Assessing Sustainability of E-Commerce Goods Distribution

By

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Executive Summary

E-commerce has the potential to make urban freight sustainable with economically viable, environmentally efficient, and socially equitable goods flow. In particular, considering the current retail landscape, the study finds that with consolidated and optimized delivery tours, e-commerce can render urban goods flow a 12% reduction in vehicle-miles traveled and a 10% reduction in greenhouse gas emissions. Additionally, the study establishes a further 80% reduction in vehicle-miles traveled and an additional 64% reduction in associated greenhouse gas emissions from urban goods distribution for a potential future landscape with e-retail dominating traditional retail.

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, as well as criteria pollutant emissions worsening local air quality and thus affecting those living close to logistics clusters. To address these concerns, the study suggests the use of alternate system-level strategies that offer improved logistics management.

In particular, the author recommends the e-retailer to establish a hybrid distribution structure with a dedicated fleet of medium-duty trucks for last-mile delivery coupled with a crowdsourced fleet that caters to customers arriving dynamically through the day. With this, the e-retailer can establish a cost-effective distribution structure that is resistant to demand uncertainty. However, considering the use of independent contractors for last-mile delivery, the e-retailer must carefully deliberate the relation between sustainability and reliability of last-mile distribution.

Alternatively, the e-retailer can deploy a fleet of electric delivery vehicles to reduce total costs of goods distribution as well as associated negative externalities. However, use of electric delivery fleet can worsen the viability of last-mile distribution, particularly when the e-retailer needs to outsource additional delivery vehicle to cater to the customer demand arriving dynamically through the day.

On the other hand, the e-retailer can establish a multi-echelon last-mile distribution structure with micro-hubs located in dense commercial and residential neighborhoods, and collection-points co-located near major traffic generators. With this, the e-retailer can mitigate some of the additional distribution costs of last-mile delivery via micro-hubs with use of collection-points outsourcing a segment of last-mile to the customer, as well as mitigate some of the negative externalities from the customer-travel for collection-point pickup with use of cargo-bikes for last-mile delivery from micro-hubs. Thus, with strategic use of micro-hubs and collection-points, the e-retailer can provide an economically viable, environmentally efficient, and socially equitable last-mile service that is fairly resistant to demand uncertainty.

With this, the author highlights the need to manage the urban freight system in general, and delivery operations and services in particular, to foster a more sustainable urban environment, in light of the growing consumer-focused trends in e-commerce distribution.

Abstract

The growth of e-commerce, spurred by the internet, has transformed urban goods flow. What would previously have been a trip to a store is now a hassle-free delivery to the home. With consolidated and optimized delivery tours, e-commerce has the potential to make urban goods flow economically viable, environmentally efficient, and socially equitable. However, as e-retailers compete with increasingly consumer-focused service, urban freight witnesses a significant increase in associated distribution costs and 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, considering the potential of e-commerce to render economically viable, environmentally efficient, and socially equitable urban goods flow, it is pertinent to understand the opportunities and challenges associated with urban freight in light of the increasingly consumer-focused e-commerce distribution. To this end, the author develops A) the impact of e-commerce on urban goods distribution, with a simulation framework founded on consumer shopping behavior simulating urban goods flow, B) the impact of key delivery environment parameters on e-commerce goods distribution, with a continuous approximation (CA) framework modeling last-mile distribution operation for an e-retailer, and C) the impact of demand uncertainty on e-commerce goods distribution, with a discrete optimization framework formulating 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 algorithm.

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Contents

List of Abbreviations and Acronyms

ADR	Autonomous Delivery Robot
ALNS	Adaptive Large Neighborhood Search
ATUS	American Time-Use Survey
CA	Continuous Approximation
CB	Cargo-Bike
CP	Collection-Point
DC	Distribution Cost
CP-PC	collection-point pickup with customer using personal car (passenger car)
DD-CSLT	direct delivery with crowdsourced fleet of light-duty trucks
DD-CSPC	direct delivery with crowdsourced fleet of passenger cars
DD-CSMD	direct delivery with crowdsourced fleet of mopeds
DD-CSXX	direct delivery with crowdsourced fleet of light-duty delivery vehicles
DD-CXDT	direct delivery with class-X diesel truck
DD-CXET	direct delivery with class-X electric truck
DDMHCP	direct delivery in addition to delivery via micro-hubs and collection-points
DS-2E-C-LRP-TW	Dynamic-Stochastic Two-Echelon Capacitated Location Routing Problem with Time-Windows
DT	Diesel Truck
EC	Emissions Cost
ET	Electric Truck
FC	Fixed Cost
LMND	Last-Mile Network Design
LRP	Location Routing Problem
LA	Los Angeles
LT	Light-Duty Truck
MD	moped
MH	Micro-Hubs
MH-CB	delivery using micro-hubs coupled with cargo-bikes
MNL	multinomial logit
MSA	Metropolitan Statistical Area
PC	Passenger Car
TC	Transportation Cost
UAV	Unmanned Aerial Vehicles
VMT	Vehicle-miles Traveled

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1. Introduction

1.1. Motivation

"Attention Shoppers: Internet Is Open" headlined the New York Times article in 1994, declaring the advent of e-commerce (Lewis, 1994). Almost three decades since, online shopping has grown to become a fundamental part of consumer shopping experience. What previously would have been a shopping trip to a 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 only 1.7% of the total retail sales in 2003 (U.S. Census Bureau, 2022). However, in the decade thereafter, the increased internet-use provided opportunities for the retailers to expand market horizon with digital enterprise, and thus, e-commerce sales grew rapidly, contributing to 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.

The 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 (Macharis et al., 2014). It has also expanded consumer access to daily essential commodities for otherwise disadvantaged communities which proved to be critical during the COVID-19 pandemic, thus improving social equity in urban goods flow – 3rd pillar of sustainability (Singh et al., 2021). Further, owing to demand consolidation and optimized delivery tours, e-commerce has enhanced goods distribution efficacy, thereby reducing transportation-related negative externalities from urban goods flow – 2nd pillar of sustainability (Edwards et al., 2010). However, the recent trends in e-retail have a significant impact on the economic viability, environmental efficiency, and social equity of e-commerce last-mile distribution.

Despite the ease of shopping online, in-store shopping is still the preferred channel for daily purchases with online shopping only amounting to 4% of the daily shopping activities (Hofferth et al., 2020). Thus, to compete with traditional retailers for market share, e-retailers establish 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 lenient return policy to compensate for the information mismatch, particularly common in the e-apparel industry. However, such consumer-focused trends in e-commerce result in frequent less-than-truckload last-mile deliveries. To this end, 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. This therefore renders urban goods distribution economically unviable, environmentally inefficient, and socially inequitable (Van Loon et al., 2015). Hence, to remain competitive, e-retailers innovate with alternate last-mile distribution strategies. These alternate strategies, such as those that include use of electric delivery trucks for last-mile operations, or 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 potentially restore sustainable urban goods flow.

1.2. Objectives

Considering the potential of e-commerce to make urban goods flow economically viable, environmentally efficient, and socially equitable, it is pertinent to understand the opportunities and challenges associated with urban goods distribution in light of the increasing consumer-focused trends in e-commerce. To this end, this work investigates sustainability of e-commerce, establishing,

A. the impact of e-commerce on urban goods distribution with a simulation framework founded on consumer shopping behavior simulating urban goods flow,

B. the impact of key delivery environment parameters on e-commerce goods distribution with a continuous approximation (CA) framework modeling last-mile distribution operations for an e-retailer, and

C. the impact of demand uncertainty on e-commerce goods distribution with a discrete optimization framework formulating a last-mile network design (LMND) problem for the e-retailer 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 algorithm.

This study is a consolidation of the author's work undertaken in pursuit of the doctoral degree at University of California, Davis including Jaller and Pahwa (2020), Pahwa and Jaller (2022), and Jaller and Pahwa (In Review).

