uncertainty about battery technology in the coming decade, and the EV range significantly impacts results.

We set the range for CFVs at 300 miles based on a standard Ford Transit van (Ford Motor Company, 2023).

Hourly labor cost was $27 per hour based on a wage of $19 per hour with an $8 markup for benefits and taxes (Indeed.com, 2023). We assumed that drivers work seven hours daily and that the average vehicle speed for travel between nodes is 45 miles per hour. The assumption for intra-region travel speed was 25 miles per hour because when a vehicle delivers orders within a region, travel between stops would typically occur on local streets. We also assumed a one-minute delay for each delivery order. This combination of working hours, vehicle speeds, and delay at node locations limits the maximum CFV detour distance to around 220 to 240 miles daily (Table 3).

Table 3. Input parameters for scenario analyses by service area.

Parameter	Los Angeles and Orange counties	Manhattan
Number of delivery nodes	69	63
Total delivery orders	1,500	1,500
Cost of EV ($/mile)	0.25	0.25
Cost of CFV ($/mile)	0.5	0.5
Range of EVs (miles)	80 and 200	80 and 200
Range of CFVs (miles)	300	300
Travel distance between regions	Google Maps directions	Google Maps directions
Travel time between regions	Google Maps assumed traffic at noon on Tuesday	Google Maps assumed traffic at noon on Tuesday
Vehicle speed between regions (mile/hour)	45	45
Vehicle speed within regions (miles/hour)	25	25
Service time per location (min)	1	1
Labor cost per hour ($/hour)	27	27
Daily working hours	7	7
Number of depots	1 or 2	1

The authors estimated CFV operation cost based on the characteristics of a standard Ford Transit van. The cost includes purchase price, depreciation, and operation. Vehicle purchase cost and depreciation rate are calculated by obtaining the price of a new vehicle from the Ford website (Ford Motor Company, 2023) and the resale price from a used vehicle website (CarMax, 2023). The study assumes the vehicle fully depreciates on a per-mile basis. We subtract the resale price from the new vehicle's purchase price and divide this by the total mileage. According to our calculation, the depreciation rate for a CFV is $0.22/mile. The operating cost, which includes fuel, tire, insurance, maintenance, and other miscellaneous costs, is obtained from the Alternative Fuels Data Center (US Department of Energy, 2023) with a tool that calculates the per-mile operating cost of different vehicle makes and models. The operating cost of a CFV is set at $0.28 per mile. Hence, the analyses assume the per-mile total cost of a CFV is $0.22 + $0.28 = $0.5/mile.

Our analyses use the same method to calculate the cost of EVs. Based on a Ford F-150, the operating cost of EVs is around $0.18 per mile. EVs' purchase cost and depreciation depend on factors different from CFVs, such as government consumer subsidies and higher manufacturing costs. In the base scenario, we assume that government subsidies for EVs affect the purchase price such that the depreciation rate for EVs is $0.07 per mile, and the total per-mile cost of EV operation is $0.25 (half the cost of CFVs). The low per-mile cost of EVs illustrates the importance of EV range on optimal fleet mix in computational experiments. Moreover, the authors perform a sensitivity analysis on EV cost and consider more realistic cost differences between EVs and CFVs in the later computational experiments.

The two cases show separate analyses to understand the impacts of EV range, service region size, and number of depots on key performance metrics, including fleet size and mix, cost, VMT, and emissions. In the service area size/structure analysis, we test the same number of delivery tasks in Manhattan, New York. We compare the results with the one-depot Los Angeles-Orange County scenario. We also compare a two-depot case to a one-depot case in the Los Angeles-Orange County region.

Results: Impact of Number of Depots per Service Region

This section analyzes the impact of service region structure on key performance indicators. We compare serving the Los Angeles-Orange County region with one depot or two depots and identify the optimal fleet mix for each situation (Figure 13).

For both cases, the number and proportion of EVs in an optimal fleet increases with the EV range. In contrast, the number of vehicles typically decreases as the EV range increases. These findings are consistent with the input tradeoffs between EVs and CFVs. Namely, CFVs have a much longer range than some EVs, permitting CFVs to serve more packages and locations further away from the depot. However, as the EV range increases, less expensive EVs can serve more packages and locations farther away from the depot, decreasing the necessary fleet size.

Interestingly, the fleet size has a non-monotonic trend in the two-depot case. It increases as the EV percentage increases until the range reaches 120 miles. When the EV range increases to 140 miles, the fleet size required to meet anticipated demand decreases.

The percentage of EVs in the fleet is significantly higher in the two-depot case than the one-depot case for the set of EV ranges between 80 and 140 miles. When the EV range increases to 160 miles in the two-depot case, the optimal fleet mix is all-EV—an EV range of 20 miles less than in the one-depot case. Both of these findings stem from the fact that, in the two-depot case, the service region size per depot is much smaller than in the one-depot case. Comparing the two- and one-depot cases indicates that having multiple depots in a service area can significantly increase the use case for EVs.

