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Coping with the Rise of E-commerce Generated Home Deliveries through Innovative Last-mile Technologies and Strategies

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Coping with the Rise of E-commerce Generated Home Deliveries through Innovative Last-mile Technologies and Strategies

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A Report from the National Center for Sustainable Transportation

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16. Abstract

E-commerce can potentially make urban goods flow economically viable, environmentally efficient, and socially equitable. However, as e-retailers compete with increasingly consumer-focused services, urban freight witnesses a significant increase in associated distribution costs and negative externalities, particularly affecting those living close to logistics clusters. Hence, to remain competitive, e-retailers deploy alternate last-mile distribution strategies. These alternate strategies, such as those that include the use of electric delivery trucks for last-mile operations, a fleet of crowdsourced drivers for last-mile delivery, consolidation facilities coupled with light-duty delivery vehicles for a multi-echelon distribution, or collection-points for customer pickup, can restore sustainable urban goods flow. Thus, in this study, the authors investigate the opportunities and challenges associated with alternate last-mile distribution strategies for an e-retailer offering expedited service with rush delivery within strict timeframes. To this end, the authors formulate a last-mile network design (LMND) problem as a dynamic-stochastic two-echelon capacitated location routing problem with time-windows (DS-2E-C-LRP-TW) addressed with an adaptive large neighborhood search (ALNS) metaheuristic.

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Disclaimer

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NCST

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Glossary

Acronym	Definition
ADR	autonomous delivery vehicle
ALNS	Adaptive large neighborhood search
CP-PC	Delivery via collection points with customer pickup
DD-C5DT	Direct delivery with a fleet of class-5 diesel trucks
DD-C5ET	Direct delivery with a fleet of class-5 electric trucks
DD-DV	Direct delivery with a fleet of diesel vans
DD-EV	Direct delivery with a fleet of electric vans
DS-2E-C-LRP-TW	Dynamic-stochastic two-echelon capacitated location routing problem with time-windows
DT	Diesel Truck
DV	Diesel Van
ECB	Electric Cargo-Bike
ET	Electric Truck
EV	Electric Van
LMND	Last-mile network design
LRP	Location routing problem
LT	Light Truck
MH-ECB	Delivery via micro-hubs using electric cargo-bikes
MMH-ADR	Delivery via mobile micro-hubs using autonomous delivery robots
MMH-UAV	Delivery via mobile micro-hubs using unmanned aerial vehicles
PC	Passenger car
UAV	Unmanned aerial vehicle

Coping with the Rise of E-commerce Generated Home Deliveries through Innovative Last-mile Technologies and Strategies

EXECUTIVE SUMMARY

E-commerce can potentially make urban freight sustainable with economically viable, environmentally efficient, and socially equitable goods flow. However, with the increasing consumer-focused trends in e-commerce, urban freight witnesses a significant increase in associated distribution costs and negative externalities, including greenhouse gas emissions advancing global climate change and criteria pollutant emissions worsening local air quality and thus affecting those living close to logistics clusters. To this end, alternate last-mile distribution strategies such as those that include the use of electric delivery trucks for last-mile operations, a fleet of crowdsourced drivers for last-mile delivery, or consolidation facilities coupled with light-duty delivery vehicles for a multi-echelon distribution, or collection-points for customer pickup, can restore sustainable urban goods flow. Thus, it is pertinent to understand the opportunities and challenges in e-commerce last-mile distribution. Hence, this work investigates the sustainability of alternate last-mile distribution strategies for an e-retailer offering expedited service.

The findings suggest that last-mile delivery using a fleet of electric delivery vehicles can render urban freight economically viable, environmentally efficient, and socially equitable goods flow. However, the higher upfront cost of electric delivery vehicles can deter e-retailer, especially when the e-retailer may need to rent out additional delivery vehicles to cope with demand uncertainty. To this end, the e-retailers can instead crowdsource last-mile delivery to cater to customers arriving dynamically through the day and, in doing so, establish a cost-effective and flexible last-mile distribution structure resistant to demand uncertainty. However, it is essential to note that using independent contractors could result in less reliable performance than company-owned delivery vehicles. To this end, the e-retailer may need to offer higher incentives to drivers to improve reliability. And thus, the e-retailer must carefully consider the relation between viability and reliability of last-mile distribution when crowdshipping. Moreover, the e-retailer must also consider the potential impact of crowdshipping on environmental efficiency and social equity associated with urban goods flow.

To this end, multi-echelon distribution strategies, such as using consolidation facilities and light-duty delivery vehicles, can reduce exposure to harmful pollutants in urban environments. However, these strategies may be less cost-effective and less resistant to demand uncertainty due to the additional handling and transportation required. To reduce these costs, e-retailers can consider having customers collect packages at collection points, which may increase negative externalities from urban goods flow. To mitigate this issue, e-retailers can locate collection points near major traffic generators to reduce the need for customers to travel.

Further, the authors investigated the potential for using delivery robots and aerial delivery vehicles. While the authors showcase the potential for such a distribution strategy to absorb

uncertainty in last-mile distribution, the limited operational range narrows down the use case of such new and innovative distribution strategies.

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

1. Introduction

"Attention Shoppers: Internet Is Open" headlined the New York Times article in 1994, proclaiming the advent of e-commerce Lewis (1994). Almost three decades since online shopping has become a fundamental part of the consumer shopping experience. What would previously have been a trip to the store is now a hassle-free delivery to the home. Yet, the first decade of e-commerce was subject to skepticism, with e-retail only amounting to 1.7% of the total retail sales in 2003 (U.S. Census Bureau, 2022). Nonetheless, the increased internet-use in the following years provided opportunities for retailers to expand the market horizon with e-commerce. Thus e-retail sales grew rapidly, contributing a share of 5.8% of the total retail sales by 2013. And despite internet penetration reaching saturation levels since e-commerce continues to expand with e-retail expected to account for 15% of the total retail sales by 2023.

This rise of e-commerce has brought prosperity for the consumer and the retailer, thereby fostering economic growth through urban goods flow – 1st pillar of sustainability (Pahwa and Jaller, 2022). It has also expanded access to essential products for otherwise disadvantaged communities, which proved critical during the COVID-19 pandemic, thus improving social equity in urban goods flow – 3rd pillar of sustainability (Pahwa and Jaller, In Review-a). Further, owing to demand consolidation and optimized delivery, e-commerce has substantially reduced transportation-related negative externalities from urban goods flow – 2nd pillar of sustainability (Jaller and Pahwa, 2020). However, the recent turn towards consumer-focused service in e-retail significantly impacts the economic viability, environmental efficiency, and social equity of e-commerce last-mile distribution.

Since online shopping only amounts to 4% of daily shopping activities (Hofferth et al., 2020), e-retailers compete with traditional retailers for market share, establishing consumer-focused services. For instance, to compensate for the lack of instant gratification, e-retailers offer expedited shipping with rush-delivery. Further, e-retailers offer a lenient return policy to compensate for the information mismatch, which is common in the e-apparel industry—however, such consumer-focused trends in e-retail result in frequent less-than-truckload last-mile deliveries. And hence urban environments witness a substantial increase in freight distribution costs and associated negative externalities, including greenhouse gas emissions advancing global climate change, as well as criteria pollutant emissions worsening local air quality and thus affecting those living close to logistics clusters. Therefore, urban goods flow economically unviable, environmentally inefficient, and socially inequitable (Pahwa and Jaller, In Review-b). Hence, to remain competitive, e-retailers innovate with alternate last-mile distribution strategies. These alternate strategies, such as those that include the use of electric delivery trucks for last-mile operations, a fleet of crowdsourced drivers for last-mile delivery, or consolidation facilities coupled with light-duty delivery vehicles for a multi-echelon distribution, or collection-points for customer pickup, can restore sustainable urban goods flow.

Thus, this work aims to establish opportunities and challenges associated with alternate last-mile distribution strategies to cope with the increasing consumer-focused trends in e-commerce towards rush delivery within strict time-windows (expedited logistics) by exploring the paradigms of economic viability, environmental efficiency, and social equity. To this end, this work formulates a last-mile network design (LMND) problem as a dynamic-stochastic two-echelon capacitated location routing problem with time-windows (DS-2E-C-LRP-TW) addressed using an adaptive large neighborhood search (ALNS) metaheuristic.

In the following section, the authors discuss pertinent literature about the sustainability of last-mile delivery. In the Methodology section, the authors formulate the LMND problem as DS-2E-C-LRP-TW and then detail the associated ALNS metaheuristic algorithm developed in this work. In Section 4, the authors develop the case study before presenting the empirical results in Section 5. In the penultimate Discussion section, the study emphasizes the managerial and policy implications for the stakeholders involved in urban freight management. The authors conclude this work with a section highlighting the novelty and limitations of this study along with the future scope of this work.

2. Literature Review

In the U.S., many freight-related occupations include, as a primary responsibility, handling goods or driving motor vehicles. The COVID-19 pandemic has significantly impacted the freight sector, and the data and projections may not reflect the long-term effects on the industry. Furthermore, employment counts are a limited metric and only a starting point in the conversation about how to steer changes in the labor market; wages and job quality are also essential to consider.

The increasing prevalence of internet marketplaces and the consequent transformation of individual shopping behaviors have raised significant academic concerns about the sustainability of urban goods flow. To this end, the literature has explored economic viability, environmental efficiency, and social equity paradigms for e-commerce last-mile delivery. In this context, some earlier works highlighted the potential for online shopping to substitute for individuals traveling for in-store shopping, thereby consolidating goods flow to render efficient distribution from point-of-sale to point-of-consumption (Cairns, 2005; Edwards et al., 2010; Siikavirta et al., 2002). Nonetheless, some of the other contemporary studies of the time cautioned, emphasizing the possibility of increased urban goods flow owing to the complementarity effect whereby online shopping induces in-store shopping (Farag et al., 2006; Ferrell, 2004; Mokhtarian, 2004). Yet, as e-retailers compete with increasingly consumer-focused service, urban environments witness not only online shopping-induced personal travel to brick-and-mortar stores but also a substantial increase in less-than-truckload freight traffic on their road network. This consequently renders a significant increase in freight distribution costs as well as negative externalities from urban goods flow, including greenhouse gas emissions advancing global climate change, criteria pollutant emissions worsening local air quality, and congestion resulting in noise pollution and traffic accidents, as made evident by Figliozzi (2007), Van Loon et al. (2015), Pahwa and Jaller (2022), and many others. Thus, e-retailers deploy alternate distribution structures for last-mile delivery to compete sustainably with traditional retailers. To this end, research work has established opportunities and challenges associated with these alternate last-mile distribution strategies.

One such distribution strategy includes the use of urban consolidation facilities coupled with the use of light-duty delivery vehicles such as electric vans, cargo-bikes, autonomous delivery vehicles (ADRs), or unmanned aerial vehicles (UAVs) for last-mile delivery, thereby moving heavy-duty delivery trucks away from core commercial and residential parts of the city. The literature has consequently showcased the potential for consolidation strategies to lower the operational costs for the e-retailers and reduce the adverse effects of freight traffic in the city (Estrada and Roca-Riu, 2017; Isa et al., 2021; Quak and Tavasszy, 2011). However, delivery using such alternate fuel delivery vehicles has logistical limitations and is precisely feasible for expedited delivery in dense urban environments where service with conventional large-sized delivery trucks may be difficult (Browne et al., 2011; Lemardelé et al., 2021; Pahwa and Jaller, 2022).

Thus, Iwan et al. (2016), Hofer et al. (2020), van Duin et al. (2020), and others alike have explored opportunities and challenges associated with yet another multi-echelon distribution strategy that instead includes the use of collection points to in fact, outsource the last few miles of the last-mile travel to the customer, thereby enabling expedited delivery at low costs for the e-retailer. 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' homes, schools, or workplaces, thereby limiting customer detours to collect packages. Nonetheless, Pahwa and Jaller (In Review-a) underscored the susceptibility of distribution via collection-points to disruption in the last-mile, considering the uncertainty about customers' willingness to collect packages.