1.3. Research Significance

Internet is the cornerstone of e-commerce; And with the prevalence of internet access, online shopping has become an integral part of consumer shopping experience, influencing product search, trial, and final purchase. The increasing consumer-focused trends in e-commerce render increased urban goods flow resulting in increase in transportation-related negative externalities worsening air quality, noise levels, and congestion in the cities. Thus, it is imperative to investigate sustainability of urban goods flow. This entails understanding opportunities and challenges pertaining to urban goods distribution and the associated system operations, vehicle technologies, logistics, and land-use planning. To do so, the study quantifies freight activity in terms of logistics cost, greenhouse gas emissions, and criteria pollutant exposure. And in this context, the study explores the potential for alternate distribution strategies to reduce costs and externalities from e-commerce last-mile distribution.

A number of previous studies have investigated the sustainability of e-commerce last-mile distribution. However, several of these studies develop poor estimates of the potential impacts of e-commerce owing to use of crude frameworks modeling the delivery environment. To this end, this study models the delivery environment with a robust multinomial logit model establishing the demand-side, and sophisticated continuous approximation and discrete optimization frameworks establishing the supply-side. And with this, the author explores potential opportunities and challenges associated with urban freight in light of the increasingly consumer-focused e-commerce goods distribution.

Without loss of generality, the author develops analyses for the city of Los Angeles, and with this, the study further advances the efforts to improve goods mobility in California, aligning with the objectives of the California Department of Transportation (Caltrans) for an urban freight system that is competitive yet safe and secure with focus on infrastructure preservation, environmentally stewardship, congestion relief, and innovative technologies and practices, as stated in the California Freight Mobility Plan (CFMP).

1.4. Structure

In the following section, the author discusses relevant literature pertaining to the sustainability of e-commerce, followed by a literature review of the various studies investigating alternate last-mile distribution strategies, and the associated assessment methods. In Methodology section, the author then presents the urban goods flow simulation framework, the last-mile distribution CA framework, and the LMND multi-level decision-making framework. In Section 4, the author develops the case study before presenting the empirical results assessing sustainability of e-commerce last-mile distribution in Section 5. Based on these empirical results, in the penultimate section, the author discusses the key managerial insights and policy implications for the stakeholders involved in urban freight management. This study concludes with a section highlighting the limitations of this work along with future scope in the context of this work.

2. Literature Review

2.1. Sustainability of e-commerce

The increasing prevalence of internet marketplaces, the subsequent consumer-focused service trends, and the consequent transformation of individual shopping behaviors have raised significant concerns pertaining to sustainability of urban goods flow. To this end, the literature has explored paradigms of economic viability, environmental efficiency, and social equity for urban freight distribution.

In this context, some of the earlier works highlighted the potential for online shopping to substitute for individuals traveling for in-store shopping and thereby consolidate 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 its 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 (Figliozzi, 2007; Van Loon et al., 2015; Wygonik and Goodchild, 2011). Thus, to cope with the increasing consumer-focused trends in e-commerce, these e-retailers must make strategic, tactical, and operational improvements to enable sustainable last-mile distribution.

2.2. Alternate last-mile distribution strategies

Conventional last-mile distribution entails door-to-door deliveries using a diesel truck fleet operating from a distant warehouse. Owing to a sizeable payload capacity, these diesel trucks enable the e-retailer to consolidate demand and carry out last-mile distribution operations at low costs. However, to cater to an increasingly consumer-focused market, distribution operations with a fleet of diesel truck necessitates frequent less-than-truckload last-mile deliveries which significantly affect sustainability of goods distribution. To this end, the e-retailer can deploy alternate last-mile distribution strategies to restore sustainability of goods flow.

One such alternate distribution strategy includes use of urban consolidation facilities coupled with use of light-duty delivery vehicles such as electric vans, cargo-bikes, autonomous delivery robots (ADRs), or unmanned aerial vehicles (UAVs) for last-mile delivery, thereby moving medium-duty delivery trucks away from core commercial and residential parts of the city. The literature has showcased the potential for such consolidation strategies to lower the operational costs for the e-retailer as well as reduce the negative effects of freight traffic in the city (Estrada and Roca-Riu, 2017; Isa et al., 2021; Quak and Tavasszy, 2011). However, delivery using such light-duty delivery vehicles has logistical limitations and is therefore specifically feasible for expedited delivery in dense urban environments where service with conventional medium-duty trucks may be difficult (Browne et al., 2011; Lemardelé et al., 2021; Tipagornwong and Figliozzi, 2014a).

Thus, Jaller et al. (2020), Hofer et al. (2020), van Duin et al. (2020), and others alike have explored opportunities and challenges associated with yet another multi-echelon distribution that instead includes use of collection-points to in fact outsource the last-mile travel to the customer, thereby enabling expedited delivery at low costs. In addition, these studies have highlighted the potential for collection-point pickups to reduce the negative externalities associated with urban goods flow if the e-retailer could establish a dense network of lockers located near customers' home or workplace and thereby limit customer-travel to collect packages. Nonetheless, Pahwa and Jaller (In Review) underscored the susceptibility of distribution via collection-points to disruption in last-mile considering the uncertainty pertaining to customers' willingness to collect packages.

Yet, the e-retailer may still outsource the entire last-mile employing a fleet of crowdsourced driver for a low-cost door-to-door expedited delivery service (Arslan et al., 2019; Guo et al., 2019; Pourrahmani and Jaller, 2021). In fact, the literature has emphasized upon the potential for crowdsourced deliveries to reduce negative externalities from last-mile deliveries assuming it does not induce vehicle-use for the purpose of 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 with distribution via collection-points, Pahwa and Jaller (In Review) highlighted that crowdsourced deliveries may also be susceptible to disruptions in last-mile owing to the uncertainty pertaining to driver availability.

Nonetheless, the COVID-19 pandemic has prompted e-retailers to further innovate 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). One such new distribution strategies include use of ADRs and UAVs from a delivery truck functioning as a mobile warehouse carrying high-demand products in anticipation of customer request (anticipatory shipping) to limit product shortages and further reduce customer lead time (Lee, 2017; Singh et al., 2021; Srinivas and Marathe, 2021)

2.3. Assessment Methods

Several studies have investigated sustainability of e-commerce last-mile distribution (Brown and Guiffrida, 2014; Durand and Gonzalez-Feliu, 2012; Shang et al., 2017; Thirumalai and Sinha, 2005; Weise, 2020; Wygonik and Goodchild, 2018). While some of these studies have highlighted the potential opportunities with online shopping to consolidate urban goods flow, equally as many studies have emphasized the potential challenges for e-commerce from increased urban commercial vehicle traffic. However, this literature has largely exaggerated the impact of e-commerce as only a few studies have previously undertaken a sophisticated modeling effort to accurately replicate the delivery environment.

To this end, Continuous Approximation (CA) method estimates delivery environment parameters as continuous density functions thus enabling decision-making when operational parameters may be needed but a precise plan cannot be established. In the context of last-mile operations, Daganzo (1984a) and Daganzo (1984b) pioneered the use of CA method. In particular, Daganzo (1984b) introduced the CA technique to establish the route of a traveling salesman visiting stops located randomly and uniformly in a service region, as in the Traveling Salesman

Problem (TSP), and thus estimated the length of the tour to be proportional to the number of stops and inversely proportional to square root of stop density. Further, Daganzo (1984a) expanded the CA model to establish distance traveled by a fleet of vehicles embarking on last-mile operations in a service region from a distant warehouse with stops located randomly and uniformly in the service region, as in a typical Vehicle Routing Problem (VRP).

Thus, the CA method renders a sound compromise between modeling accuracy and feasibility thereby prompting further use in operations research literature. For instance, Figliozzi (2008) modeled last-mile delivery operations for a service region with non-randomly located stops, while Çavdar and Sokol (2015) modeled these delivery operations for a service region with stops located non-uniformly. In the context of e-commerce last-mile delivery, the CA method has been deployed to model the impact of time-windows on last-mile operations (Figliozzi, 2009), assess the viability of consolidation strategies (Estrada and Roca-Riu, 2017), establish the efficacy of delivery using cargo-bikes (Tipagornwong and Figliozzi, 2014a), evaluate the competitiveness of electric delivery vehicles (Davis and Figliozzi, 2013), develop the use-case for last-mile delivery with ADRs and UAVs (Lemardelé et al., 2021), assess the potential for multi-echelon distribution (Jahangiriesmaili et al., 2017), and much more.