Next, we compare the cost metric between two-depot and one-depot scenarios (Figure 14). As expected, the transportation cost in the two-depot scenario is definitively lower than the transportation cost in the one-depot scenario across all EV ranges. Depending on the EV range, the cost is 5 to 13% less in the two-depot case. Even for the three range cases of 100, 120, or 140 miles, where the two-depot scenario uses a larger fleet than the one-depot scenario, the total cost of the two-depot scenario is lower.

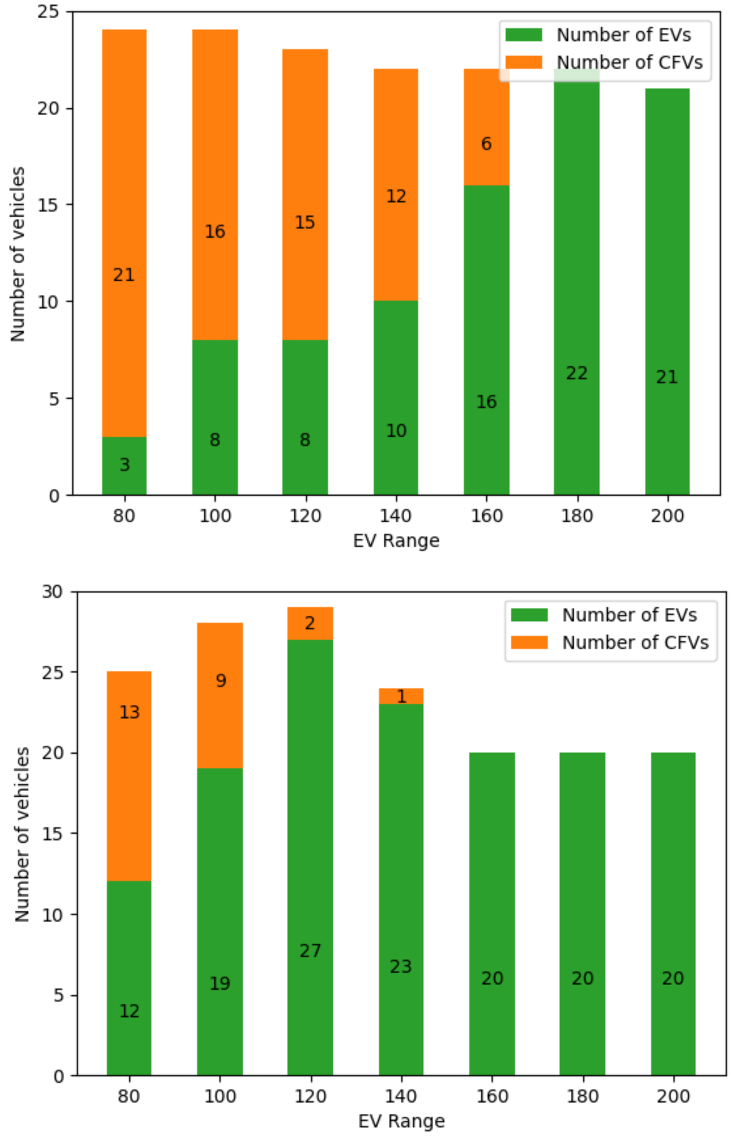

Figure 13. Optimal fleet mix for one-depot (top) and two-depot (bottom) scenarios.

These cost results indicate that adding another depot can reduce the transportation cost for logistics companies. However, logistics companies need to weigh the reduction in transportation costs with the increased costs associated with an additional depot. We leave a detailed cost analysis considering fixed facility and transportation costs for future research.

Vehicle miles traveled is the final metric we compare between the two-depot and one-depot scenarios (Figure 15). Similar to the figure for total cost, VMT is 2 to 12% lower in the two-depot case. In the two-depot scenario, VMT for CFVs (orange dashed line) is significantly lower than VMT for CFVs (orange solid line) from the base scenario. The largest difference in VMT for CFVs occurs when the EV range is 120 miles.

Interestingly and importantly, as the EV range increases in some cases (e.g., two-depot cases with an EV range between 80 and 120 miles), the total VMT increases. The reason for this seemingly paradoxical finding is that as EV range increases, the number of EVs and vehicles in the fleet increases (see Figure 13), and EV routes are less efficient than CFV routes in terms of miles per package served when EVs have considerably shorter ranges than CFVs.Conversely, when the fleet is fully electrified, fleet size and VMT decrease with increases in EV range. Given that there are no CFVs in the fleet, the vehicle routes increase efficiency as the EV range increases (i.e., a single route can serve more packages).