Yet, the e-retailer may still outsource the entire last-mile employing a fleet of crowdsourced drivers for a 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 it does not induce vehicle use for crowdshipping alone. However, De Ruyter et al. (2018) raised equity and welfare concerns associated with the gig-work considering the independent contractor status of crowdsourced drivers. Moreover, much like collection-point pickup, Pahwa and Jaller (In Review-a) highlighted that crowdsourced deliveries might also be susceptible to last-mile disruptions due to the uncertainty about driver availability.

Nonetheless, the COVID-19 pandemic has prompted e-retailers to innovate further and develop not only sustainable delivery methods with an economically viable, environmentally efficient, and socially equitable distribution structure that is capable of handling high-probability low-severity fluctuations in the last-mile but also resilient delivery methods with robust, redundant, resourceful, and rapid distribution structure that is capable of handling low-probability high-severity last-mile disruptions (Pahwa and Jaller, In Review-a). One such new distribution strategies include the use of ADRs and UAVs from a delivery truck functioning as a mobile warehouse carrying high-demand products in anticipation of customer requests (anticipatory shipping) to limit product shortages and further reduce customer lead time (Lee, 2017; Singh et al., 2021; Srinivas and Marathe, 2021).

Yet, the successful implementation of any distribution strategy requires a thorough appraisal of the efficacy of the distribution structure (Dolati Neghabadi et al., 2019; Zenezini and De Marco, 2016). And while in-situ examination with pilot testing renders an ideal ground to assess a distribution strategy in the context of the delivery environment of operation, in-vitro examination using modeling, simulation, and optimization tools provide a broader opportunity to assess the distribution strategy across multiple synthesized delivery environments. One such in-vitro methods include formulating a last-mile network design (LMND) problem to configure and optimize the distribution structure and determine the distribution facilities to operate (type, number, and location), the fleet choice (size and composition), the customer allocation, and consequently the order of customer visits (Janjevic et al., 2021; Merchán and Winkenbach, 2018; Rautela et al., 2021; Snoeck et al., 2018; Zhou et al., 2019).

To this end, some earlier works modeled simplistic distribution structures (Jamil et al., 1994; Laporte et al., 1988; Salhi and Nagy, 1999). However, improvements in computational power have instigated research to incorporate more complex features into the problem, including resource constraints (Barreto et al., 2007; Pirkwieser and Raidl, 2010; Schwengerer et al., 2012), customer time windows (Aksen and Altinkemer, 2008; Crainic et al., 2011; Li and Keskin, 2014), multi-echelon distribution (Contardo et al., 2012; Govindan et al., 2014; Wang et al., 2018), stochastic elements (Ahmadi Javid and Azad, 2010; Nadizadeh and Nasab, 2014; Schiffer and Walther, 2018), dynamic elements (Albareda-Sambola et al., 2012; Koç, 2016; Rabbani et al., 2019), etc. Further, considering the NP-hard nature of the problem, the literature has developed solution algorithms using meta-heuristic frameworks with local search methods such as simulated annealing (Ahmadi-Javid and Seddighi, 2013; Ferreira and de Queiroz, 2018; Lin et al., 2011), tabu search (Caballero et al., 2007; Klibi et al., 2010; Lin and Kwok, 2006), variable neighborhood search (Melechovský et al., 2005; Veenstra et al., 2018; Zhang et al., 2019), adaptive large neighborhood search (Hemmelmayr et al., 2017; Koç, 2019; Tunalıoğlu et al., 2016); evolutionary computation techniques such as Genetic Algorithm (Derbel et al., 2012; Fazayeli et al., 2018; Hu et al., 2018), Evolutionary Algorithm (Prins et al., 2006; Prodhon, 2011; Sun, 2015); and swarm intelligence algorithms such as Ant-Colony Optimization (Gao et al., 2016; Herazo-Padilla et al., 2015; Ting and Chen, 2013), Particle Swarm Optimization (Marinakis, 2015; Peng et al., 2017; Rabbani et al., 2018). For a comprehensive overview of recent developments in the field of location routing problems, the interested reader may refer to Prodhon and Prins (2014), Drexl and Schneider (2015), and Mara et al. (2021).

Considering that this work aims to establish the sustainability of e-commerce last-mile distribution for an e-retailer offering expedited service with rush delivery within strict time-windows, this work formulates the LMND problem for this e-retailer as a dynamic-stochastic two-echelon capacitated location routing problem with time-windows (DS-2E-C-LRP-TW). To address this complex LMND problem, the authors develop an associated adaptive large neighborhood search (ALNS) metaheuristic algorithm. As per the authors' knowledge, no previous work has addressed the LMND problem for e-commerce distribution in a delivery environment with dynamic and stochastic customers.

3. Methodology

In this section, the authors detail the last-mile network design (LMND) problem, which essentially involves 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.

3.a Formulating the location routing problem (LRP)

The authors split the LMND problem into its constituent strategic, tactical, and operational decisions in this work. Here, the strategic decisions undertake long-term planning to develop a distribution structure with appropriate distribution facilities and a suitable delivery fleet to service the expected customer demand in the planning horizon. The tactical decisions pertain to medium-term day-to-day planning of last-mile delivery operations to establish efficient goods flow in this distribution structure to service the daily stochastic customer demand. And finally, operational decisions involve immediate short-term planning to fine-tune this last-mile delivery to service the requests arriving dynamically through the day. Considering this distribution environment, 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 1), catering to a market with a stochastic and dynamic daily customer demand requesting delivery within time-windows.

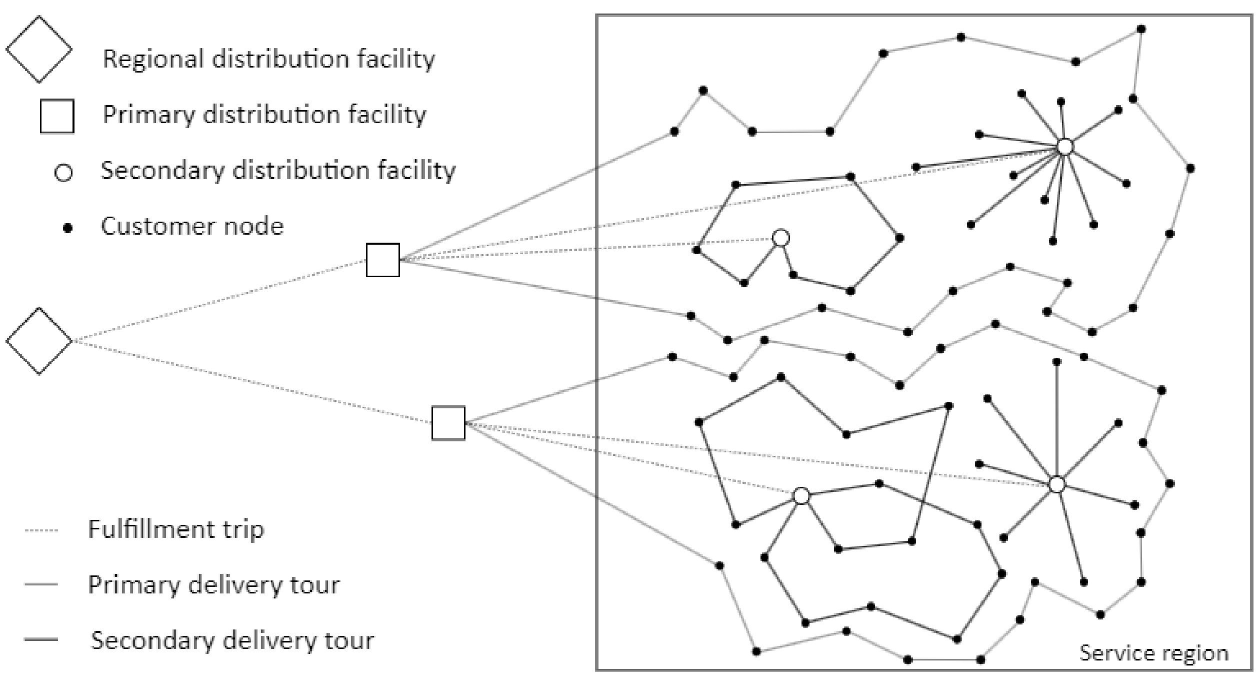


Figure 1. A typical e-retail two-echelon last-mile distribution structure

Below is the list of notations for parameters and variables used in the LRP formulation developed in this work.

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 $j \in N; \{k; (k,j) \in A\}$
H_j	:	Set of head nodes (successors) to node $j \in N; \{k; (j,k) \in A\}$

Indices

i	:	Node index
c	:	Customer node index
d	:	Distribution facility index
p	:	Primary distribution facility index
s	:	Secondary distribution facility index
ij	:	Arc index for arc connecting nodes i and j
v	:	Vehicle index
r	:	Route 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 : Re-fueling 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
$\bar{k}_v$: 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

$$\min \Pi = \sum_{p\in P}\left(\pi_p^f + \sum_{s\in S}\pi_p^o f_{ps} + \sum_{v\in V_p}\left(\pi_v^f + \sum_{r\in R_v}\sum_{(i,j)\in A}\pi_v^{od}x_{ij}^r l_{ij} + \pi_v^{ot}(t_v^e - t_v^s)\right)y_v\right)y_p +$$

$$\sum_{s\in S}\left(\pi_s^f + \sum_{s\in S}\pi_s^o f_{ps} + \sum_{v\in V_s}\left(\pi_v^f + \sum_{r\in R_v}\sum_{(i,j)\in A}\pi_v^{od}x_{ij}^r l_{ij} + \pi_v^{ot}(t_v^e - t_v^s)\right)y_v\right)y_s \qquad (1)$$

Subject to,

$$\sum_{r\in R} z_{cr} = 1 \qquad \forall\, c \in C \qquad (2)$$

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

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

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

$$\sum_{c\in C} z_{cr}q_c \le q_v y_v \qquad \forall\, r \in R_v; v \in V \qquad (6)$$

$$\sum_{v\in V_s}\sum_{r\in R_v}\sum_{c\in C} z_{cr}q_c \le q_s y_s \qquad \forall\, s \in S \qquad (7)$$

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

$$t_c^a + M(1 - x_{ic}^r) \ge \begin{cases} t_r^s; & i \in D \\ t_i^d; & i \in C \end{cases} + x_{ic}^r \frac{l_{ic}}{s_v} \qquad \forall\, i \in T_c; c \in C; r \in R_v; v \in V \qquad (9)$$

$$t_c^d \ge t_c^a + max(0, t_c^e - t_c^a) + \tau_c^V \qquad \forall\, c \in C \qquad (10)$$

$$t_c^a \le t_c^l \qquad \forall\, c \in C \qquad (11)$$

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

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

$$t_v^s = t_d^s \qquad \forall\, v \in V \qquad (14)$$

$$t_v^e = t_{r_v^{\bar{k}_v}}^e \qquad \forall\, v \in V \qquad (15)$$

$$t_v^e \le min(t_v^s + w_v, t_d^e) \qquad \forall\, v \in V_d; d \in D \qquad (16)$$

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

$$f_{ps} \in I^+ \qquad \forall\, p \in P; s \in S \qquad (18)$$

$$x_{ij}^r \in \{0,1\} \qquad \forall\, (i,j) \in A; r \in R \qquad (19)$$

$$y_v \in \{0,1\} \qquad \forall\, v \in V \qquad (20)$$

$$y_s \in \{0,1\} \qquad \forall\, s \in S \qquad (21)$$

$$y_p \in \{0,1\} \qquad \forall\, p \in P \qquad (22)$$

$$z_{cr} \in \{0,1\} \qquad \forall\, c \in C; r \in R \qquad (23)$$

To begin with, 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 delivery 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, respectively.