Yet, more sophisticated discrete mathematical models formulating the Location Routing Problem (LRP) enable a more comprehensive decision-making 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 of the 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 to 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 et al., 2016; Rabbani et al., 2019), etc.

Considering the NP-hard nature of the problem, the literature has developed solution algorithms using metaheuristic frameworks including 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), and 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), etc.

For a comprehensive review of transportation studies employing the CA method, interested reader may refer to Ansari et al. (2018). Further, for a comprehensive overview of recent developments in the field of LRPs, interested reader may refer to Prodhon and Prins

(2014), Drexl and Schneider (2015), and Mara et al. (2021).

Considering the objective of this work is to investigate economic viability, environmental efficiency, and social equity of urban goods flow in light of the increasingly consumer-focused service in e-commerce, the author develops

A. a simulation framework founded on consumer shopping behavior simulating urban goods flow – to first establish the impact of e-commerce on urban goods distribution,

B. a CA framework modeling last-mile distribution operations for an e-retailer – to then establish the impact of key delivery environment parameters on e-commerce goods distribution, and,

C. a discrete optimization framework formulating the LMND problem for an e-retailer as DS-2E-C-LRP-TW, addressed using the ALNS metaheuristic algorithm – to establish the impact of demand uncertainty on e-commerce goods distribution.

3. Methodology

3.1. Simulation framework

To estimate the impact of e-commerce on urban goods flow, the author here develops a simulation framework simulating shopping-related travel for a synthetic population with individuals reconstructed using appropriate Categorical distributions (Bernoulli/Multinoulli distribution) consistent with the demographics of the region under study. In particular, this work models consumer shopping behavior as a multinomial logit (MNL) model (equation 3.1.1) using the American Time-Use Survey (ATUS), focusing on the choice of shopping channel, including – to shop exclusively in-store, to shop exclusively online, to shop both in-store as well as online, and no-shopping (Figure 1). Using this consumers' shopping-channel choice model, this study identifies the in-store and online consumers in the synthetic population. And finally, for these individuals, the author estimates the shopping-related travel assuming individuals travel in their personal vehicles to make in-store purchases while a diesel truck performs door-to-door delivery to fulfill purchases made online.

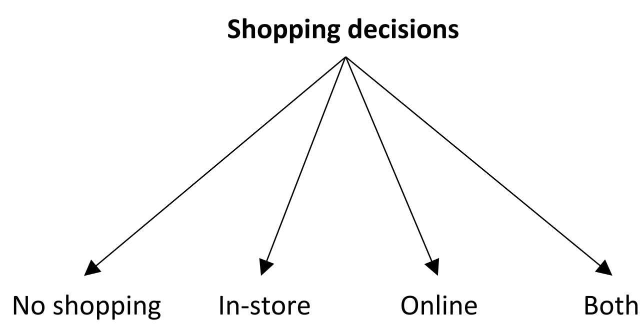


Figure 1. Alternatives for shopping

$$log\left(pr_i/\left(1-\sum_i pr_i\right)\right) = \boldsymbol{\beta_i X} \qquad \forall\ i \in [instore, online, both] \qquad (3.1.1)$$

To this end, this work considers shopping travel statistics depicting a typical in-store and online shopping activity (Figure 2). And thus, for in-store shopping travel, this study first considers the distribution for the number of tours per person per day involving some in-store shopping activity, regardless of whether shopping was the primary purpose or not (Figure 2a). Then, contingent on the number of stops in the tour, the author estimates the length of these tours (Figure 2b and 2c). Finally, to estimate the amount of travel accountable to in-store shopping, this work assumes a share amounting to the fraction of in-store shopping activities in the personal tour consistent with Figure 2d. In doing so, the author establishes the distance traveled by an individual in for a typical in-store shopping activity. On the hand, for online shopping travel, this work considers a typical parcel delivery tour with delivery tour length following Weibull distribution (Figure 2e) and number of stops in this delivery tour following Triangular distribution (Figure 2f). And thus, to account for the travel associated with online shopping, the author assumes a share amounting to distance traveled by a delivery vehicle per delivery stop. In doing so, this work establishes the distance attributable to an online-shopping activity.

Note, the author here develops urban goods flow for the current retail landscape with consumers shopping in-store as well as online (omni-channel), the traditional retail scenario with consumers making all purchases at brick-and-mortar stores (single-channel in-store), and a potential future retail scenario with consumers making only online purchases (single-channel online). To ensure robust estimates, this work develops the simulation framework using Monte-Carlo technique, generating 100 replicates in every simulation. With this, the author establishes the current and potential future impact of e-commerce on urban goods flow in terms of shopping-travel related externalities.