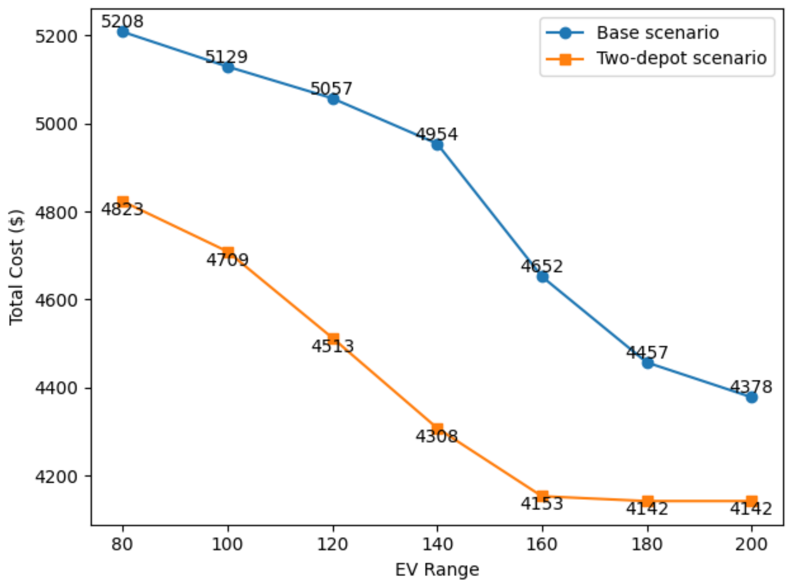

Figure 14. Total cost comparison between one- and two-depot scenarios.

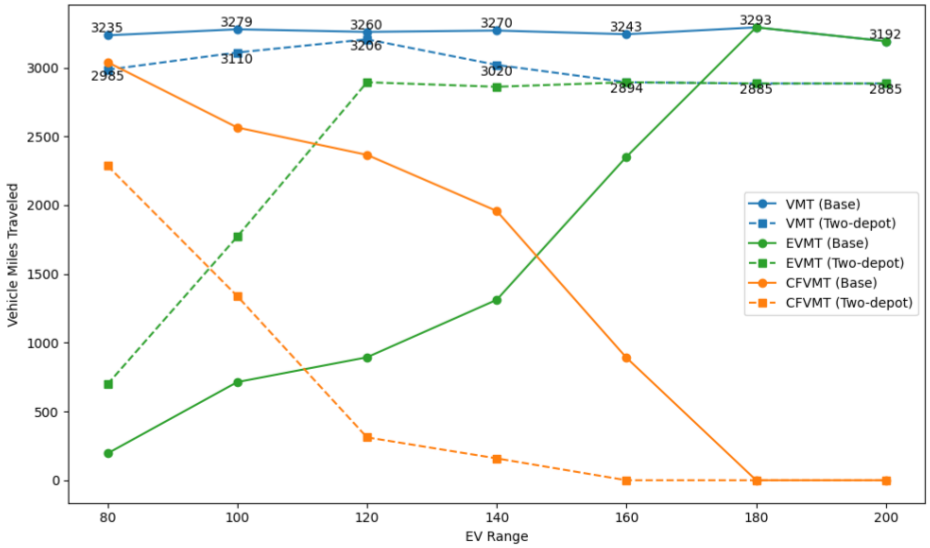

Figure 15. VMT comparisons between one- and two-depot scenarios.

Comparing tailpipe emissions for the one- and two-depot cases shows that consistent with VMT results, the two-depot scenario yields significantly lower emissions than the base scenario in all cases (Table 4). However, improving the EV range is the most important factor for policymakers interested in reducing tailpipe emissions from medium-duty delivery vehicles.

Table 4. Tailpipe emission by pollutant type compared between one- and two-depot scenarios (grams), categorized by EV range (US Department of Energy, 2024).

			One-depot Scenario			
EV Range	80	100	120	140	160	180
Pollutant Type						
HC	854.2	720.8	664.8	550.2	250.4	0
CO	13,701	11,560	10,663	8,824	4,015	0
NOx	808.6	682.3	629.4	520.8	237.0	0
PM2.5	18.2	15.4	14.2	11.7	5.3	0
			Two-depot Scenario			
EV Range	80	100	120	140	160	180
Pollutant Type						
HC	642.6	376.3	87.7	44.7	0	0
CO	10,307	6,034	1,406	716	0	0
NOx	608.3	356.2	83.0	42.3	0	0
PM2.5	13.722	8.034	1.872	0.954	0	0

Tailpipe emission per vehicle mile (grams): Hydrocarbon (HC) = 0.281, CO = 4.507, NOx = 0.266, PM2.5 = 0.006.

Results: Comparing Service Region Size and Structure in Los Angeles-Orange County and Manhattan

The results show that an all-EV fleet can serve Manhattan even when the EV range is 80 miles. Moreover, given the cost benefits of EVs that we assume, the optimal solution is a fleet of 15 EVs and 0 conventionally fueled vehicles. This result is unsurprising given the small area of the service region and the frequency of demand locations, and it suggests that all-EV delivery fleets are highly feasible in dense cities. Such areas have large populations that are typically exposed to air pollution from vehicles so EV adoption would bring health benefits to many people in such scenarios.