Considering the goal of 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 (equation 2), flow constraints (vehicle flow - equations 3 and 4; commodity flow - equation 5), capacity constraints (vehicle capacity - equation 6, secondary distribution facility capacity - equation 7, primary distribution facility - equation 8), customer time-window constraint (equation 11) with equations 9 and 10 establishing arrival time t_c^a, and departure time t_c^d, at the customer node, respectively, route start and end time constraints (equations 12 and 13), vehicle start and end time constraints (equations 14 - 16), and constraints on vehicle range l_r (equation 17). The decision variables pertain to primary distribution facility use y_p, and likewise secondary distribution facility 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, equation 18 enforces integer constraint on the commodity flow variable, while equation 19 constrains the arc flow variable as binary. Further, equations 20 - 22 enforce binary values on resource-use variables (vehicle, secondary distribution facility, and primary distribution facility), and equation 23 imposes a binary constraint on the customer-route allocation variable. Thus, with this LRP formulation, the authors split the LMND problem into its constituent strategic, tactical, and operational decisions.

In particular, the strategic decisions establish the type, number, and location of the primary and secondary distribution facilities, as well as the size and composition of the associated delivery fleet, to serve the expected customer demand for the e-retailer in the planning horizon. To this end, at the strategic level, the decision variables of the LRP pertain to primary distribution facility use y_p, secondary distribution facility 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-route allocation z_{cr}.

The tactical decisions then define the order of customer visits for each day of the planning horizon 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. Thus, at the tactical level, the decision variables for the LRP include commodity flow between each primary and secondary distribution facility, vehicle use, vehicle flow on arc on a given route, and customer-route allocation, with primary distribution and secondary distribution facility use taking values from the strategic stage.

And finally, the operational decisions then fine-tune the last-mile delivery for the e-retailer considering the dynamic arrival of customer requests requiring service by the end of the day. Hence, the operational decision variables are the same as those at the tactical level but only limited to customers yet to be served at any point during the day.

Considering this stochastic and dynamic nature of the delivery environment, the authors develop a Monte-Carlo framework simulating each day in the planning horizon. Each day is divided into timeslots, and each timeslot accepts customer requests for service by the end of the day. In particular, the framework assumes the e-retailer delays route commitments until the last-feasible timeslot to accumulate customer requests and assign them to an uncommitted delivery route. Note a delivery route is committed once the e-retailer starts loading packages assigned to this delivery route onto the delivery vehicle assigned for this delivery route. At the end of every timeslot, this framework assumes the e-retailer integrates the new customer requests by inserting these customer nodes into such uncommitted delivery routes in a manner that results in the slightest increase in distribution cost keeping the customer-distribution facility allocation fixed. Thus, the framework iterates through the timeslots with the e-retailer processing route commitments, accumulating customer requests, and subsequently integrating them into the delivery operations for the day.

3.b Developing the adaptive large neighborhood search (ALNS) meta-heuristic

The LMND problem formulated as an LRP constitutes three subproblems: facility location, customer allocation, and vehicle routing problems, each of which are NP-hard combinatorial optimization problems. To this end, the authors develop an adaptive large neighborhood search (ALNS) meta-heuristic algorithm that *searches* through the *neighborhood* by destroying and consequently repairing the solution, thereby reconfiguring *large* portions of the solution with specific operators that are chosen *adaptively* in each iteration of the algorithm, hence the name adaptive large neighborhood search (Ropke and Pisinger, 2006). The interested reader may refer to the work of Hendel (2022) for a discussion on recent developments in ALNS. Considering the destroy and repair principle of the ALNS, the literature has investigated many destroy and repair operators to improve exploration and exploitation of the search space, each of which presents unique opportunities and challenges. However, this work simplifies the choice of operators to deploy by categorizing and detailing the fundamental principles of each operator. The authors here detail the specifics of the ALNS meta-heuristic developed in this work.

Adaptive Large Neighborhood Search (ALNS) parameters - χ

n	:	Number of ALNS iterations in an ALNS segment
k	:	Number of ALNS segments
m	:	Number of local search iterations
j	:	Number of ALNS segments triggering a local search
Ψ_r	:	Set of removal operators (destroy)
Ψ_i	:	Set of insertion operators (repair)
Ψ_l	:	Set of local search operators
σ_1	:	Operators score if the new solution is unique and better than the best solution
σ_2	:	Operators score if the new solution is unique and better than the current solution
σ_3	:	Operators score if the new solution is unique, worse, yet accepted as the current solution
ω	:	Start temperature control threshold
τ	:	Start temperature control probability
θ	:	Temperature cooling rate
$\underline{C}$	:	Minimum customer nodes to remove
$\overline{C}$	:	Maximum customer nodes to remove
$\underline{\mu}$	:	Minimum removal fraction
$\overline{\mu}$	:	Maximum removal fraction
ρ	:	Reaction factor

Objective function. The constraints formulated for the LRP modeled in this work significantly restrict the feasible search space; hence, to enable the ALNS meta-heuristic algorithm to explore the search space comprehensively, the authors develop the algorithm to iterate through infeasible solutions. 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.

Algorithm: Adaptive Large Neighborhood Search (ALNS)

$ALNS(\chi, s)$
Input: χ – ALNS parameters, s – Initial solution
Output: s – Final solution

Step 1. Initialize

$s^* \leftarrow s$

$S \leftarrow \{s\}$

for $r \in \Psi_r$ **do** $w_r \leftarrow 1$ **end for**

for $i \in \Psi_i$ **do** $w_i \leftarrow 1$ **end for**

$T \leftarrow \omega f(s)/\ln(1/\tau)$

Step 2. Loop over segments

$h \leftarrow 1$

while $h \leq k$ **do**

Step 2.1. Reset count and score for every removal and insertion operator

for $r \in \Psi_r$ **do** $c_r, \pi_r \leftarrow 0, 0$ **end for**

for $i \in \Psi_i$ **do** $c_i, \pi_i \leftarrow 0, 0$ **end for**

Step 2.2. Update selection probability for every removal and insertion operator

for $r \in \Psi_r$ **do** $p_r \leftarrow w_r / \sum_{r \in \Psi_r} w_r$ **end for**

for $i \in \Psi_i$ **do** $p_i \leftarrow w_i / \sum_{i \in \Psi_i} w_i$ **end for**

Step 2.3. Loop over iterations within the segment

repeat n **times**

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

$R \sim p(R = r) = p_r$

$I \sim p(I = i) = p_i$

$r \overset{R}{\leftarrow} R$

$i \overset{R}{\leftarrow} I$

$c_r \leftarrow c_r + 1$

$c_i \leftarrow c_i + 1$

Step 2.3.2. Using the selected removal and insertion operators, destroy and repair the current solution to develop a new solution

$\Lambda \sim U(0,1)$

$\lambda \overset{R}{\leftarrow} \Lambda$

$q \leftarrow \left[(1-\lambda) * \min\left(\underline{C}, \underline{\mu}|C|\right) + \lambda * \min\left(\overline{C}, \overline{\mu}|C|\right)\right]^{-}$

$s' \leftarrow i\left(r(q, s)\right)$

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

if $f(s') < f(s^*)$ **then**

$s^* \leftarrow s'$

$s \leftarrow s'$

$\pi_r \leftarrow \pi_r + \sigma_1$

$\pi_i \leftarrow \pi_i + \sigma_1$

$S \leftarrow S \cup \{s\}$

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

else if $f(s') < f(s)$ **then**

$s \leftarrow s'$

if $s \notin S$ **then**

$\pi_r \leftarrow \pi_r + \sigma_2$

$\pi_i \leftarrow \pi_i + \sigma_2$

end if

$S \leftarrow S \cup \{s\}$

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

else

$\Lambda \sim U(0,1)$

$\lambda \overset{R}{\leftarrow} \Lambda$

if $\lambda < \exp\left(-\left(f(s') - f(s)\right)/T\right)$ **do**

$s \leftarrow s'$

if $s \notin S$ **then**

$\pi_r \leftarrow \pi_r + \sigma_3$

$\pi_i \leftarrow \pi_i + \sigma_3$

end if

$S \leftarrow S \cup \{s\}$

end if

end if

$T \leftarrow \varphi T$

end repeat

Step 2.4. Update weights for every removal and insertion operator

for $r \in \Psi_r$ **do if** $c_r \neq 0$ **then** $w_r \leftarrow \rho\pi_r/c_r + (1-\rho)w_r$ **end if end for**

for $i \in \Psi_i$ **do if** $c_i \neq 0$ **then** $w_i \leftarrow \rho\pi_i/c_i + (1-\rho)w_i$ **end if end for**

Step 2.5. Perform local search

if $j \bmod h$ **for** $l \in \Psi_l$ $s \leftarrow l(s, m)$ **end for end if**

if $f(s) < f(s^*)$ **then** $s^* \leftarrow s$ **end if**

$h \leftarrow h + 1$

end while

Step 3. Return the best solution

return s^*

Initial solution. In this work, the ALNS meta-heuristic algorithm initiates the adaptive large neighborhood search with an initial solution built by selecting a random distribution facility node, a random delivery vehicle operating from this distribution facility, a random delivery route for this delivery vehicle, and after that inserting a randomly selected customer node between this distribution facility node and the first node on this route until all customers are inserted into the route.

Framework. Starting from this initial solution, the ALNS meta-heuristic algorithm performs n iterations 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 that are chosen *adaptively* from a given set of removal operators Ψ_r and insertion operators Ψ_i based on the performance of the operators in the previous iterations. 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.

Operator selection. In every algorithm iteration, the selected removal operator removes customer nodes from the current solution rendering a partial solution. The selected insertion operator reinserts these removed customer nodes into the partial solution to thus develop a new solution. The choice of a removal and insertion operator is contingent on the previous performance of the operators in improving the quality of the solution quantified using operator weights w_r and w_i, respectively. Specifically, in every iteration, the algorithm selects a removal and insertion operator using the roulette wheel selection method considering the operator selection probabilities p_r and p_i, respectively, set equal for every removal and insertion operator.

Operator selection. In every iteration, the ALNS meta-heuristic algorithm selects a removal and an insertion operator using the roulette wheel selection method considering the operator selection probabilities p_r and p_i, respectively, evaluated using operator weights w_r and w_i each. With these operator weights set to one for every operator at the initialization, the algorithm quantifies the operators' performance in improving the solution's quality.

Operator scoring. In every iteration of the ALNS meta-heuristic algorithm, the selected removal operator removes specific customer nodes from the current solution, rendering a partial solution. The selected insertion operator subsequently re-inserts these customer nodes into the partial solution to thus develop a new 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.

Adaptive mechanism. At the end of the segment, the ALNS meta-heuristic 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 $(1-\rho)$. Note operator count c_r and c_i is the number of times the algorithm chose a removal and an insertion operator, respectively, in the just terminated segment. With these updated operator weights, the algorithm updates operator selection probabilities evaluated as the ratio of operator weight to the sum of weights of all removal/insertion operators.

Acceptance criteria. In every iteration, the ALNS meta-heuristic algorithm sets the current solution s, to the new solution s', if this new solution is better than the current solution. However, to enable a comprehensive exploration of the search space, the algorithm also accepts a worse new solution as the current solution with a probability $\exp\left(-\left(f(s')-f(s)\right)/T\right)$, reducing through every iteration of the algorithm by a factor of $\exp(1/\theta)$. This simulated annealing acceptance criteria gradually narrows down the solution space analogous to the physical annealing process wherein a material is heated to a liquid state and then slowly cooled down to re-crystalize. Note, the ALNS algorithm developed in this work assumes an initial temperature, $T=\omega f(s)/\ln(1/\tau)$, 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.

Removal operators. The goal of a removal operator is to remove a certain q number of customer nodes from the solution, thereby rendering a partial solution. In this work, the ALNS meta-heuristic algorithm employs twelve removal operators with three distinct principles of removal, namely, random removal, related removal, and worst removal, each working on four distinct parts of the solution.

To begin with, random removal operators operate by randomly removing customer nodes. In particular, the *random-customer* removal operator selects q random customer nodes and removes them from the solution. However, the *random-route* removal operator iteratively selects a random delivery route and subsequently removes the customer nodes from the route until exactly q customer nodes are removed. Likewise, the *random-vehicle* removal operator iteratively selects a random delivery vehicle and consequently iterates through its delivery routes, removing customers until at least q customer nodes are removed from the solution. And similarly, the *random-facility* removal operator iteratively selects a random distribution facility and consequently iterates through its delivery vehicles until at least q customer nodes are removed.