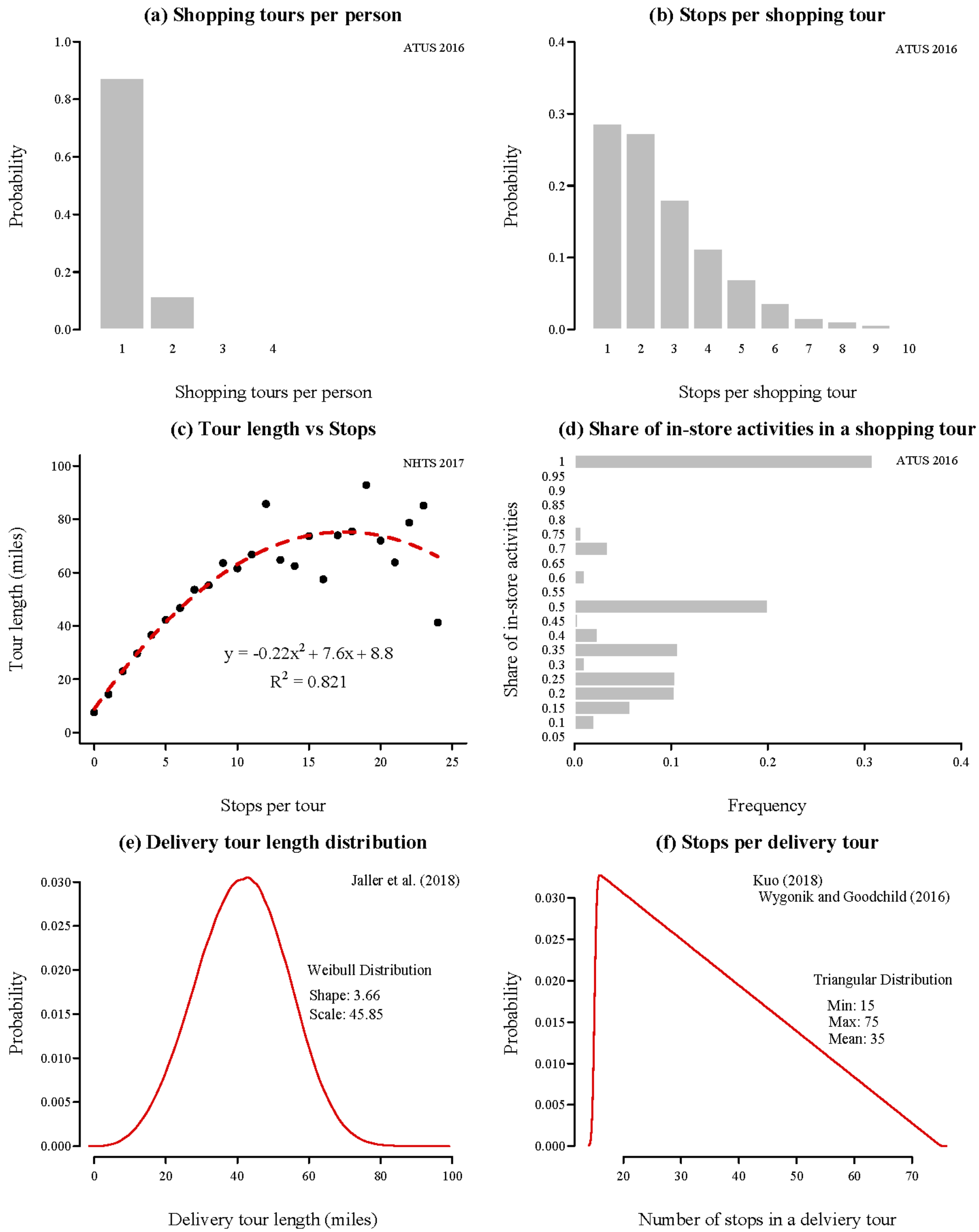


Figure 2. Shopping travel statistics

3.2. Continuous Approximation framework

To establish the impact of key delivery environment parameters on e-commerce goods distribution, the author here employs Continuous Approximation (CA) techniques to model the last-mile distribution operations for an e-retailer with a two-echelon distribution structure (Figure 3) serving n customers in a compact and convex shaped service region, just fitting within $a \times a$ square, in distinct time-periods of length t_{TW}. This distribution structure includes a regional distribution facility that fulfills a primary distribution facility which in turn serves customers and fulfills secondary distribution facilities including n^{MH} micro-hub facilities that deliver a p^{MH} share of packages, and n^{CP} collection-point facilities that cater to a p^{CP} share of customers. Note, the e-retailer positions the regional distribution facility away from the service region at ρ_x', ρ_y' and locates the primary distribution facility closer at ρ_x, ρ_y relative to the center of the service region. As for the secondary distribution facilities, the e-retailer locates micro-hubs and collection-points randomly and uniformly in the service region.

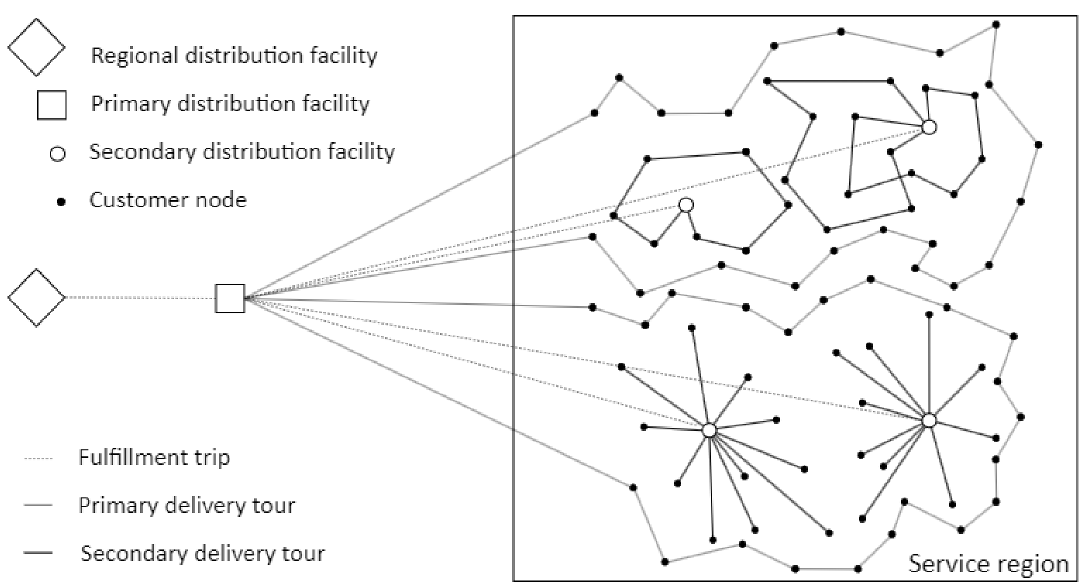


Figure 3. A typical e-retail two-echelon last-mile distribution structure

Thus, distribution operations in this distribution structure include fulfillment trips from the regional facility to the primary facility (tour-type 1), delivery tour from the primary facility serving $n(1 - p^{MH} - p^{CP})$ customers and fulfilling n^{MH} micro-hubs as well as n^{CP} collection-points (tour-type 2), delivery tour from each micro-hub serving a total of np^{MH} customers (tour-type 3), and np^{CP} customers traveling to the nearest collection-point (tour-type 4).

Below is a list of notations of parameters and variables employed in this CA framework.

Sets

E	:	Set of pollutants
I	:	Set of time-periods
J	:	Set of tour-types

Indices

e	:	Pollutant index
i	:	Time-period index
j	:	Tour-type index

Distribution parameters

a	:	Dimension of the smallest square fitting the service region
ρ_x'	:	Location of regional distribution facility along x-axis
ρ_y'	:	Location of regional distribution facility along y-axis
t_{TW}	:	Length of time-window
n	:	Total demand
n_i	:	Customer demand in time-period i
n^{MH}	:	Number of micro-hubs
n^{CP}	:	Number of collection-points
p^{MH}	:	Share of packages served via micro-hubs
p^{CP}	:	Share of packages picked up at collection-points
n_i	:	Total demand in time-period i
δ_i^C	:	Customer density in time-period i
δ^F	:	Density of re-fueling station
ϕ_i	:	Congestion factor in time-period i
w	:	Driver working hours
η	:	Amortization factor
π_D^f	:	Fixed cost of distribution facility operating tour-type j

Vehicle parameters

l_j	:	Range of vehicle operating tour-type *j*
q_j	:	Capacity of vehicle operating tour-type *j*
v_j^r	:	Speed on a rural road of vehicle operating tour-type *j*
v_j^u	:	Speed on an urban road of vehicle operating tour-type *j*
τ_j^C	:	Service time at customer stop of vehicle operating tour-type *j*
τ_j^D	:	Service time at distribution facility of vehicle operating tour-type *j*
ζ_j^D	:	Re-fueling time at distribution facility of vehicle operating tour-type *j*
ζ_j^F	:	Re-fueling time at re-fueling station of vehicle operating tour-type *j*
π_V^f	:	Fixed cost of vehicle operating tour-type *j*
π_V^{ol}	:	Distance-based operational cost of vehicle operating tour-type *j*
π_V^{ot}	:	Time-based operational cost of vehicle operating tour-type *j*

Distribution operation variables

ρ_{ij}	:	Long-haul length for time-period i tour-type *j*
λ_{ij}	:	Long-haul duration for time-period i tour-type *j*
γ_{ij}^D	:	Re-fueling time at distribution facility for time-period i tour-type *j*
γ_{ij}^F	:	Re-fueling time at re-fueling station for time-period i tour-type *j*
Ω_{ij}	:	Frequency of visits to the re-fueling station for time-period i tour-type *j*
l_{ij}	:	Delivery tour length for time-period i tour-type *j*
t_{ij}	:	Delivery tour duration for time-period i tour-type *j*
φ_{ij}^L	:	Binary variable
φ_i^T	:	Binary variable

Decision variables

ρ_x	:	Location of e-commerce fulfillment facility along x-axis
ρ_y	:	Location of e-commerce fulfillment facility along y-axis
f_{ij}	:	Fleet size in time-period i tour-type *j*
m_{ij}	:	Number of delivery tours per vehicle in time-period i tour-type *j*
c_{ij}	:	Total stops in a delivery tour in time-period i tour-type *j*
c_{ij}^C	:	Customer stops in a delivery tour in time-period i tour-type *j*
c_{ij}^{MH}	:	Micro-hub stops in a delivery tour in time-period i tour-type *j*
c_{ij}^{CP}	:	Collection-point stops in a delivery tour in time-period i tour-type *j*

This work assumes the e-retailer to minimize the total cost of distribution monetizing economic viability, environmental efficiency, and social equity for the associated last-mile delivery operations as fixed and operational cost of distribution (equation 3.2.1) subject to customer service constraints (equations 3.2.2 - 3.2.7), vehicle capacity constraints (equation 3.2.8 - 3.2.10), time-window constraints (equation 3.2.11 - 3.2.12), and driver working hours constraints (equation 3.2.13 - 3.2.15).

$$\min \Pi = \sum_{j \in J} \left(\pi_D^f + \pi_V^f \max_i f_{ij} + \sum_{i \in I} \left(\pi_V^{ol} l_{ij} + \pi_V^{ot} t_{ij} \right) m_{ij} f_{ij} \right) \qquad (3.2.1)$$