The structure of logistics networks will play a critical role in the electrification of delivery fleets. In the case of existing logistics networks, where depots serve relatively small areas, current EV technology permits full electrification. In contrast, depots serving medium to large service areas may struggle to electrify under current battery technology fully. Hence, logistics companies must continue using CFVs or reconfigure their logistics networks with more depots so that each depot has a smaller service area.

In the Manhattan case study, the necessary fleet size does not decrease as EV ranges increase; the ideal vehicle fleet size is always 15 vehicles. The drivers' working hour limit constraint is a significant factor in restricting daily operations and the number of customers to serve, as opposed to route length, even when the EV range is short.

If the maximum drivers' working hours are increased, there is a significant reduction in the required fleet size, total cost, and VMT (Figure 16). This finding indicates that, in highly congested regions, driver working hours are likely to constrain the efficiency of vehicle routes.

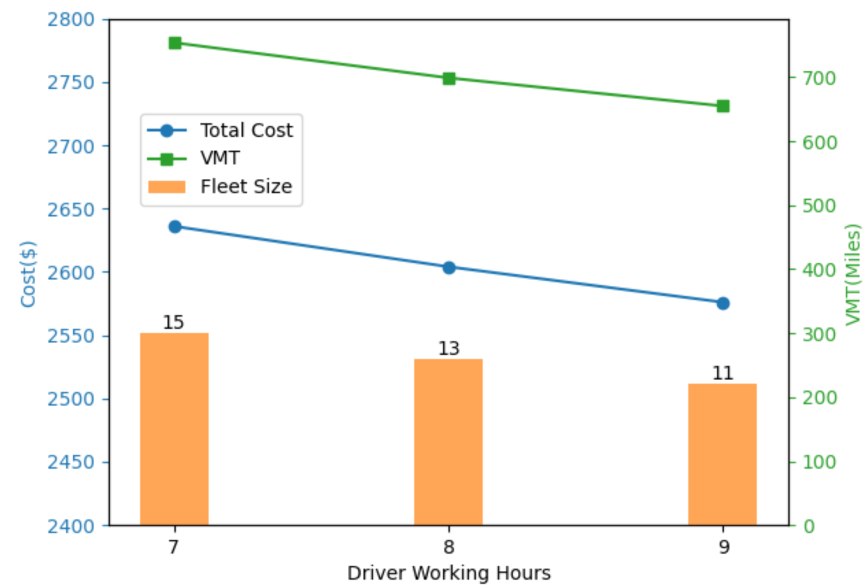

Figure 16. The required EV fleet size is for the Manhattan area.

Conclusions

This study analyzed the costs and opportunities of implementing alternative last-mile delivery strategies in response to increased e-commerce and demand for residential delivery. The study focused on case studies in California and New York.

This first case study developed an LMND problem formulated as a two-echelon capacitated location routing problem with time windows. The objective of the case study was to investigate opportunities and challenges associated with the different last-mile distribution strategies to cope with the rising e-commerce deliveries. The second case study evaluated the costs and potential greenhouse gas emissions reductions achieved by replacing conventionally fueled vehicles with electric fleets. It modeled the decisions as a fleet-size-and-mix vehicle routing problem.

Our findings suggest that last-mile delivery using a fleet of electric delivery vehicles can provide environmentally efficient and socially equitable freight distribution and an economically viable goods flow compared to last-mile delivery with diesel trucks in urban areas. However, the higher upfront cost of electric delivery vehicles could present a barrier to some carriers adopting electric delivery vehicles for last-mile distribution. Alternatively, e-retailers may crowdsource last-mile delivery to cater to customers and establish a cost-effective and flexible last-mile distribution structure. However, hiring independent contractors may result in less reliable performance than company-owned delivery vehicles. Thus, the e-retailer may need to offer higher incentives to drivers to improve reliability and must carefully consider the tradeoff between viability and reliability of last-mile distribution when crowdshipping. The e-retailer must also consider the potential impact of crowdshipping on environmental efficiency and social equity associated with urban goods flow.

This study investigated using consolidation facilities coupled with light-duty delivery vehicles. The authors found such a distribution strategy less cost-effective than other distribution strategies due to the additional handling and transportation required to move packages between the consolidation facilities and final delivery locations. On the other hand, consolidation facilities coupled with cargo bikes for last-mile delivery would yield the greatest reduction in residents' exposure to harmful criteria pollutants.

The e-retailer may outsource a last-mile segment and have customers collect packages at collection points to offset additional handling and transportation costs. However, customers traveling to self-collect necessitates vehicle travel, thus increasing negative externalities from urban goods flow. To this end, the e-retailer can co-locate collection points near major traffic generators and mitigate the need for customers to travel further to collect a package.