However, unlike random removal operators, related removal operators remove the most "related" customer nodes. Here, relatedness estimates the potential for improving the solution quality by removing and re-inserting such "related" customer nodes into the solution. Thus, the *related-customer* removal operator selects a random pivot customer node and subsequently removes q customer nodes most related to this pivot customer (equation 24). Further, the *related-route* removal operator randomly selects a pivot delivery route and iterates through the most related delivery routes until exactly q customer nodes are removed from the solution (equation 27). Similarly, the *related-vehicle* removal operator selects a pivot delivery vehicle and iterates through the delivery routes of the most related delivery vehicles until at least q customer nodes are removed (equation 30). However, the *related-facility* removal operator selects a pivot distribution facility node and subsequently removes q customer nodes most related to the pivot customer (equation 33). Note the authors develop these measures of relatedness heuristically considering the previous use of related removal in the literature.

$$\phi(c_1, c_2) = \frac{|q_{c_1} - q_{c_2}| + \varphi(c_1, c_2)}{l_{c_1c_2} + |t^s_{c_1} - t^s_{c_2}| + |t^e_{c_1} - t^e_{c_2}|} \qquad \forall\, c_1, c_2 \in C \qquad (24)$$

where,

$$\varphi(c_1, c_2) = \begin{cases} 4, & \text{if } r_1 = r_2 \\ 3, & \text{else if } v_1 = v_2 \\ 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, c_1, c_2 \in C \qquad (25)$$

$$l_{c_1c_2} = \sqrt{\left(x_{c_1} - x_{c_2}\right)^2 + \left(y_{c_1} - y_{c_2}\right)^2} \qquad \forall\, c_1, c_2 \in C \qquad (26)$$

with, $z_{c_1r_1} = 1, r_1 \in R_{v_1}, v_1 \in V_{d_1};\ z_{c_2r_2} = 1, r_2 \in R_{v_2}, v_2 \in V_{d_2}$

$$\phi(r_1, r_2) = \frac{\left|\sum_{c\in C}\left(q_c z_{cr_1} - q_c z_{cr_2}\right)\right| + \varphi(r_1, r_2)}{l_{r_1r_2} + |t^s_{r_1} - t^s_{r_2}| + |t^e_{r_1} - t^e_{r_1}|} \qquad \forall\, r_1, r_2 \in R \qquad (27)$$

where,

$$\varphi(r_1, r_2) = \begin{cases} 3, & \text{else if } v_1 = v_2 \\ 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, r_1, r_2 \in R \qquad (28)$$

$$l_{r_1r_2} = \sqrt{\left(\frac{\sum_{c\in C} x_c z_{cr_1}}{\sum_{c\in C} z_{cr_1}} - \frac{\sum_{c\in C} x_c z_{cr_2}}{\sum_{c\in C} z_{cr_2}}\right)^2 + \left(\frac{\sum_{c\in C} y_c z_{cr_1}}{\sum_{c\in C} z_{cr_1}} - \frac{\sum_{c\in C} y_c z_{cr_2}}{\sum_{c\in C} z_{cr_2}}\right)^2} \qquad \forall\, r_1, r_2 \in R \qquad (29)$$

with, $r_1 \in R_{v_1}, v_1 \in V_{d_1};\ r_2 \in R_{v_2}, v_2 \in V_{d_2}$

$$\phi(v_1, v_2) = \frac{\left|\sum_{c\in C}\left(\sum_{r\in R_{v_1}} q_c z_{cr} - \sum_{r\in R_{v_2}} q_c z_{cr}\right)\right| + \varphi(v_1, v_2)}{l_{v_1 v_2} + \left|t^s_{v_1} - t^s_{v_2}\right| + \left|t^e_{v_1} - t^e_{v_2}\right|} \qquad \forall\, v_1, v_2 \in V \qquad (30)$$

where,

$$\varphi(v_1, v_2) = \begin{cases} 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, v_1, v_2 \in V \qquad (31)$$

$$l_{v_1 v_2} = \sqrt{\left(\frac{\sum_{r\in R_{v_1}}\sum_{c\in C} x_c z_{cr}}{\sum_{r\in R_{v_1}}\sum_{c\in C} z_{cr}} - \frac{\sum_{r\in R_{v_2}}\sum_{c\in C} x_c z_{cr}}{\sum_{r\in R_{v_2}}\sum_{c\in C} z_{cr}}\right)^2 + \left(\frac{\sum_{r\in R_{v_1}}\sum_{c\in C} y_c z_{cr}}{\sum_{r\in R_{v_1}}\sum_{c\in C} z_{cr}} - \frac{\sum_{r\in R_{v_2}}\sum_{c\in C} y_c z_{cr}}{\sum_{r\in R_{v_2}}\sum_{c\in C} z_{cr}}\right)^2} \qquad \forall\, v_1, v_2 \in V \qquad (32)$$

with, $v_1 \in V_{d_1};\ v_2 \in V_{d_2}$

$$\phi(c_o, d_o) = \frac{\varphi(c_o, d_o)}{l_{c_o d_o}} \qquad \forall\ c_o \in C; d_o \in D \qquad (33)$$

where,

$$\varphi(c_o, d_o) = \begin{cases} 2, & \text{if } z_{c_o r_o} = 1; r_o \in R_{v_o}, v_o \in V_{d_o} \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, c_o \in C; d_o \in D \qquad (34)$$

$$l_{c_o d_o} = \sqrt{\left(x_{c_o} - x_{d_o}\right)^2 + \left(y_{c_o} - y_{d_o}\right)^2} \qquad \forall\, c_1, c_2 \in C \qquad (35)$$

And finally, the worst removal operators operate by removing customer nodes from poorly optimized parts of the solution. Specifically, the *worst-customer* removal operator iteratively removes the customer node that renders the worst impact on the objective function from being included in the solution in the first place until exactly q such worst customer nodes are removed. However, the *worst-route* removal operator iteratively selects the route with the least vehicle capacity utilization and subsequently removes customer nodes from the routing unit exactly q customer nodes are removed from the solution. Similarly, the *worst-vehicle* removal operator iteratively selects the delivery vehicle with the least capacity utilization. Consequently, it iterates through its delivery routes until at least q customer nodes are removed. And likewise, the *worst-facility* removal operator iteratively removes the facility with the least capacity utilization and consequently iterates through its delivery vehicles until at least q customer nodes are removed from the solution.

Insertion operators. The goal of an insertion operator is to re-insert the customer nodes back into the solution considering the change in objective function value of the solution from inserting a customer node into the solution, defined as the insertion cost of the customer node. In this work, the ALNS meta-heuristic algorithm employs six insertion operators with three distinct insertion principles: best insertion, greedy insertion, and regret insertion, each with two different insertion measures.

In particular, the best insertion operators iteratively re-insert a randomly selected customer node at its best position until all customer nodes are re-inserted into the solution. In this work, the authors develop a precise and perturbed version of this insertion method: *best-precise* and *best-perturb*. The former employs precise values of insertion cost, while the latter perturbs insertion cost by $\pm 20\%$ thus preventing the same solution from recycling through the iterations.

However, unlike the best insertion operators, the greedy insertion operators iteratively re-insert the customer node with the least insertion cost at its best position in the solution until all customer nodes are re-inserted into the solution. Again, the authors develop a precise and perturb version of this insertion method, wherein *greedy-precise* uses the precise values of insertion cost while *greedy-perturb* perturbs the insertion cost.

Nonetheless, both best and greedy insertion operators are myopic. Thus, to cope with this issue, the authors employ regret insertion operators that iteratively re-insert the customer node with the highest regret cost at its best position until all customer nodes are re-inserted into the solution. This regret cost is the opportunity cost of inserting the customer node at a position other than its best position. More precisely, the regret-k cost is the sum of the opportunity cost of inserting the customer node at 1^{st}, 2^{nd}, 3^{rd}, …, k^{th} best position instead of its best position. To this end, the algorithm employs *regret-2* and *regret-3,* insertion operators.

Local search. After iterating through every j segment ($n \times j$ iterations), the ALNS meta-heuristic algorithm initiates a local search. In doing so, the algorithm further exploits the solution space making minor modifications to fine-tune the solution. In this work, the algorithm employs six such local search operators with three distinct principles of local search: move local search, 2-opt local search, and swap local search, each working on two distinct parts of the solution.

Specifically, the move local search operators iteratively select a node and move it to its best position in the solution. This could be a customer node, as with the *move-customer* local search operator, or a distribution facility node, as is the case with the *move-facility* local search operator. This distinction is necessary since the move-facility operator moves the distribution facility node in every route initiated at this distribution facility.

On the other hand, the 2-opt local search operators iteratively take two random arcs and reconfigure them if it improves the quality of the solution. While the *intra-opt* local search operator is restricted to choosing the two arcs from the same route, the *inter-opt* local search operator must select these two arcs from two different routes.

And finally, the swap local search operators iteratively select two random nodes and swap them into each other's position. In particular, the *swap-customer* local search operator swaps customer nodes. In contrast, the *swap-facility* local search operator swaps distribution facility nodes and the associated delivery vehicles, delivery routes of these delivery vehicles, and customer nodes visited on these delivery routes.

Stopping criteria. Finally, after a total of $n \times k$ iterations, the ALNS algorithm terminates, returning 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 associated Monte-Carlo simulation framework encompassing the ALNS meta-heuristic for LRP. For a comprehensive description of the algorithms and the corresponding Julia code, refer to the GitHub release LML v1.0 (Pahwa, 2022).

4. Case Study

Without loss of generality, this work focuses on the region of southern California, particularly the city of Los Angeles, with a population of 3.3 million. To this end, the authors model last-mile distribution operations for an e-retailer operating in this region with a distribution structure encompassing a regional distribution facility located in San Bernardino, 50 miles east of downtown LA, along with primary and secondary distribution facilities located strategically in the region.

The e-retailer sorts packages for an overnight (off-hours) delivery to specific primary distribution facilities using a heavy-duty delivery vehicles. At these primary distribution facilities, each equipped with a fleet of medium-duty delivery vehicles, the e-retailer further sorts packages, some for a direct delivery to the customer, and others for a delivery from one of the secondary distribution facilities, by the end of the day. These secondary distribution facilities include micro-hubs, each with a fleet of light-duty delivery vehicles for last-mile delivery, and/or collection-points, wherein customers traverse the last-mile to collect packages. Hence, the study considers a typical delivery process to begin at this regional distribution facility.

Considering the configuration of the distribution structure, the distribution strategy could encompass a single-echelon distribution structure with direct deliveries form the primary distribution facilities to the customers' doorstep with a fleet of medium-duty delivery vehicles such as class-5 diesel trucks (DD-C5DT), class-5 electric trucks (DD-C5ET), diesel vans (DD-DV), 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 the secondary distribution facilities, including 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 deploy a hybrid strategy using mobile micro-hubs, i.e., delivery vans coupled with light-duty delivery vehicles such as autonomous delivery robots (MMH-ADR) or unmanned aerial vehicles (MMH-UAV). Refer to Table 1 for a review of vehicle characteristics of the heavy-, medium-, and light-duty vehicles employed in the distribution structures modeled in this work.