Subject to,

$$c_{i1} m_{i1} f_{i1} = n_i \qquad \forall\, i \in I \qquad (3.2.2)$$

$$c_{i2}^{C} m_{i2} f_{i2} = n_i (1 - p^{MH} - p^{CP}) \qquad \forall\, i \in I \qquad (3.2.3)$$

$$c_{i2}^{MH} m_{i2} f_{i2} = n^{MH} \qquad \forall\, i \in I \qquad (3.2.4)$$

$$c_{i2}^{CP} m_{i2} f_{i2} = n^{CP} \qquad \forall\, i \in I \qquad (3.2.5)$$

$$c_{i3}^{C} m_{i3} f_{i3} = n_i p^{MH} \qquad \forall\, i \in I \qquad (3.2.6)$$

$$m_{i4} f_{i4} = n_i p^{CP} \qquad \forall\, i \in I \qquad (3.2.7)$$

$$c_{i1} \le q_1 \qquad \forall\, i \in I \qquad (3.2.8)$$

$$c_{i2}^{C} + c_{i2}^{MH} \frac{n_i p^{MH}}{n^{MH}} + c_{i2}^{CP} \frac{n_i p^{CP}}{n^{CP}} \le q_2 \qquad \forall\, i \in I \qquad (3.2.9)$$

$$c_{i3} \le q_3 \qquad \forall\, i \in I \qquad (3.2.10)$$

$$t_{i2} m_{i2} \le t_{TW} \qquad \forall\, i \in I \qquad (3.2.11)$$

$$t_{i3} m_{i3} \le t_{TW} \qquad \forall\, i \in I \qquad (3.2.12)$$

$$\sum_{i \in I} t_{i1} m_{i1} \le w \qquad \forall\, i \in I \qquad (3.2.13)$$

$$\sum_{i \in I} t_{i2} m_{i2} \le w \qquad \forall\, i \in I \qquad (3.2.14)$$

$$\sum_{i \in I} t_{i3} m_{i3} \le w \qquad \forall\, i \in I \qquad (3.2.15)$$

where,

To begin with, delivery vehicles from the regional distribution facility fulfill the primary distribution facility with direct fulfillment trips, stopping at re-fueling stations enroute if needed (tour-type 1). The author thus models the length of this trip in equation 3.2.16 as the distance traveled from the regional to the primary facility including any distance traveled for re-fueling. Further, the model estimates the duration of this fulfillment trip in equation 3.2.17 as the sum of service time loading packages at the regional facility, re-fueling time at the regional facility, travel time, service time unloading packages at the primary distribution facility, and re-fueling time at a re-fueling station, represented by each term in the equation, respectively.

Considering that large part of this fulfillment trip includes travel on highways, this work estimates distances in L_1 metric (equation 3.2.18). Further, owing to the proximity of re-fueling stations to such highways, the author assumes any detours for re-fueling to be small, modeled as constant β. Moreover, the formulation here assumes the delivery vehicle traveling between the regional and primary distribution facility to traverse the fastest path (equation 3.2.19)

Note, the re-fueling time is contingent on the length of the fulfillment trip, number of fulfillment trips per delivery vehicle, and the vehicle range (equation 3.2.20 and 3.2.21). In particular, if the distance traveled by a delivery vehicle on a fulfillment trip exceeds the vehicle range (equation 3.2.22), then the driver must re-fuel the vehicle to a full tank at the regional facility before departing for the primary facility, and enroute, the driver must then re-fuel for the deficit at the nearest re-fueling station. However, if the delivery vehicle can execute a fulfillment trip without having to re-fuel but the total distance traveled on all fulfillment trips exceeds the vehicle range (equation 3.2.23), then the driver must re-fuel the vehicle at the regional facility such that by the end of the day the fuel tank of the delivery vehicle is just about empty.

$$l_{i1} = 2\rho_{i1} + \varphi_{i1}^{L}\beta \qquad \forall\, i \in I \qquad (3.2.16)$$

$$t_{i1} = \tau_1^{D} c_{i1} + \gamma_{i1}^{D} + 2\lambda_{i1} + \tau_1^{D} c_{i1} + \varphi_{i1}^{L}\gamma_{i1}^{F} \qquad \forall\, i \in I \qquad (3.2.17)$$

$$\rho_{i1} = |\rho_x' - \rho_x| + |\rho_y' - \rho_y| \qquad \forall\, i \in I \qquad (3.2.18)$$

$$\lambda_{i1} = \frac{\rho_{i1}}{\phi_i v_1^r} + 2\frac{1}{\phi_i}\left(\frac{1}{v_1^u} - \frac{1}{v_1^r}\right) \times$$

$$\begin{cases} 0 & , \text{ if } \rho_x > \frac{a}{2} \text{ or } \rho_y > \frac{a}{2} \\ \begin{cases} \frac{a}{2} - \rho_x & , \text{ if } \rho_x' > \frac{a}{2} \text{ and } \rho_y' \in \left[\frac{-a}{2}, \frac{a}{2}\right] \\ \frac{a}{2} + \min(-\rho_x, \rho_y) & , \text{ if } \rho_x' > \frac{a}{2} \text{ and } \rho_y' < \frac{-a}{2} \\ \frac{a}{2} + \rho_y & , \text{ if } \rho_x' \in \left[\frac{-a}{2}, \frac{a}{2}\right] \text{ and } \rho_y' < \frac{-a}{2} \\ \frac{a}{2} + \min(\rho_x, \rho_y) & , \text{ if } \rho_x' < \frac{-a}{2} \text{ and } \rho_y' < \frac{-a}{2} \\ \frac{a}{2} + \rho_x & , \text{ if } \rho_x' < \frac{-a}{2} \text{ and } \rho_y' \in \left[\frac{-a}{2}, \frac{a}{2}\right] \\ \frac{a}{2} + \min(\rho_x, -\rho_y) & , \text{ if } \rho_x' < \frac{-a}{2} \text{ and } \rho_y' > \frac{a}{2} \\ \frac{a}{2} - \rho_y & , \text{ if } \rho_x' \in \left[\frac{-a}{2}, \frac{a}{2}\right] \text{ and } \rho_y' > \frac{a}{2} \\ \frac{a}{2} + \min(\rho_x, \rho_y) & , \text{ if } \rho_x' > \frac{a}{2} \text{ and } \rho_y' > \frac{a}{2} \end{cases} & , \text{ if } \rho_x \le \frac{a}{2} \text{ and } \rho_y \le \frac{a}{2} \end{cases} \qquad \forall\, i \in I \qquad (3.2.19)$$

$$\gamma_{i1}^{D} = \varphi_{i1}^{L}\zeta_1^{D} + (1 - \varphi_{i1}^{L})\varphi_{i1}^{T}\frac{\left(\sum_{i \in I} l_{i1} m_{i1} / l_1 - 1\right)}{\sum_{i \in I} m_{i1}}\zeta_1^{D} \qquad \forall\, i \in I \qquad (3.2.20)$$

$$\gamma_{i1}^{F} = (l_{i1}/l_1 - 1)\zeta_1^{D} \qquad \forall\, i \in I \qquad (3.2.21)$$

$$\varphi_{i1}^{L} = \begin{cases} 1, & \text{if } l_{i1} > l_1 \\ 0, & \text{otherwise} \end{cases} \qquad \forall\, i \in I \qquad (3.2.22)$$

$$\varphi_{i1}^{T} = \begin{cases} 1, & \text{if } \sum_{i \in I} l_{i1} m_{i1} > l_1 \\ 0, & \text{otherwise} \end{cases} \qquad \forall\, i \in I \qquad (3.2.23)$$

Upon fulfillment from the regional distribution facility, delivery vehicles from the primary distribution facility depart stopping at $\left[c_{i2}^{C}/\theta\right]^{+}$customer stops each with θ customers, $[c_{i2}^{MH}]^{+}$ micro-hubs, $[c_{i2}^{CP}]^{+}$ collection-points, and at Ω_{i2} re-fueling station(s) if needed, before returning back to the primary distribution facility (tour-type 2). The author estimates the length of this delivery tour in equation 3.2.24, as the sum of the long-haul distance and last-mile distance, represented by each of the two terms in the equation, respectively. While the tour time, given by equation 3.2.25, is the sum of service time loading packages at the primary facility, re-fueling time at the primary facility, long-haul travel time, last-mile travel time, service time delivering packages at customer-stops, service time unloading packages at the secondary distribution facilities, and the re-fueling time, represented by each term in the equation, respectively.