Deliveries using autonomous delivery robots and unmanned aerial delivery vehicles from a delivery van acting as a mobile micro-hub are another possible method for moving goods to customers' doorsteps. Aerial delivery vehicles have an advantage over delivery robots owing to faster last-foot operations. Issues such as theft, damage, privacy, and limited operational range remain. This narrows the use-case of such new and innovative distribution strategies.

The structure of the built environment can be an important factor to consider when choosing delivery methods. The type of network, customer density, and traffic conditions, among other factors, can significantly affect the efficiency of the distribution system. Successful delivery strategies will likely differ in sprawling suburbs and dense urban areas. These are important considerations as different delivery strategies have different advantages and limitations under various settings, especially when considering delivery speeds, the need for additional distribution layers, or vehicle capacities.

These findings provide valuable insights for e-retailers. Various technological options are available for companies looking to optimize last-mile distribution operations and balance sustainability and reliability to cater to a market demanding increasingly consumer-focused services.

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Appendix A

Methodology: Last-Mile Network Design

In the following subsection, the authors formulate the last-mile network design (LMND) problem as a two-echelon capacitated location routing problem with time-windows optimizing the configuration of the last-mile distribution structure for an economically viable, environmentally efficient and socially equitable, i.e., sustainable last-mile delivery while accounting for supply and demand constraints. The authors then follow this up with a subsection detailing the adaptive large neighborhood search (ALNS) algorithm developed in this work addressing the LMND problem.

Formulating the Two-Echelon Capacitated Location Routing Problem With Time-Windows

Here, the authors model the problem as a location routing problem (LRP) for an e-retailer with a capacitated two-echelon distribution structure - typical in e-retail last-mile distribution (Figure 17), catering to a market with a customer demand requesting delivery within time-windows.

In particular, the authors define the LMND problem on a directed graph $G = (N, A)$ with node set N encompassing customer nodes C, and potential distribution facility nodes $D = \{P \cup S\}$, where P and S represent the set of primary and secondary distribution facility nodes, respectively, while A represents the set of arcs connecting these nodes, with a vehicle traversing the arc connecting nodes i and j spanning a length l_{ij}. Further, each distribution facility node $d \in D$ has an associated set of delivery vehicles V_d, capacity q_d, service start and end time t_d^s and t_d^e, respectively, as well as fixed cost π_d^f, and operational cost π_d^o per package. And each customer node $c \in C$ has an associated service time τ_c^d and demand q_c, which the e-retailer must fulfill within the specified time window $[t_c^e, t_c^l]$ with a delivery vehicle either directly from one of the primary distribution facilities or via one of the secondary distribution facilities. These delivery vehicles have an associated set of delivery routes R_v, capacity q_v, range l_v, refueling time τ_v^f, loading time per package τ_v^d, driver working hours w_v, fixed cost π_v^f, and operational costs π_v^{od} per unit distance and π_v^{ot} per unit time.

Sets

N	:	Set of nodes
C	:	Set of customer nodes
D	:	Set of distribution facility nodes
P	:	Set of primary distribution facility nodes
S	:	Set of secondary distribution facility nodes
A	:	Set of arcs

V : Set of delivery vehicles
R : Set of vehicle routes
T_j : Set of tail nodes (predecessors) to node $j \in N; \{(k, j) \in A\}$
H_j : Set of head nodes (successors) to node $j \in N; \{(j, k) \in A\}$