Table 1. Vehicle characteristics for certain delivery vehicles in last-mile distribution

Vehicle characteristics	Vehicle type	
Heavy-duty vehicles		
	Class-8 DT	Class-8 ET
Purchase cost [a] ($)	120k	200k*
Capacity (customers per tour)	1800	1800
Range (mi)	1000	500
Speed on rural network (mph)	50	50
Speed on urban network (mph)	15	15
Delivery time at customer (hour)	-	-
Loading time at facility (hour)	1	1
Re-fueling time at station (hour)	0.208	0.9
Re-fueling time at facility (hour)	0.06	0.9
Driver cost [b] ($/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] ($)	80k	45k	150k*	70k*
Capacity (customers per tour)	360	360	360	360
Range (mi)	500	350	150	150
Speed on rural network (mph)	55	55	55	55
Speed on urban network (mph)	20	20	20	20
Delivery time at customer (hour)	0.017	0.017	0.017	0.017
Loading time at facility (hour)	1.8	1.8	1.8	1.8
Re-fueling time at station (hour)	0.083	0.039	0.800	0.534
Re-fueling time at facility (hour)	0.025	0.011	0.800	0.534
Driver cost [b] ($/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] ($)	-	6.5k*	4k*	4k*	-
Capacity (customers per tour)	30	30	1	1	20
Range (mi)	500	30	30	6	500
Speed on rural network (mph)	60	10	1.5	15	60
Speed on urban network (mph)	25	10	1.5	15	25
Delivery time at customer (hour)	0.008	0.008	0.050	0.008	0.008
Loading time at facility (hour)	0.250	0.150	0.008	0.008	0.167
Re-fueling time at station (hour)	0.050	0.121	-	-	0.020
Re-fueling time at facility (hour)	0.050	0.604	0.875	0.493	0.020
Driver cost [b] ($/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, DV: Diesel Van, ET: Electric Truck, EV: Electric Van, LT: Light-duty Truck, PC: Passenger Car
DT re-fueling rate - 10gal/min at re-fueling station, 35gal/min at a 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 light-duty electric vehicles (Nicholas, 2019).
[a] Burke and Miller (2020) [b] Caltrans (2016) [c] AAA (2019) [d] California Air Resource Board (2018)
*Charging infrastructure cost excluded

Note, this work amortizes fixed costs considering last-mile operations for a planning horizon of 10 years, each with 330 working days, with 9 working hours every day. To establish the fixed cost of distribution facilities, the authors employ CoStar (2020) sales and lease data for industrial facilities in southern California, thus estimating facility fixed cost as $\$356.37(x^2 + y^2)^{-0.115}$ per sq. ft. for a distribution facility located at x, y relative to downtown LA. Note, here, the authors estimate the floor space requirement of a distribution facility assuming a consolidation of 0.2 customers per sq. ft. based on interviews and field study experience. Further, for last-mile operations with electric delivery vehicles, this work accounts for fixed costs of installing private charging infrastructure at the distribution facilities in vehicle purchase costs. In particular, the authors assume the e-retailer to re-fuel the electric truck fleet with Level-3 chargers ($20k per charger) while Level-1 chargers re-fuel the light-duty electric delivery vehicles.

Note, the analyses here account for emission costs from last-mile distribution for CO_2, CO, NO_x, and PM emissions in vehicle operational cost, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively (Caltrans, 2017; Marten and Newbold, 2012).

5. Empirical Results

This section presents the empirical results assessing the sustainability of e-commerce last-mile distribution for an e-retailer with a 1% market share, operating in LA, offering expedited service with rush delivery by the end of the day (same-day delivery). Figure 2 presents the last-mile distribution structure for this e-retailer encompassing a regional distribution facility located 50 miles east of downtown LA, potential primary distribution facility locations, potential secondary distribution facilities including micro-hubs and collection-points, and potential customer locations in the service region.

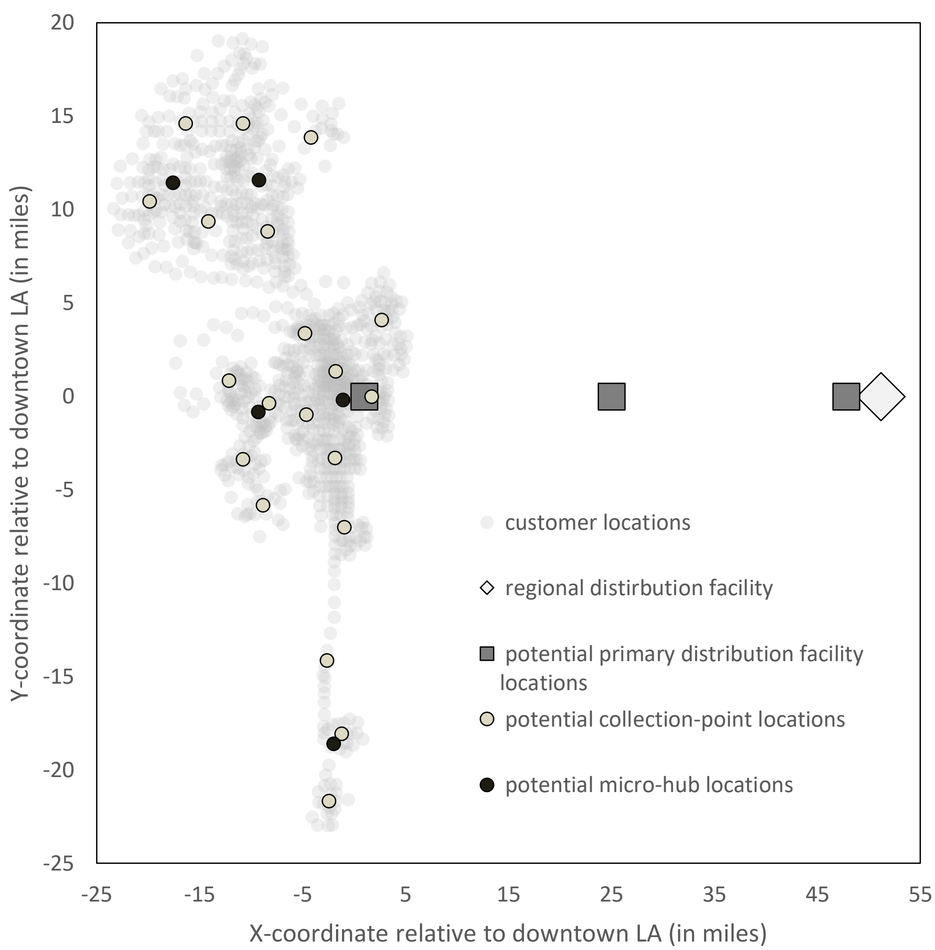
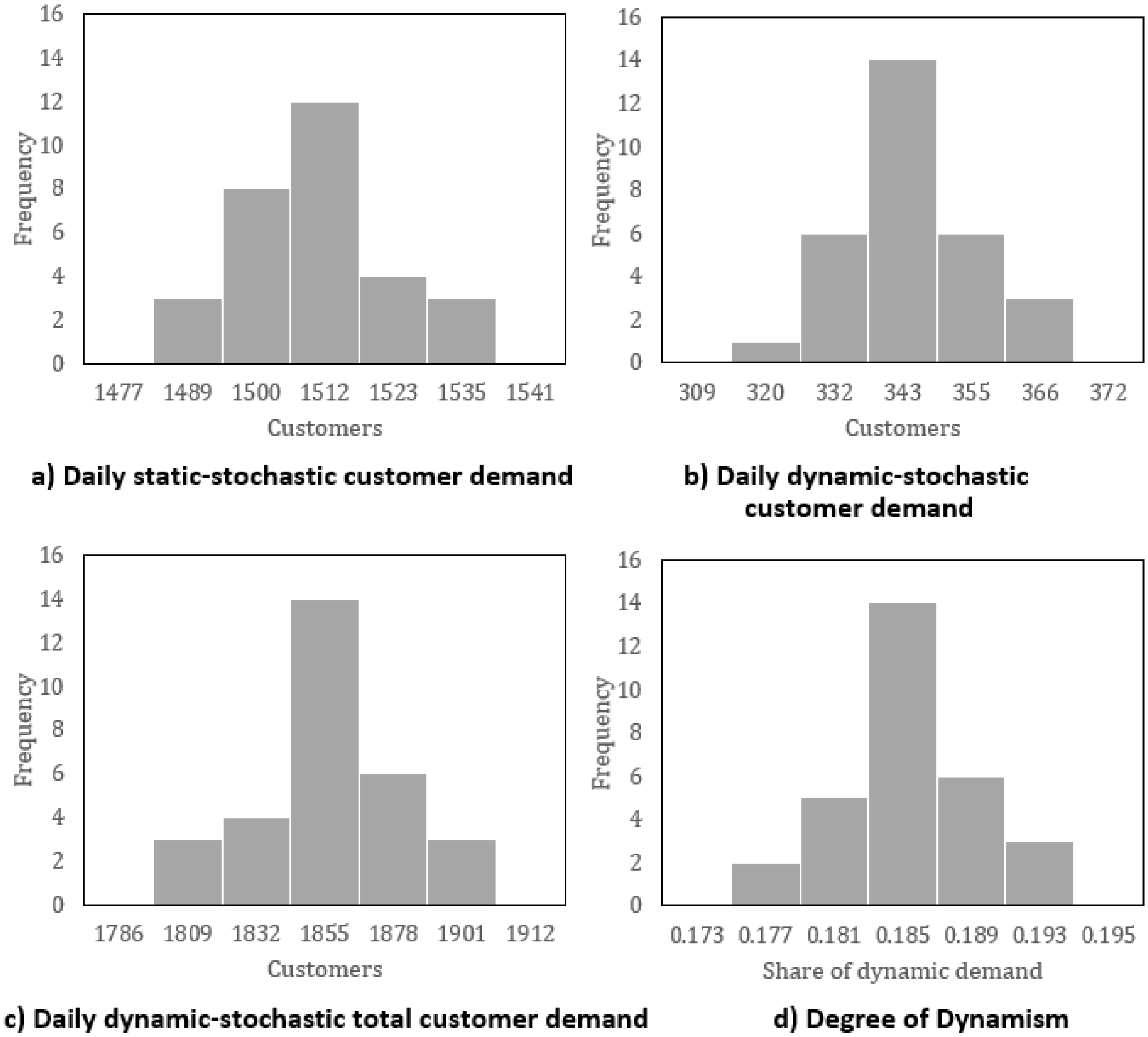


Figure 2. Last-mile distribution structure of the e-retailer

A day's work for this e-retailer includes last-mile operations catering to the static customer demand accrued since the previous working day (Figure 3a) and additional service of dynamic customer demand arriving through the day (Figure 3b). And therefore, for this e-retailer, the authors investigate the opportunities and challenges associated with the different last-mile distribution strategies to cope with daily dynamic-stochastic total customer demand (Figure 3c and 3d). To this end, the authors simulate the decision-making process for this e-retailer with the Monte-Carlo simulation framework encompassing the LMND problem formulated as DS-2E-

C-LRP-TW and addressed with an ALNS metaheuristic algorithm, as discussed above in the Methodology section.



a) Daily static-stochastic customer demand

b) Daily dynamic-stochastic customer demand

c) Daily dynamic-stochastic total customer demand

d) Degree of Dynamism

Figure 3. Daily customer demand

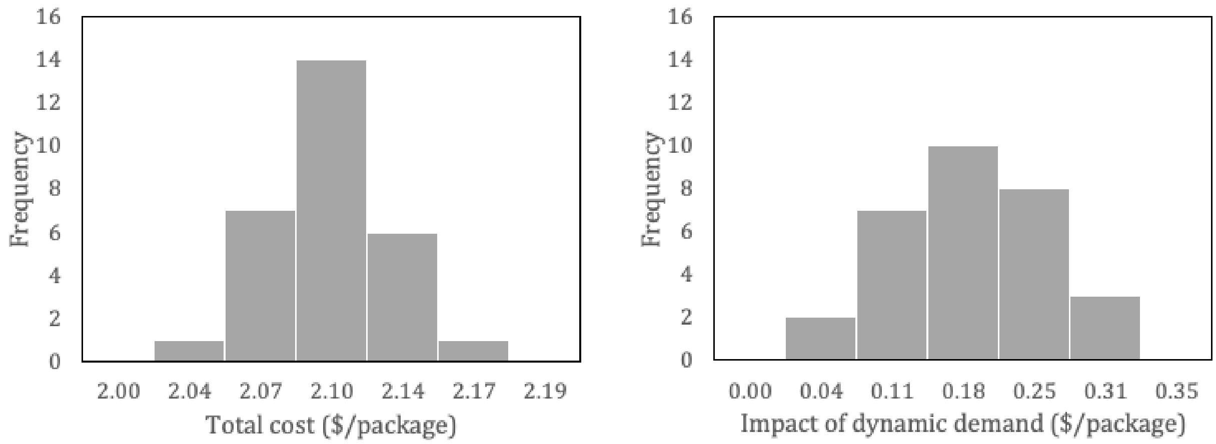
This simulation framework begins with the strategic decision-making process wherein the e-retailer establishes the type, number, and location of the primary and secondary distribution facilities, as well as the size and composition of the associated delivery fleet, to serve the expected customer demand over a planning horizon spanning 10 years. The framework then simulates the tactical 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 associate delivery vehicle fleet. And finally, the simulation framework develops the operational decision-making process wherein the e-retailer fine-tunes the last-mile delivery in every hourlong timeslot in the day considering the dynamic arrival of specific customer requests requiring service by the end of this day. In particular, the authors assume the e-retailer delays route commitments until the last-feasible timeslot to accumulate customer requests and assign them to an uncommitted delivery route. At the end of every timeslot, the e-retailer integrates the new customer requests by inserting these customer nodes into uncommitted delivery routes in a manner that results in the slightest increase in distribution cost keeping the customer-distribution facility allocation fixed.