Here, the model estimates the long-haul (travel distance - equation 3.2.26, travel time - equation 3.2.27) by the average distance traveled by a delivery vehicle from the primary distribution facility located at ρ_x, ρ_y to the customers located randomly and uniformly in the service region (refer to Appendix A for more details). On the other hand, the author continuously approximates last-mile proportional to the stops and inversely proportional to the density of stops in the delivery tour. As discussed, the stops on a tour-type 2 delivery tour include customer-stops, micro-hub stops, collection-point stops, and visits to the re-fueling station(s) (established in equation 3.2.28).

Again, the re-fueling time is contingent on the length of the delivery tour, number of delivery tour per delivery vehicle, and the vehicle range (equation 3.2.29 and 3.2.30). In particular, if the length of a delivery tour exceeds the vehicle range (equation 3.2.31), then the driver must re-fuel the vehicle to a full tank at the primary facility before departing for last-mile delivery, and enroute, the driver must then re-fuel for the deficit making visits to the nearest re-fueling station(s). However, if the delivery vehicle can execute a delivery tour without having to re-fuel but the total distance traveled during the day exceeds the vehicle range (equation 3.2.32), then the driver must re-fuel the vehicle at the primary facility such that by the end of the day the fuel tank of the delivery vehicle is just about empty.

$$l_{i2} = 2\rho_{i2} + \frac{k\left(\left[\frac{c_{i2}^{C}}{\theta}\right]^{+} + \left[c_{i2}^{MH}\right]^{+} + \left[c_{i2}^{CP}\right]^{+} + \varphi_{i2}^{L}\Omega_{ij}\right)}{\sqrt{\frac{\delta_i^C}{\theta}(1 - p^{MH} - p^{CP}) + \delta^{MH} + \delta^{CP} + \varphi_{i2}^{L}\delta^{F}}} \qquad \forall\ i \in I \qquad (3.2.24)$$

$$t_{i2} = c_{i2}\tau_2^D + \gamma_{i2}^D + 2\lambda_{i2} + \frac{k\left(\left[\frac{c_{i2}^{C}}{\theta}\right]^{+} + \left[c_{i2}^{MH}\right]^{+} + \left[c_{i2}^{CP}\right]^{+} + \varphi_{i2}^{L}\Omega_{ij}\right)}{\phi_i v_2^u \sqrt{\frac{\delta_i^C}{\theta}(1 - p^{MH} - p^{CP}) + \delta^{MH} + \delta^{CP} + \varphi_{i2}^{L}\delta^{F}}} + c_{i2}^C\tau_2^C + c_{i2}^{MH}\frac{n_i p^{MH}}{n^{MH}}\tau_2^D + c_{i2}^{CP}\frac{n_i p^{CP}}{n^{CP}}\tau_2^D + \varphi_{i2}^L\gamma_{i2}^F \qquad \forall\ i \in I \qquad (3.2.25)$$

$$\rho_{i2} = \begin{cases} |\rho_x| + |\rho_y| \quad , & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| \geq a/2 \\ |\rho_x| + \dfrac{\rho_y^2}{a} + \dfrac{a}{4}, & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| < a/2 \\ \dfrac{\rho_x^2}{a} + |\rho_y| + \dfrac{a}{4}, & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| \geq a/2 \\ \dfrac{\rho_x^2 + \rho_y^2}{a} + \dfrac{a}{2} \quad , & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| < a/2 \end{cases} \qquad \forall\ i \in I \qquad (3.2.26)$$

$$\lambda_{i2} = \begin{cases} \dfrac{|\rho_x| + |\rho_y|}{v^r} + a\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right) \quad , & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| \geq a/2 \\ \dfrac{|\rho_x|}{v^r} + \dfrac{\left(\dfrac{\rho_y^2}{a} + \dfrac{a}{4}\right)}{v^u} + \dfrac{a}{2}\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right), & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| < a/2 \\ \dfrac{\left(\dfrac{\rho_x^2}{a} + \dfrac{a}{4}\right)}{v^u} + \dfrac{|\rho_y|}{v^r} + \dfrac{a}{2}\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right), & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| \geq a/2 \\ \dfrac{\left(\dfrac{\rho_x^2 + \rho_y^2}{a} + \dfrac{a}{2}\right)}{v^u} \quad , & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| < a/2 \end{cases} \qquad \forall\ i \in I \qquad (3.2.27)$$

$$\Omega_{i2} = [l_{i2}/l_2 - 1]^+ \qquad \forall\ i \in I \qquad (3.2.28)$$

$$\gamma_{i2}^D = \varphi_{i2}^L\zeta_2^D + (1 - \varphi_{i2}^L)\varphi_{i2}^T\frac{\left(\sum_{i\in I} l_{i2}m_{i2}/l_2 - 1\right)}{\sum_{i\in I} m_{i2}}\zeta_2^D \qquad \forall\ i \in I \qquad (3.2.29)$$

$$\gamma_{i2}^F = (l_{i2}/l_2 - 1)\zeta_2^D \qquad \forall\ i \in I \qquad (3.2.30)$$

$$\varphi_{i2}^L = \begin{cases} 1, & \text{if } l_{i2} > l_2 \\ 0, & \text{otherwise} \end{cases} \qquad \forall\ i \in I \qquad (3.2.31)$$

$$\varphi_{i2}^T = \begin{cases} 1, & \text{if } \sum_{i\in I} l_{i2}m_{i2} > l_2 \\ 0, & \text{otherwise} \end{cases} \qquad \forall\ i \in I \qquad (3.2.32)$$

Upon fulfillment from the primary distribution facility, delivery vehicles from the micro-hubs (secondary distribution facility) depart stopping at $\left[c_{i3}^{C}/\theta\right]^{+}$customer stops each with θ customers, and at Ω_{i3} re-fueling station(s) if needed, before returning back to the micro-hub (tour-type 3). This work estimates the length of this delivery tour in equation 3.2.33 as the sum of long-haul distance and last-mile distance, represented by each of the two terms in the equation, respectively. On the other hand, the tour time, established in equation 3.2.34, is the sum of the service time loading packages onto the delivery vehicle at the micro-hub, delivery vehicle re-fueling time at the micro-hub, long-haul travel time to the first customer-stop and from the last customer-stop on the delivery tour, last-mile travel time traveling to customer-stops, service time delivering packages at the customer-stop, and re-fueling time, represented by each term in the equation, respectively.

The author estimates the long-haul (travel distance - equation 3.2.35, travel time - equation 3.2.36) by the average distance between a micro-hub and customer-stops using equation 3.2.27 (see Appendix B for more details), while the model continuously approximates the last-mile as a function of number of stops and stop density. Note, the stops on a tour-type 3 delivery tour include customer-stops and visits to the re-fueling station(s) (established in equation 3.2.37).