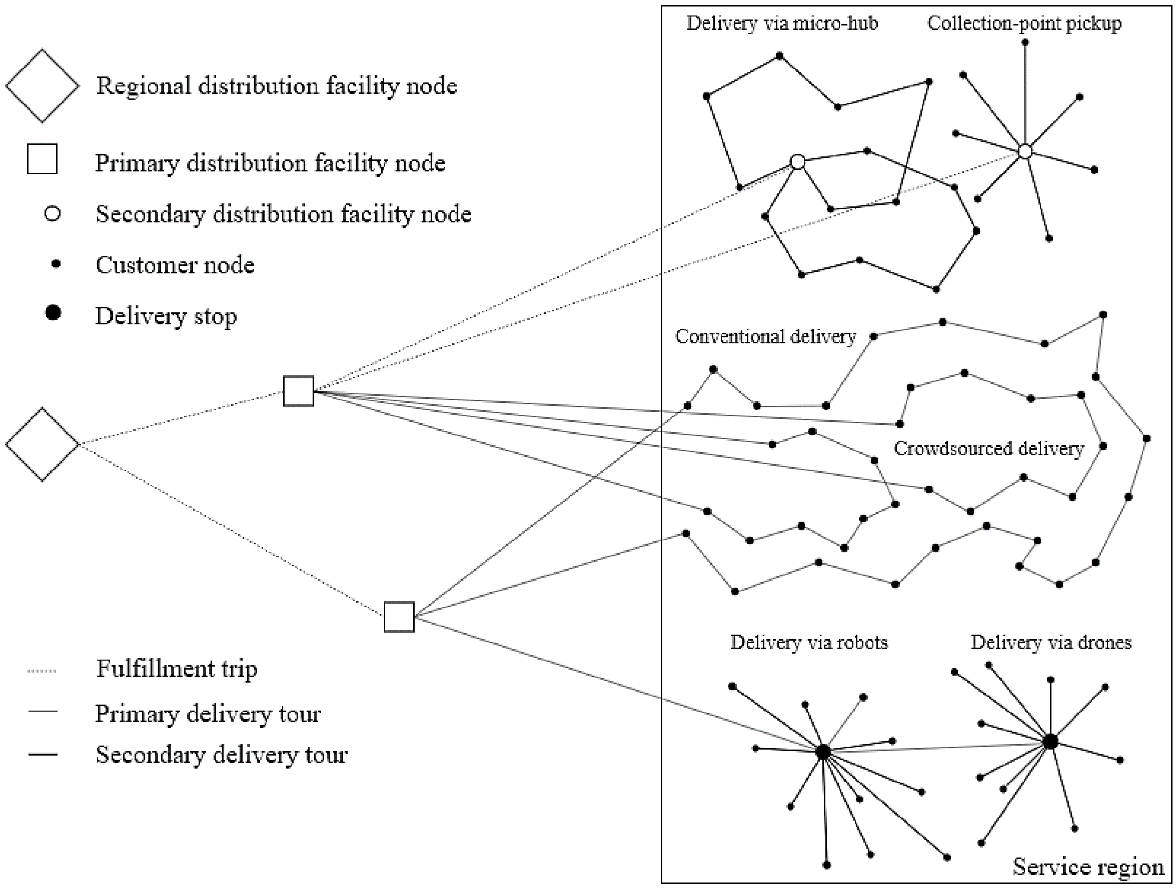

Figure 17. An e-retail last-mile distribution structure and the various distribution strategies.

Indices

i : Node index
c : Customer node index
d : Distribution facility node index
p : Primary distribution facility node index
s : Secondary distribution facility node index
ij : Arc index for arc connecting nodes i and j
r : Route index
v : Vehicle index

Customer parameters

x_c	:	Location of customer node c along the x-axis
y_c	:	Location of customer node c along the y-axis
q_c	:	Commodity demand for customer node c
τ_c^V	:	Service time delivering package at customer node c
t_c^e	:	Earliest service start time at customer node c
t_c^l	:	Latest service start time at customer node c

Distribution facility parameters

x_d	:	Location of distribution facility d along the x-axis
y_d	:	Location of distribution facility d along the y-axis
q_d	:	Capacity of distribution facility d
t_d^s	:	Service start time at distribution facility d
t_d^e	:	Service end time at distribution facility d
π_d^f	:	Fixed cost for distribution facility d
π_d^o	:	Operational cost for distribution facility d
V_d	:	Set of delivery vehicles at distribution facility d

Vehicle parameters

l_v	:	Range of vehicle v
q_v	:	Capacity of vehicle v
s_v	:	Speed of vehicle v
τ_v^D	:	Service time loading packages for vehicle v at a distribution facility
ζ_v^D	:	Refueling time for vehicle v at a distribution facility
w_v	:	Driver working hours for vehicle v
π_v^f	:	Fixed cost of vehicle v
π_v^{od}	:	Distance-based operational cost of vehicle v
π_v^{ot}	:	Time-based operational cost of vehicle v
$\underline{k}_v$	:	Maximum number of delivery routes allowed for vehicle $v \in V$
r_v^k	:	k^{th} route for vehicle $v \in V$
R_v	:	Set of routes of vehicle v

Distribution operation variables

l_r	:	Length of route r
t_c^a	:	Vehicle arrival time at customer node c
t_c^d	:	Vehicle departure time at customer node c
t_r^s	:	Start time of route r
t_r^e	:	End time of route r
t_v^s	:	Start time for vehicle v
t_v^e	:	End time for vehicle v

Decision variables

f_{ps}	:	Commodity flow from primary p to the secondary distribution facility node s
x_{ij}^{r}	:	Vehicle flow on arc ij in route r
y_p	:	Facility use of primary distribution facility p
y_s	:	Facility use of secondary distribution facility s
y_v	:	Use of vehicle v
z_{cr}	:	Allocation of customer node c to route r

$$\Pi = \sum_{p\in P} \left(\pi_p^f + \sum_{s\in S} \pi_p^o f_{ps} + \sum_{v\in V_p} \left(\pi_v^f + \sum_{r\in R_v} \sum_{(i,j)\in A} \pi_v^{od} x_{ij}^r l_{ij} + \pi_v^{ot}(t_v^e - t_v^s)\right) y_v\right) y_p + \sum_{s\in S} \left(\pi_s^f + \sum_{s\in S} \pi_s^o f_{ps} + \sum_{v\in V_s} \left(\pi_v^f + \sum_{r\in R_v} \sum_{(i,j)\in A} \pi_v^{od} x_{ij}^r l_{ij} + \pi_v^{ot}(t_v^e - t_v^s)\right) y_v\right) y_s \qquad (SEQ\ Equation \setminus *\ ARABIC\ 1)$$