With this, the authors develop the impact of demand uncertainty on last-mile distribution (Table 2). To this end, the analysis establishes expected distribution cost for each distribution structure with a counterfactual scenario assuming the e-retailer has complete knowledge of the delivery environment. Hereafter, this work develops an operational variance metric, estimating the coefficient of variance of the total cost, to assess the impact of stochastic customer demand. And to investigate the impact of dynamic customer demand, this study develops the value of information metric, comparing the counterfactual scenario with the actual scenario wherein customers arrive dynamically throughout the day.

Table 2. Impact of demand uncertainty on last-mile distribution

Distribution structure	Expected distribution cost	Operational variance	Value of Information
DD-C5DT	\$2.09	1.58%	\$0.14
DD-DV	\$1.95	1.23%	\$0.12
DD-C5ET	\$1.96	1.13%	\$0.11
DD-EV	\$1.84	1.12%	\$0.11
DD-CSLT	\$1.87	0.70%	\$0.12
MH-ECB	\$2.80	3.22%	\$0.21
CP-PC	\$1.85	1.53%	\$0.13
MMH-ADR	\$3.89	0.83%	\$0.21
MMH-UAV	\$2.37	0.85%	\$0.14

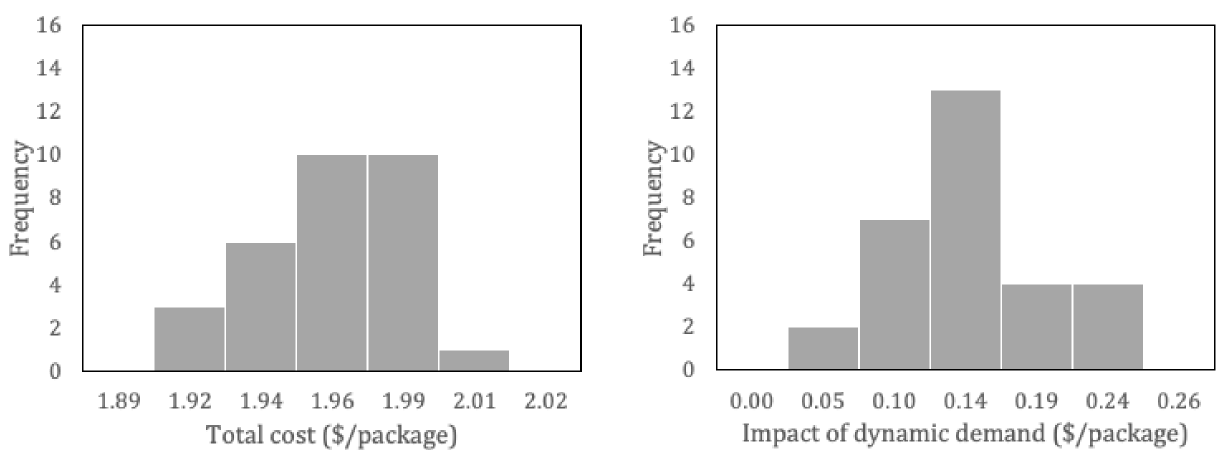
DD-C5DT. Here, the e-retailer establishes a single-echelon distribution structure with direct delivery using a fleet of class-5 diesel trucks operating from a primary distribution facility fulfilled by the regional distribution facility located in San Bernardino with a fleet of class-8 diesel trucks (Figure 4). The strategic decision-making process guides the e-retailer to deploy a fleet of 5 class-5 diesel trucks operating from a primary distribution facility close to downtown LA to cater to the expected demand over the planning horizon. With this, the e-retailer can cater to the daily total customer demand at a total cost of \$2.09 per package, with fixed and operational costs amounting to \$0.78 and \$1.31 per package, respectively. However, owing to the stochastic nature of this customer demand, the e-retailer observes a 1.58% operational variance in distribution costs. Moreover, the dynamic nature of the customer demand further exacerbates the viability of last-mile operations, increasing distribution costs by \$0.14 per package. Note, in such a distribution structure, goods flow from the regional distribution facility to the customers' doorstep renders on average 0.35 miles of distance traveled per package, resulting in 409g of CO_2, 0.3g of CO, 1.6g of NO_x, and 0.05g of PM emissions, thus accruing \$0.17 in emissions cost per package.



a) Total cost per package **b) Value of Information**

Figure 4. Direct delivery with a fleet of class-5 diesel trucks (DD-C5DT)

DD-DV. In contrast, the e-retailer can cater to the daily total customer demand with direct delivery from the downtown LA primary distribution facility using a fleet of diesel vans (Figure 5) at a total cost of only $1.95 per package, with operational costs rendering the most savings. Owing to this lower operational cost of a diesel van fleet compared to a class-5 diesel truck fleet, the stochastic customer demand renders only 1.23% in daily operational variance and $0.12 in additional cost per package, respectively. Further, due to a diesel van's lower emissions rate compared to a class-5 diesel truck, last-mile distribution renders 246g of CO_2, 0.2g of CO, 1g of NO_x, and 0.01g of PM emissions per package. Thus each package accounts for only $0.1 in emissions cost despite requiring a similar 0.35 miles of vehicle travel, as in DD-C5DT.



a) Total cost per package **b) Value of Information**

Figure 5. Direct delivery with a fleet of diesel vans (DD-DV)

DD-C5ET. Unlike with the DD-C5DT, here the e-retailer establishes direct delivery using a fleet of class-5 electric trucks, each with an operating range of 150 miles, operating from a primary distribution facility fulfilled by the regional distribution facility a fleet of class-8 diesel trucks (Figure 6). Yet much like with DD-C5DT, the e-retailer establishes the primary distribution facility next to downtown LA, deploying 5 class-5 electric trucks to cater to the expected customer demand. With this alternate fuel delivery vehicle fleet, the e-retailer can serve the daily total customer demand at a total cost of $1.95 per package with fixed costs as high as $0.88 per package, while operational costs only amounting to $1.07 per package, including $0.03 in tailpipe emissions. These results, therefore, highlight the potential of electric trucks in rendering operational improvements in last-mile delivery despite their higher fixed cost. Due to these operational improvements, the stochastic and dynamic uncertainties in daily customer demand render only as much as 1.13% in daily operational variance and $0.11 in additional distribution cost, respectively. Outsourcing additional electric trucks to cater to this dynamic-stochastic customer demand can significantly affect the viability of last-mile distribution owing to the high rental fee associated with electric trucks.

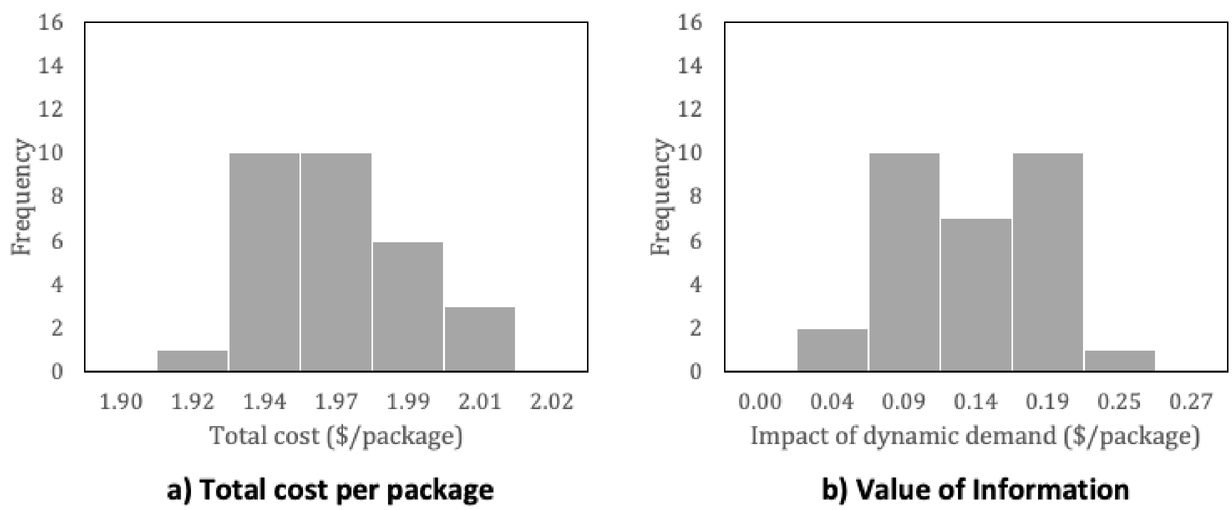
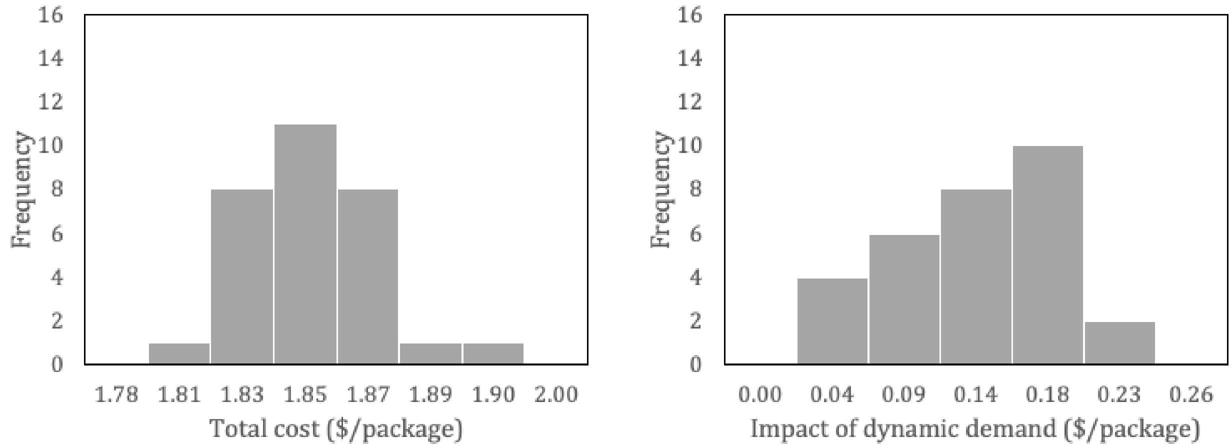