Further, the model develops re-fueling time for a delivery vehicle operating tour-type 3 (equations 3.2.40 - 3.2.41) analogous to the re-fueling time for a delivery vehicle operation tour-type 2.

$$l_{i3} = 2\rho_{i3} + \frac{k\left(\left[\frac{c_{i3}^{C}}{\theta}\right]^{+} + \varphi_{i3}^{L}\Omega_{i3}^{L}\right)}{\sqrt{\frac{\delta_{i}^{C}}{\theta}(1-p^{MH}) + \varphi_{i3}^{L}\delta^{F}}} \qquad \forall\, i \in I \qquad (3.2.33)$$

$$t_{i3} = c_{i3}^{C}\tau_{3}^{D} + \gamma_{i3}^{D} + 2\lambda_{i3} + \frac{k\left(\left[\frac{c_{i3}^{C}}{\theta}\right]^{+} + \varphi_{i3}^{L}\Omega_{i3}^{L}\right)}{\phi_{i}v_{3}^{u}\sqrt{\frac{\delta_{i}^{C}}{\theta}(1-p^{MH}) + \varphi_{i3}^{L}\delta^{F}}} + c_{i3}^{C}\tau_{i3}^{C} + \varphi_{i3}^{L}\gamma_{i3}^{F} \qquad \forall\, i \in I \qquad (3.2.34)$$

$$\rho_{i3} = \frac{2a}{3\sqrt{n^{MH}}} \qquad \forall\, i \in I \qquad (3.2.35)$$

$$\lambda_{i3} = \frac{\rho_{i3}}{v_{3}^{u}} \qquad \forall\, i \in I \qquad (3.2.36)$$

$$\Omega_{i3} = [l_{i3}/l_{3} - 1]^{+} \qquad \forall\, i \in I \qquad (3.2.37)$$

$$\gamma_{i3}^{D} = \varphi_{i3}^{L}\zeta_{3}^{D} + (1 - \varphi_{i3}^{L})\varphi_{i3}^{T}\frac{\left(\sum_{i\in I} l_{i3}m_{i3}/l_{3} - 1\right)}{\sum_{i\in I} m_{i3}}\zeta_{3}^{D} \qquad \forall\, i \in I \qquad (3.2.38)$$

$$\gamma_{i3}^{F} = (l_{i3}/l_{3} - 1)\zeta_{3}^{D} \qquad \forall\, i \in I \qquad (3.2.39)$$

$$\varphi_{i3}^{L} = \begin{cases} 1, & \text{if } l_{i3} > l_{3} \\ 0, & \text{otherwise} \end{cases} \qquad \forall\, i \in I \qquad (3.2.40)$$

$$\varphi_{i3}^{T} = \begin{cases} 1, & \text{if } \sum_{i\in I} l_{i3}m_{i3} > l_{3} \\ 0, & \text{otherwise} \end{cases} \qquad \forall\, i \in I \qquad (3.2.41)$$

Similarly, upon fulfillment from the primary distribution facility, customers travel to the nearest collection-point (secondary distribution facility) to collect packages (tour-type 4). The author estimates this trip as the average distance from a customer's location to the nearest collection-point (equations 3.2.42 - 3.2.45).

$$l_{i4} = 2\rho_{i4} \qquad \forall\, i \in I \qquad (3.2.42)$$

$$t_{i4} = 2\lambda_{i4} \qquad \forall\, i \in I \qquad (3.2.43)$$

$$\rho_{i4} = \frac{2a}{3\sqrt{n^{CP}}} \qquad \forall\, i \in I \qquad (3.2.44)$$

$$\lambda_{i4} = \frac{\rho_{i4}}{\phi_{i}v_{4}^{u}} \qquad \forall\, i \in I \qquad (3.2.45)$$

3.3. Discrete optimization framework

To establish the impact of demand uncertainty on e-commerce goods distribution, the author here develops a discrete optimization framework modeling a last-mile network design (LMND) problem for an e-retailer with a two-echelon distribution structure (Figure 4) catering to a market with dynamic-stochastic customer demand.

The LMND problem for this e-retailer encompasses distinct strategic, tactical, and operation decision-making processes. In particular, 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 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.

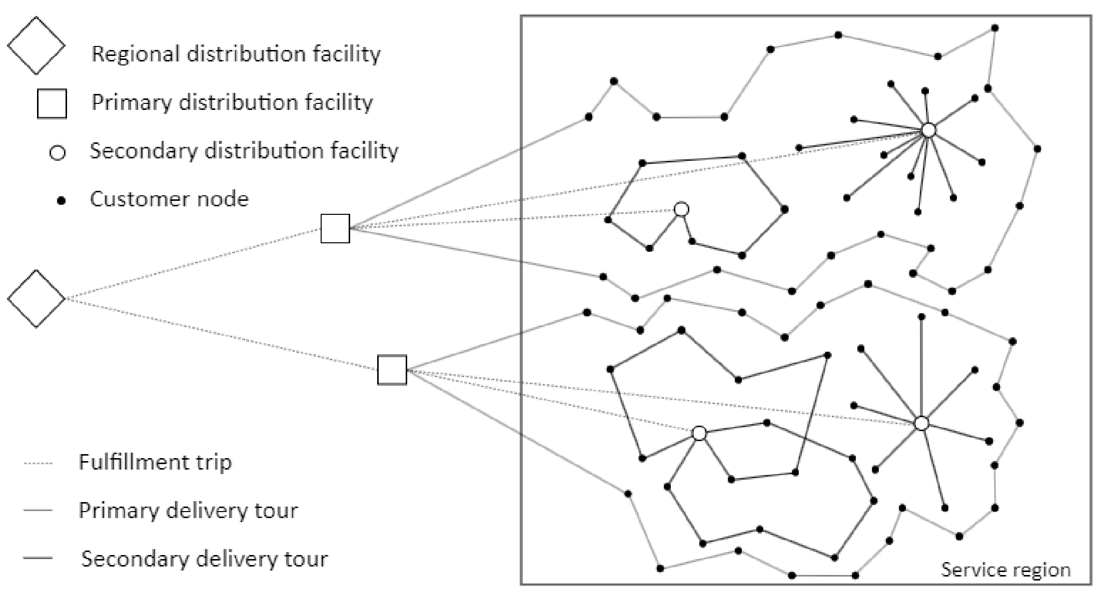


Figure 4. A typical e-retail two-echelon last-mile distribution structure

3.3.1. Formulating the location routing problem (LRP)

All things considered, the author here 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). Below is a list of notations employed in this LRP formulation.

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 tome 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

To begin with, the author here defines 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; 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 time t_d^s and end time t_d^e, fixed cost π_d^f, and operational cost π_d^o per package. Each customer node $c \in C$ has an associated service time τ_c^d and demand q_c which the e-retailer must cater to 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 operation cost π_v^{od} per unit distance and π_v^{ot} per unit time, respectively.

$$\min \Pi = \sum_{p \in P} \left(\pi_p^f + \sum_{s \in S} \pi_p^o f_{ps} + \sum_{v \in V_p} \left(\pi_v^f + \sum_{r \in R_v} \sum_{(i,j) \in A} \pi_v^{od} x_{ij}^r l_{ij} + \pi_v^{ot} (t_v^e - t_v^s) \right) y_v \right) y_p + \sum_{s \in S} \left(\pi_s^f + \sum_{p \in P} \pi_s^o f_{ps} + \sum_{v \in V_s} \left(\pi_v^f + \sum_{r \in R_v} \sum_{(i,j) \in A} \pi_v^{od} x_{ij}^r l_{ij} + \pi_v^{ot} (t_v^e - t_v^s) \right) y_v \right) y_s \qquad (3.3.1)$$

Subject to,

$$\sum_{r \in R} z_{cr} = 1 \qquad \forall\, c \in C \qquad (3.3.2)$$

$$\sum_{j \in H_c} x_{cj}^r = z_{cr} \qquad \forall\, c \in C; r \in R \qquad (3.3.3)$$

$$\sum_{i \in T_j} x_{ij}^r = \sum_{k \in H_j} x_{jk}^r \qquad \forall\, j \in N; r \in R \qquad (3.3.4)$$

$$\sum_{p\in P} f_{ps} = \sum_{v\in V_s}\sum_{r\in R_v}\sum_{c\in C} z_{cr}q_c \qquad \forall\, s\in S \qquad (3.3.5)$$

$$\sum_{c\in C} z_{cr}q_c \le q_v y_v \qquad \forall\, r\in R_v;\, v\in V \qquad (3.3.6)$$

$$\sum_{v\in V_s}\sum_{r\in R_v}\sum_{c\in C} z_{cr}q_c \le q_s y_s \qquad \forall\, s\in S \qquad (3.3.7)$$

$$\sum_{s\in S} f_{ps} + \sum_{v\in V_p}\sum_{r\in R_v}\sum_{c\in C} z_{cr}q_c \le q_p y_p \qquad \forall\, p\in P \qquad (3.3.8)$$

$$t_c^a + M(1-x_{ic}^r) \ge \begin{cases} t_r^s; & i\in D \\ t_i^d; & i\in C \end{cases} + x_{ic}^r\, l_{ij}/s_v \qquad \forall\, i\in T_c;\, c\in C;\, r\in R_v;\, v\in V \qquad (3.3.9)$$