Subject to,

$$\sum_{r\in R} z_{cr} = 1 \qquad \forall c \in C \qquad (SEQ\ Equation \setminus *\ ARABIC\ 2)$$

$$\sum_{j\in H_c} x_{cj}^r = z_{cr} \qquad \forall c \in C; r \in R \qquad (SEQ\ Equation \setminus *\ ARABIC\ 3)$$

$$\sum_{i\in T_j} x_{ij}^r = \sum_{k\in H_j} x_{jk}^r \qquad \forall j \in N; r \in R \qquad (SEQ\ Equation \setminus *\ ARABIC\ 4)$$

$$\sum_{p\in P} f_{ps} = \sum_{v\in V_s} \sum_{r\in R_v} \sum_{c\in C} z_{cr} q_c \qquad \forall s \in S \qquad (SEQ\ Equation \setminus *\ ARABIC\ 5)$$

$$\sum_{c\in C} z_{cr} q_c \leq q_v y_v \qquad \forall\, r \in R_v; v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 6)$$

$$\sum_{v\in V_s} \sum_{r\in R_v} \sum_{c\in C} z_{cr} q_c \leq q_s y_s \qquad \forall\, s \in S \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 7)$$

$$\sum_{s\in S} f_{ps} + \sum_{v\in V_p} \sum_{r\in R_v} \sum_{c\in C} z_{cr} q_c \leq q_p y_p \qquad \forall\, p \in P \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 8)$$

$$t_c^a + M(1 - x_{ic}^r) \geq \{t_r^s;\ \ i \in D\ t_i^d;\ \ i \in C\ + x_{ic}^r \frac{l_{ic}}{s_v} \qquad \forall\, i \in T_c; c \in C; r \in R_v; v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 9)$$

$$t_c^d \geq t_c^a + (0, t_c^e - t_c^a)\ + \tau_c^V \qquad \forall\, c \in C \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 10)$$

$$t_c^a \leq t_c^l \qquad \forall\, c \in C \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 11)$$

$$t_{r_v^1}^s = t_d^s \qquad \forall\, r_v \in R_v; v \in V_d \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 12)$$

$$t_{r_v^k}^s = t_{r_v^{k-1}}^e + \zeta_v^D \sum_{(i,j)\in A} x_{ij}^{r_v^k} \frac{l_{ij}}{s_v} + \tau_v^d \sum_{c\in C} z_{cr_v^k} q_c \qquad \forall\, r_v^{k-1}; r_v^k \in R_v; v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 13)$$

$$t_v^s = t_d^s \qquad \forall\, v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 14)$$

$$t_v^e = t_{r_v^{k_v}}^e \qquad \forall\, v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 15)$$

$$t_v^e \leq (t_v^s + w_v, t_d^e) \qquad \forall\, v \in V_d; d \in D \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 16)$$

$$\sum_{r\in R_v} \sum_{(i,j)\in A} x_{ij}^r l_{ij} \leq l_v \qquad \forall\, v \in V \qquad (\,SEQ\ Equation \setminus *\ ARABIC\ 17)$$

$$f_{ps} \in I^+ \quad \forall\, p \in P; s \in S \qquad (SEQ\ Equation \backslash *\ ARABIC\ 18)$$

$$x_{ij}^r \in \{0,1\} \quad \forall\, (i,j) \in A; r \in R \qquad (SEQ\ Equation \backslash *\ ARABIC\ 19)$$

$$y_v \in \{0,1\} \quad \forall\, v \in V \qquad (SEQ\ Equation \backslash *\ ARABIC\ 20)$$

$$y_s \in \{0,1\} \quad \forall\, s \in S \qquad (SEQ\ Equation \backslash *\ ARABIC\ 21)$$

$$y_p \in \{0,1\} \quad \forall\, p \in P \qquad (SEQ\ Equation \backslash *\ ARABIC\ 22)$$

$$z_{cr} \in \{0,1\} \quad \forall\, c \in C; r \in R \qquad (SEQ\ Equation \backslash *\ ARABIC\ 23)$$

Considering the goal of the LMND problem to configure the last-mile distribution structure for a sustainable last-mile delivery, the authors formulate the encompassing LRP with an objective function minimizing the total distribution cost (equation 1) with economic viability, environmental efficiency and social equity monetized as fixed and operational cost of distribution, while accounting for customer service constraint, flow constraints (vehicle flow; commodity flow), capacity constraints (vehicle capacity, secondary distribution facility capacity, primary distribution facility), customer time-window constraints. Establishing arrival time t_c^a, and departure time t_c^d, at the customer node, route start and end time constraints, vehicle start and end time constraints, and constraints on vehicle range l_r. The decision variables pertain to primary distribution facility use y_p, and likewise, secondary distribution facilities use y_s, the amount of commodity flow between each primary and secondary distribution facility f_{ps}, vehicle use y_v, vehicle flow on arc on a given route x_{ij}^r, and customer allocation to a delivery route z_{cr}. In addition, the model enforces integer constraints on the commodity flow variable and constraints arc flow variable to be binary. Further, it enforces binary values on resource-use variables (vehicle, secondary distribution facility, and primary distribution facility) and imposes a binary constraint on the customer-route allocation variable.