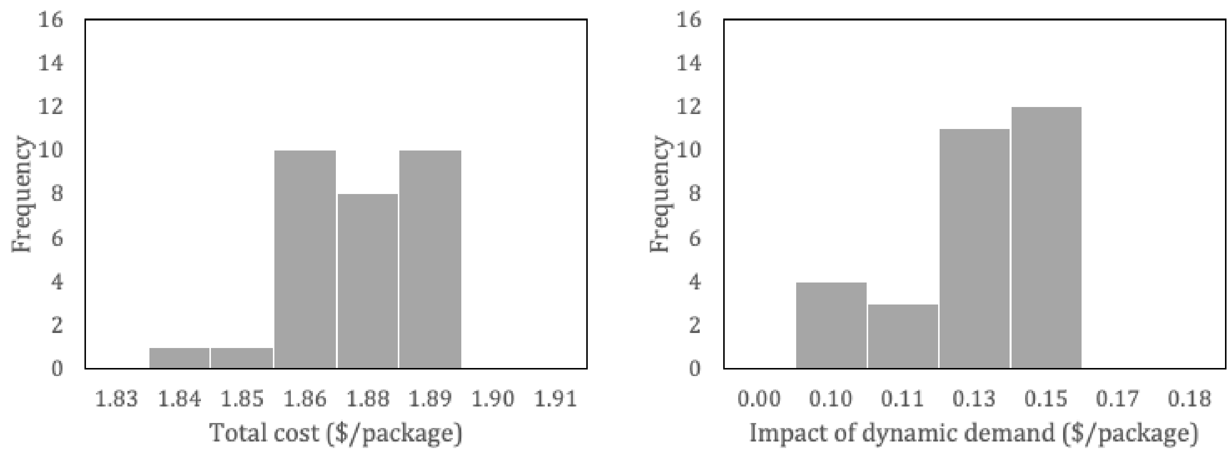
Figure 6. Direct delivery with a fleet of class-5 electric trucks (DD-C5ET)

DD-EV. Similarly, the e-retailer can cater to the daily total customer demand with direct delivery from the downtown LA primary distribution facility using a fleet of electric vans (Figure 7) at a total cost of only $1.84 per package with $0.77 in fixed costs and $1.07 in operational costs including $0.03 in tailpipe emissions. Much like with the class-5 electric truck fleet (DD-C5ET), the operational improvements in last-mile distribution due to using the electric delivery van fleet restrict daily operational variance due to the stochastic customer demand to 1.12% and additional distribution costs due to the dynamic customer demand to $0.11. Further, due to the lower fixed costs of an electric van, outsourcing additional delivery vans to cater to this dynamic-stochastic customer demand does not pose significant viability concerns, as is the case with last-mile distribution using electric trucks (DD-C5ET). These results, therefore, bolster the case for using electric delivery vehicles, especially electric delivery vans, for last-mile delivery.



a) Total cost per package **b) Value of Information**

Figure 7. Direct delivery with a fleet of electric vans (DD-EV)



a) Total cost per package **b) Value of Information**

Figure 8. Direct delivery with crowdsourced fleet of light-duty trucks (DD-CSLT)

DD-CSLT. Here, the e-retailer establishes direct delivery with a fleet of crowdsourced drivers using light-duty trucks to perform last-mile operations operating from a primary distribution facility (Figure 8). Like DD-C5DT and DD-C5ET, the e-retailer fulfills this primary distribution facility using a fleet of class-8 diesel trucks from the regional distribution facility 50 miles east of downtown LA. However, unlike in DD-C5DT and DD-C5ET, the e-retailer here does not own the fleet of delivery vehicles (at the primary distribution facility). Therefore, the e-retailer remunerates these crowdsourced drivers only for their labor at $20/hour while saving on vehicle maintenance and fuel costs. Considering this incentive structure, the authors assume the crowdsourced drivers only perform at most two delivery tours per day for the e-retailer. And thus, to cater to the daily total customer demand, the e-retailer needs a fleet of 63 crowdsourced drivers from the primary distribution facility a mile from downtown LA. This results in a total cost of $1.87 per package, with fixed costs accounting for $0.69 per package and operational costs amounting to $1.18 per package, lower than last-mile delivery with an e-retailer-owned fleet. Further, owing to the flexible nature of crowdsourced delivery, the stochastic and dynamic uncertainties in daily customer demand render only as much as 0.7% in daily operational variance and $0.12 in additional distribution cost, respectively. Nonetheless, owing to the limitations of this light-duty truck fleet, crowdsourcing delivery renders the inefficient flow of goods, with every package necessitating 1.1 miles of vehicle travel resulting in 477g of CO_2 and 1.8g of CO emissions.

MH-ECB. Unlike the above-discussed last-mile distribution strategies, the e-retailer establishes a two-echelon distribution structure with the additional layer encompassing micro-hubs, each with a fleet of cargo bikes (Figure 9). Note, the regional distribution facility fulfills the primary distribution facility using class-8 diesel trucks, and the primary distribution facility fulfills the micro-hub facilities with class-5 diesel trucks. The e-retailer groups the expected customer demand and appropriately locates 5 micro-hub facilities. Thus, the e-retailer can cater to daily total customer demand with this distribution structure. Some customers receive packages via one of the 3 class-5 diesel trucks directly from the primary distribution facility located a mile east of downtown LA. In contrast, other customers receive packages from micro-hubs via one of the 51 cargo bikes. These last-mile delivery operations result in a distribution cost of $2.80 per package with $1.20 in fixed costs and $1.70 in operational costs, both significantly higher than that rendered by the conventional distribution strategy (DD-C5DT), owing to the additional costs of the additional echelon. Fine-tuning last-mile operations to serve the customers arriving dynamically through the day results in an additional distribution cost of $0.21 per package for the e-retailer, with stochastic customer demand rendering as much as 3.2% operational variance in distribution costs. Further, owing to the multi-echelon nature of the distribution structure, each package generates 0.55 vehicle miles traveled, substantially higher than a single-echelon distribution structure. Nonetheless, owing to the use of cargo bikes for last-mile delivery, the tailpipe emissions in such a distribution structure amount to $0.14 per package.

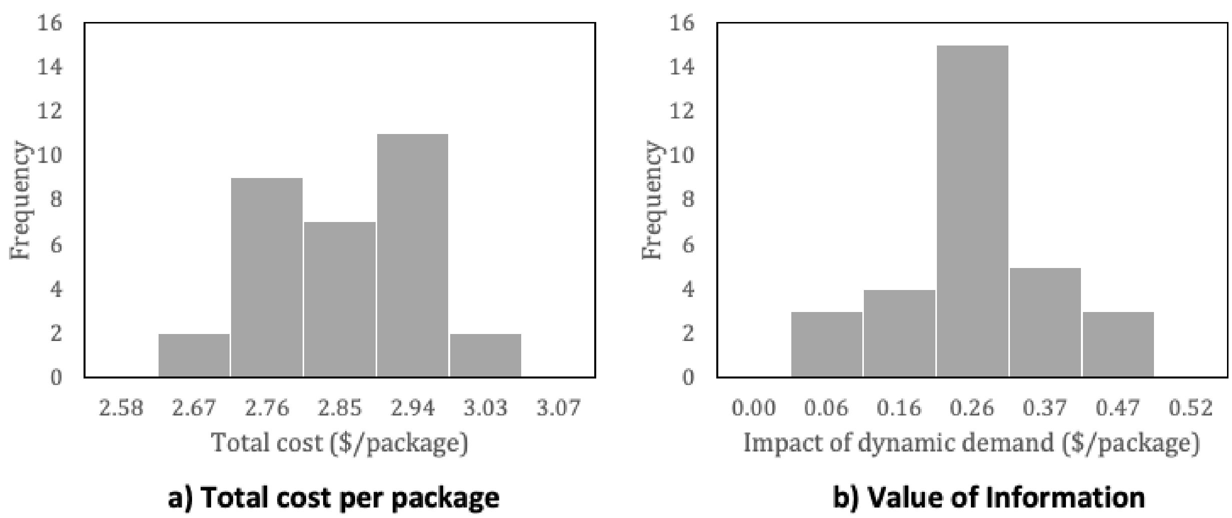


Figure 9. Delivery via micro-hubs using electric cargo bikes (MH-ECB)

CP-PC. Again, the e-retailer establishes a two-echelon distribution structure with the additional layer, including collection points fulfilled by the regional distribution facility via the primary distribution facility (Figure 10). To this end, the e-retailer groups the expected customer demand and appropriately operates 15 potential 20 collection-point facilities. Thus, with this distribution structure, the e-retailer can cater to the daily total customer demand. Note, the author assumes customers must travel at most 5 miles to self-collect packages. Some packages travel directly via one of the 3 class-5 diesel trucks operating from the primary distribution facility near downtown LA, while other customers self-collect packages by driving to collection points. With this, the e-retailer can effectively outsource a segment of the last-mile to the customer and thus cater to its customers at just \$1.85 per package with fixed costs amounting to \$1.05 per package and operational costs accounting for \$0.80 per package. This lower operational cost for last-mile distribution reduces the impact of demand uncertainty (in contrast to DD-C5DT), with stochastic customer demand rendering a 1.5% operational variance in distribution cost, while dynamic customer demand results in an additional \$0.13 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 2.18miles and consequently generating 1029g of CO_2, 2.2g of CO, 2.1g of NO_x, and 0.06g of PM tailpipe emissions that amount to a cost of \$0.27 per package.

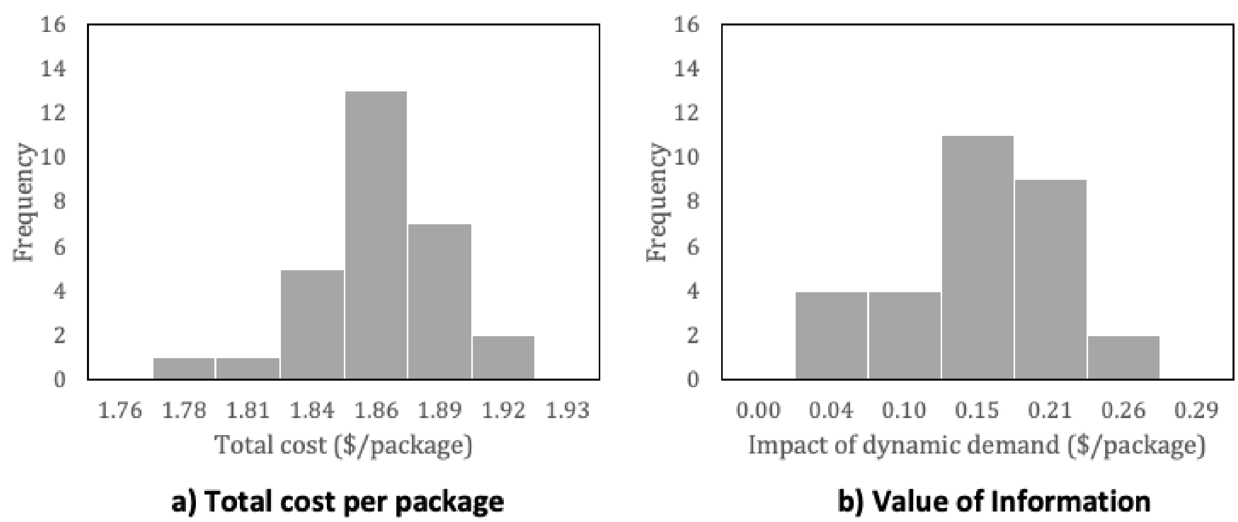
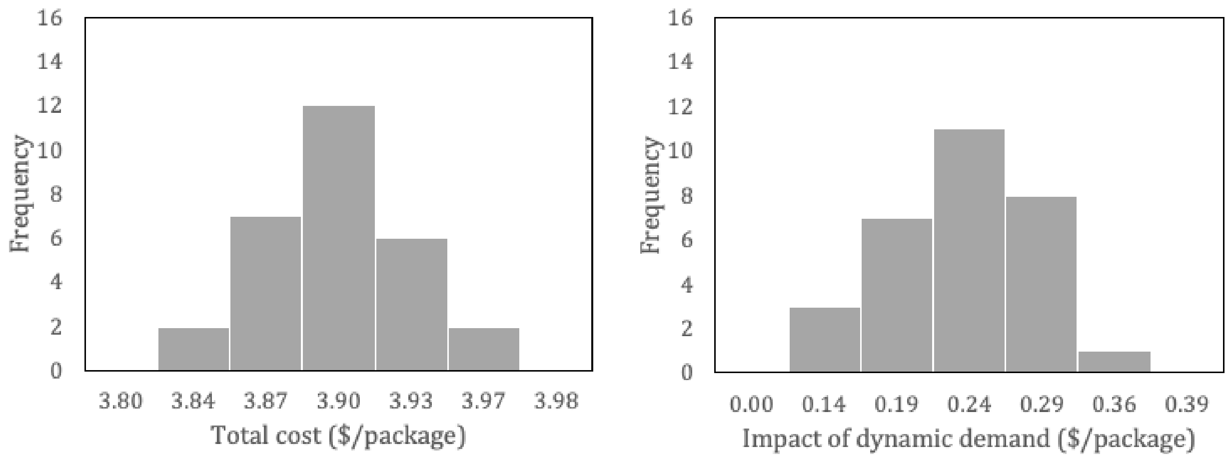


Figure 10. Delivery via collection points with customer pickup (CP-PC)

MMH-ADR. Considering a hybrid distribution strategy, the e-retailer deploys mobile micro-hubs, i.e., delivery vans coupled with autonomous delivery robots (Figure 11). The delivery vans stop at predetermined locations while the delivery robots carry out the last-foot travel. Here, due to the low operating speed of a delivery robot, the e-retailer employs as many as 15 delivery vans (and 45 delivery robots) to cater to the daily total customer demand by the end of the day, thus rendering a total cost of \$3.88 per package with fixed and amounting to \$0.85 per package but operational costs accounting for \$3.03 per package. Further, due to such operational limitations of the delivery robot, the e-retailer observes an additional distribution cost of \$0.21 per package to cater to the customers arriving dynamically through the day.