Developing the Adaptive Large Neighborhood Search Metaheuristic

To address the above-developed LMND problem, the authors develop an ALNS metaheuristic algorithm. Starting from this initial solution developed using a k-means clustering algorithm. The ALNS metaheuristic algorithm performs n iterations, each in a batch of k segments. In each such iteration, the algorithm searches through the neighborhood by removing and subsequently re-inserting customer nodes into the solution, thereby reconfiguring large portions of the solution using removal and an insertion operator, chosen adaptively, hence the name adaptive large neighborhood search (Ropke and Pisinger, 2006). Interested readers may refer to the work of Hendel (2022) for a discussion on recent developments in ALNS. The authors here detail the specifics of the ALNS meta-heuristic developed in this work.

Algorithm: Adaptive Large Neighborhood Search

Step 1. Initialize
Step 2. Loop over segments
Step 2.1. Reset count and score for every removal and insertion operator
Step 2.2. Update selection probability for every removal and insertion operator
Step 2.3. Loop over iterations within the segment
Step 2.3.1. Randomly select a removal and an insertion operator based on operator selection probabilities and consequently update the count for the selected operators
Step 2.3.2. Using the selected removal and insertion operators, destroy and repair the current solution to develop a new solution
Step 2.3.3. If this new solution is better than the best solution, then set the best solution and the current solution to the new solution, and accordingly update scores of the selected removal and insertion operators by σ_1
Step 2.3.4. Else, if this new solution is only better than the current solution, then set the current solution to the new solution and accordingly update scores of the selected removal and insertion operators by σ_2
Step 2.3.5. Else, set the current solution to the new solution conditional upon the acceptance criterion and accordingly update the scores of the selected removal and insertion operators by σ_3
Step 2.4. Update weights for every removal and insertion operator
Step 2.5. Perform local search
Step 3. Return the best solution

Specifically, in each iteration, the ALNS metaheuristic algorithm selects a removal and an insertion operator from a given set of removal operators Ψ_r and insertion operators Ψ_i, respectively, using a roulette wheel selection procedure, i.e., based on operator selection probabilities p_r and p_i established using operator weights w_r and w_i that quantify the performance for each operator in the previous iterations. The selected removal operator removes specific customer nodes from the current solution (ranging from a minimum of $\underline{C}$ to maximum of $\underline{C}$ customer nodes) rendering a partial solution, and subsequently, the selected insertion operator re-inserts these customer nodes into the partial solution to thus develop a new solution (reconfiguring $\underline{\mu}$ to $\underline{\mu}$ of the original solution). Tantamount to the uniqueness and quality of this new solution in comparison to the current and the best solution, these operators accumulate score π_r and π_i each, set to zero for every operator at the start of a segment of the algorithm. In particular, the algorithm updates these scores for the selected removal and insertion operators by, σ_1 - if the new solution is unique and better than the best solution; σ_2 - if the new solution is still unique but only better than the current solution; and σ_3 - if the new unique solution is worse than the current solution yet accepted as the current solution. Note, to enable a comprehensive exploration of the search space, the algorithm accepts a worse new solution as the current solution with a probability $exp\ exp\ \left(-\frac{\left(f(s')-f(s)\right)}{T}\right)$, reducing through every iteration of the algorithm by a factor of $exp\ exp\ \left(\frac{1}{\theta}\right)$ with the initial temperature set to $T = \omega f(s)/ln\ (1/\tau)$, such that the algorithm could accept a solution ω times worse than the initial solution with a probability of τ, cooled off by a factor of θ every iteration of the algorithm. At the end of the segment, the ALNS metaheuristic algorithm updates the operator weights using the operator scores accumulated in the segment normalized by operator count and additionally adjusted by a reaction factor ρ, while also accounting for scores accumulated through the previous segments of the algorithm, adjusted by a factor of $(1-\rho)$. Further, after every j segment, the algorithm employs local search operators from the set Ψ_l, each for at most m

iterations, stopping at the first improvement. Finally, after a total of $n \times k$ iterations, the algorithm terminates, returning the best-found solution.

Note that the constraints formulated for the LRP modeled in this work significantly restrict the feasible search space; hence, the authors develop the algorithm to iterate through infeasible solutions to enable the ALNS metaheuristic algorithm to explore the search space comprehensively. To this end, the authors consider a modified objective function f, taking the total cost of distribution and adding up a penalty for constraint violation equivalent to the magnitude of violation in the order of distribution cost.