However, owing to the predetermined nature of delivery van routing, such a distribution strategy absorbs much of the uncertainty. Hence, the e-retailer observes a 0.83% operational variance due to stochastic customer demand. Finally, as far as emissions are concerned, a large chunk of distribution emissions results from the last-mile travel performed by the diesel delivery vans. To this end, the e-retailer can 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. In contrast, delivery robots traverse the last foot.



a) Total cost per package **b) Value of Information**

Figure 11. Delivery via mobile micro-hubs using autonomous delivery robots (MMH-ADR)

MMH-UAV. Much like MMH-ADR, the e-retailer establishes a hybrid distribution strategy with delivery vans acting and stopping at predetermined locations, each coupled with 3 unmanned aerial vehicles traversing the last foot (Figure 12). However, unlike delivery robots, aerial delivery vehicles allow for fast last-foot operations. Therefore the e-retailer employs 6 delivery vans (and 18 aerial delivery vehicles) to cater to the daily total customer demand rendering a total cost of $2.37 per package, with fixed and operational costs accounting for $0.75 and $1.61 per package, respectively. And thus, with aerial delivery vehicles making the last-foot travel, dynamic customers necessitate an additional distribution cost of only $0.14 per package in contrast to $0.21 when delivery robots traverse the last foot instead. However, as is the case with MMH-ADR, this distribution strategy absorbs much of the uncertainty considering the predetermined nature of delivery van routing. Hence, the e-retailer observes an operational variance of 0.85% due to the stochastic nature of the customer demand. Here again, a significant portion of distribution-related emissions stem from the last-mile travel executed by the diesel delivery vans. And as discussed earlier, to address this issue, the e-retailer could opt to utilize electric delivery vans, which can recharge at predetermined stops equipped with suitable charging infrastructure during their idle time as delivery robots cover the last foot of the journey.

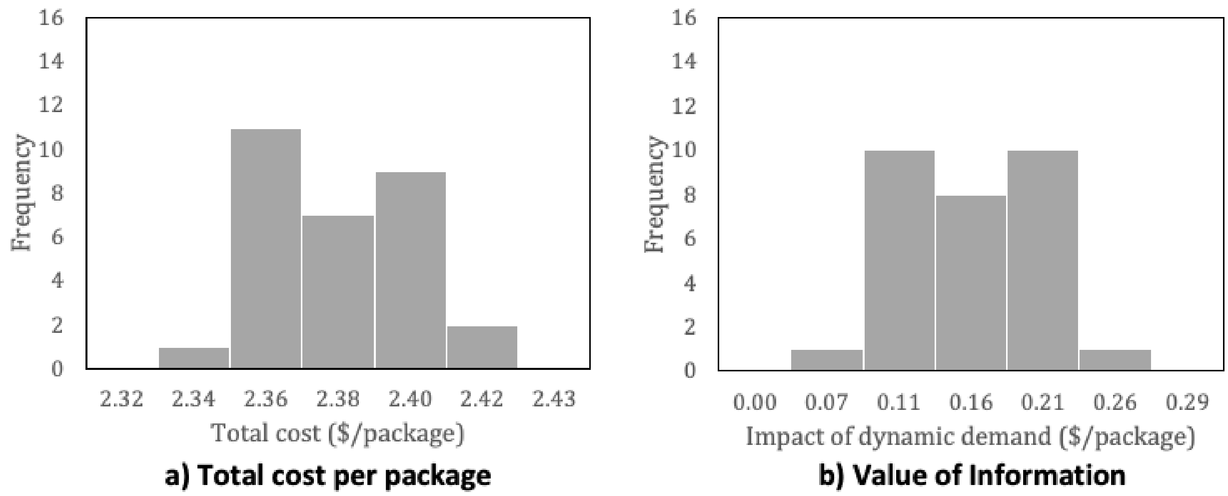


Figure 12. Delivery via mobile micro-hubs using unmanned aerial vehicles (MMH-UAV)

6. Discussion

E-commerce has the potential to provide an economically viable, environmentally efficient, and socially equitable flow of goods. However, as e-retailers compete with traditional retailers for market share by employing consumer-focused service models with expedited and reverse logistics, urban environments witness frequent less-than-truckload last-mile deliveries. This, therefore, results in a substantial increase in freight distribution costs and associated negative externalities, including greenhouse gas emissions advancing global climate change, as well as criteria pollutant emissions worsening local air quality and thus affecting those living close to logistics clusters. Thus, such consumer-focused trends in e-commerce render last-mile distribution economically unviable, environmentally inefficient, and socially inequitable. To this end, alternate last-mile distribution strategies such as those that include the use of electric delivery trucks for last-mile operations, or fleet of crowdsourced drivers for last-mile delivery, or consolidation facilities coupled with light-duty delivery vehicles for a multi-echelon distribution, or collection points for customer pickup, can restore sustainable urban goods flow. Thus, in this work, the authors established opportunities and challenges in e-commerce last-mile distribution for the different distribution structures considering the recent consumer-focused trends in e-commerce. The results of this study have important implications for e-retailers seeking to optimize their last-mile distribution operations and balance cost, reliability, and sustainability.

To begin with, the findings here suggest that last-mile delivery using a fleet of electric delivery trucks can render urban freight with environmentally efficient and socially equitable distribution and an economically viable goods flow compared to last-mile delivery with diesel trucks. These results, therefore, highlight the potential for electric delivery vehicles to render operational improvements in last-mile distribution. However, it is worth considering the potential barriers to adopting electric trucks for last-mile delivery. One of the main challenges is the higher upfront cost of electric delivery vehicles, which can be a deterrent for e-retailer, especially when the e-retailer may need to rent out additional delivery vehicles to cope with demand uncertainty (stochastic and dynamic customer demand).

To this end, the e-retailers can instead crowdsource last-mile delivery to cater to customers arriving dynamically through the day and, in doing so, establish a cost-effective and flexible last-mile distribution structure resistant to demand uncertainty. However, it is essential to note that using independent contractors may result in less reliable performance than company-owned delivery vehicles. To this end, the e-retailer may need to offer higher incentives to drivers to improve reliability. And thus, the e-retailer must carefully consider the relationship between viability and reliability of last-mile distribution when crowdshipping. Moreover, the e-retailer must also consider the potential impact of crowdshipping on environmental efficiency and social equity associated with urban goods flow.

In addition to these single-echelon distribution strategies, this study investigated opportunities and challenges with multi-echelon distribution strategies. One such multi-echelon distribution strategy includes using consolidation facilities and light-duty delivery vehicles. This study found such a distribution strategy less cost-effective and less resistant to demand uncertainty than other distribution strategies due to the additional handling and transportation required to move packages between the consolidation facilities and the final delivery location. Yet, despite this additional goods flow in the urban environment, using cargo bikes for last-mile delivery can substantially reduce exposure to harmful criteria pollutants for individuals living in such dense urban environments.

Nonetheless, to cope with additional handling and transportation costs, the e-retailer can outsource a last-mile segment and have customers collect packages at collection points. This study found the e-retailer to establish cost-effective goods flow and resistance to demand uncertainties. 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 significant traffic generators and mitigate the need for customers to travel further to collect a package.

Further, the authors investigated the potential for using autonomous delivery robots and unmanned aerial delivery vehicles from a delivery van acting as a mobile micro-hub. The results highlight the advantage of aerial delivery vehicles over delivery robots owing to faster last-foot operations. In addition, the authors showcase the potential for such a distribution strategy to absorb uncertainty in last-mile distribution. Nonetheless, issues about theft, damage, privacy, and, more importantly, limited operational range remain, narrowing down the use case of such new and innovative distribution strategies.

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

7. Conclusions

This study developed a last-mile network design (LMND) problem for an e-retailer to configure and optimize distribution structure for last-mile delivery in a service region with a stochastic and dynamic daily customer demand requesting delivery within time windows. To this end, the authors formulated a dynamic-stochastic two-echelon capacitated location routing problem with time windows (DS-2E-C-LRP-TW). Consequently, this work developed a state-of-the-art adaptive large neighborhood search (ALNS) metaheuristic algorithm to address the problem.

In doing so, the authors established a comprehensive analysis of the sustainability of various last-mile distribution structures, considering the recent turn towards consumer-focused trends in e-commerce. This analysis accounted for economic viability, environmental efficiency, and social equity of last-mile distribution with fixed and operational distribution costs. The parameter values employed in this analysis reflect the industry structures, regulations, geographies, urban forms, and consumer behaviors in the Los Angeles region.

However, future work must address this work's limitations to develop a robust understanding of the sustainability of last-mile distribution. Future work must consider intra-route re-fueling for delivery vehicles to model last-mile operations comprehensively. Further, future work must model the willingness of crowdsourced drivers to engage in last-mile delivery and, in doing so, account for any supply constraints in crowdshipping. Similarly, future work can model the willingness of customers to collect package accounting for customers' value of time. Importantly, future work must consider synchronization between the different echelons to model the last-mile operations in a multi-echelon distribution structure thoroughly. Further, considering that this work assessed the sustainability of last-mile distribution accounting for high-probability low-severity fluctuations in the delivery environment, future work can extend this analysis to assess reliability of last-mile distribution accounting for low-probability high-severity disruptions in the delivery environment.

Yet, despite such limitations, this work develops significant insight highlighting the opportunities and challenges in e-commerce last-mile distribution for the different distribution structures considering the recent consumer-focused trends in e-commerce.

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Data Summary

Products of Research

Socio-demographic data - The team used publicly available data from the U.S. Census Bureau. This data generated a synthetic population for the empirical analyses and during model development.

LML v1.0 - The team developed and deployed Julia project LML v1.0.

Data Format and Content

Socio-demographic data. The files used will be saved in Comma-delimited (csv) format.

LML v1.0 - The Julia code will be available in the. jl format.

Data Access and Sharing

The project uses publicly available information. Any dataset compiled during the project using the various data sources follows the same access and sharing policies as the original data. The team will make available the datasets used in this work. The research team does not anticipate the use of any data with private or confidential information. Any other user should reference the research team and this project as directed by the National Center for Sustainable Transportation and the Pacific Southwest Region UTC.

Reuse and Redistribution

Any user should follow the copyright guidelines of the original datasets. For other sets produced by the research team, third-party users should cite the work and email the PI, mjaller@ucdavis.edu, to inform about the use of the data. The data may be cited as follows:

> Pahwa, Anmol; Jaller, Miguel (2023), Coping with the Rise of E-commerce Generated Home Deliveries through Innovative Last-mile Technologies and Strategies, Dryad, Dataset, https://doi.org/10.25338/B8W93S