$$t_c^d \ge t_c^a + max(0, t_c^e - t_c^a) + \tau_c^V \qquad \forall\, c\in C \qquad (3.3.10)$$

$$t_c^a \le t_c^l \qquad \forall\, c\in C \qquad (3.3.11)$$

$$t_{r_v^1}^s = t_d^s \qquad \forall\, r_v\in R_v;\, v\in V_d \qquad (3.3.12)$$

$$t_{r_v^k}^s = t_{r_v^{k-1}}^e + \zeta_v^D \textstyle\sum_{(i,j)\in A} x_{ij}^{r_v^k}\, l_{ij}/l_v + \tau_v^d \sum_{c\in C} z_{cr_v^k}\, q_c \qquad \forall\, r_v^{k-1}; r_v^k\in R_v;\, v\in V \qquad (3.3.13)$$

$$t_v^s = t_{r_v^1}^s \qquad \forall\, v\in V \qquad (3.3.14)$$

$$t_v^e = t_{r_v^{\bar{k}_v}}^e \qquad \forall\, v\in V \qquad (3.3.15)$$

$$t_v^e \le min(t_v^s + w_v, t_d^e) \qquad \forall\, v\in V_d;\, d\in D \qquad (3.3.16)$$

$$\sum_{r\in R_v}\sum_{(i,j)\in A} x_{ij}^r\, l_{ij} \le l_v \qquad \forall\, v\in V \qquad (3.3.17)$$

$$f_{ps} \in I^+ \qquad \forall\, p\in P;\, s\in S \qquad (3.3.18)$$

$$x_{ij}^r \in \{0,1\} \qquad \forall\, (i,j)\in A;\, r\in R \qquad (3.3.19)$$

$$y_v \in \{0,1\} \qquad \forall\, v\in V \qquad (3.3.20)$$

$$y_s \in \{0,1\} \qquad \forall\, s\in S \qquad (3.3.21)$$

$$y_p \in \{0,1\} \qquad \forall\, p\in P \qquad (3.3.22)$$

$$z_{cr} \in \{0,1\} \qquad \forall\, c\in C;\, r\in R \qquad (3.3.23)$$

Considering that the goal of a LMND problem is to establish a distribution structure for a sustainable last-mile delivery, this study formulates the LRP with an objective function minimizing the total distribution cost (equation 3.3.1) with economic viability, environmental efficiency, and social equity monetized as fixed and operational cost of distribution, while accounting for customer service constraint (equation 3.3.2), flow constraints (vehicle flow – equations 3.3.3 and 3.3.4, commodity flow – equation 3.3.5), capacity constraints (vehicle capacity – equation 3.3.6, secondary facility capacity – equation 3.3.7, primary facility capacity – equation 3.3.8), customer time-window constraint (equation 3.3.11) with equations 3.3.9 and 3.3.10 establishing arrival and departure time3.3.1 respectively, start and end time constraints (route - equations 3.3.12 and 3.3.13, vehicle – equations 3.3.14 and 3.3.15), driver working hours constraint (equation 3.3.16), and vehicle range constraint (equation 3.3.17). This formulation additionally imposes integer constraint on commodity flow variable in equation 3.3.18, while equation 3.3.19 constraints arc flow variable to be binary. Further, equations 3.3.20 - 3.3.22 enforce binary value on resource-use variables (vehicle-use, secondary facility-use, and primary facility-use), and equation 3.3.23 imposes binary constraint on customer-route allocation variable.

With this LRP formulation, the author replicates the distinct strategic, tactical, and operational decisions encompassing the LMND problem for the e-retailer. In particular, the strategic decisions establish the type, number, and location for 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 facility- and secondary distribution facility- use variables taking values from the strategic stage. And finally, the operational decisions then fine-tune the last-mile delivery considering the dynamic arrival of customer requests through the day. Note, this work assumes a day divided into smaller time slots accepting customer requests for service by the end of the day. The author here assumes the e-retailer to delay route commitments until the last-feasible time-slot to accumulate customer requests and consequently 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 time-slot then, the author assumes the e-retailer to integrate the new customer requests by inserting these customer nodes into such uncommitted delivery routes in a manner that results in least increase in distribution cost keeping the customer-distribution facility allocation fixed. Thus, the simulation iterates through the time-slots with the e-retailer processing route commitments, accumulating customer requests, and subsequently integrating them into the delivery operations for the day. Hence, the decision variables at the operational level are same as that at the tactical level but only limited to customers yet to be served at any point during the day.

3.3.2. Developing the adaptive large neighborhood search (ALNS) metaheuristic

The above developed DS-2E-C-LRP-TW constitutes three subproblems, namely, the facility location problem, customer allocation problem, and vehicle routing problem. Each of the three subproblems is a non-polynomial deterministic hard (NP-hard) combinatorial optimization problem necessitating a heuristic approach. To this end, the author develops an adaptive large neighborhood search (ALNS) metaheuristic algorithm that *searches* through the *neighborhood* by destroying and consequently repairing the solution thereby reconfiguring *large* portions of the solution using specific operators that are chosen *adaptively* in each iteration of the algorithm based on the performance of operators in the previous iterations, hence the name adaptive large neighborhood search (Ropke and Pisinger, 2006). Interested reader may refer to the work of Hendel (2022) for a discussion on recent developments in ALNS. The author here details the specifics of the ALNS metaheuristic algorithm developed in this work.

ALNS parameters

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 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	:	Score if the new solution is unique and better than the best solution
σ_2	:	Score if the new solution is unique and better than the current solution
σ_3	:	Score if the new solution is unique but 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 various supply and demand constraints of the LRP significantly restricts the feasible search space, hence, to enable the ALNS metaheuristic algorithm to comprehensively explore through the search space, the author develops the algorithm to iterate through infeasible solutions. To this end, the algorithm considers 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.

Initial solution. In this work, the ALNS metaheuristic algorithm initiates the search with an initial solution built selecting a random distribution facility node, a random delivery vehicle operating from this distribution facility, a random delivery route for this delivery vehicle, and thereafter 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 metaheuristic algorithm performs n iterations in 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 a removal and an insertion operator that are chosen *adaptively* from a given set of removal operators Ψ_r and insertion operators Ψ_i, respectively, based on the performance of the operators in the previous iterations. Further, after every *j* segments, 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.

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 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^*

Operator selection. In every iteration, the ALNS metaheuristic 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 performance of the operators in improving the quality of the solution.

Operator scoring. In every iteration of the ALNS metaheuristic algorithm, the selected removal operator removes certain customer nodes from the current solution rendering a partial solution and subsequently the selected insertion operator re-inserts these customer nodes into the partial solution to thus develop a new solution. 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 metaheuristic algorithm updates the operator weights using the operator scores accumulated in the segment normalized by operator count and additionally adjusted by a reaction factor ρ, while also accounting for scores accumulated through the previous segments of the algorithm, adjusted by a factor of $(1 - \rho)$. 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 metaheuristic 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 metaheuristic algorithm employs a total of 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 removing customer nodes in a random manner. 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 exactly q customer nodes from such routes. Likewise, the *random-vehicle* removal operator iteratively selects a random delivery vehicle and consequently iterates through its delivery routes 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 the solution has at least q customer nodes 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 thereafter re-inserting such "related" customer nodes together into the solution. Thus, *related-customer* removal operator selects a random pivot customer node and subsequently removes q customer nodes most related to this pivot customer (equation 3.3.24). Further, *related-route* removal operator randomly selects a pivot delivery route and iterates through the most related delivery routes removing exactly q customer nodes from the solution (equation 3.3.27). Similarly, *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 3.3.30). However, *related-facility* removal operator selects a pivot distribution facility node and subsequently removes exactly q customer nodes most related to the pivot customer (equation 3.3.33). Note, the author develops these measures of relatedness heuristically considering the previous use of related removal in the literature.

$$\phi(c_1, c_2) = \frac{|q_{c_1} - q_{c_2}| + \varphi(c_1, c_2)}{l_{c_1 c_2} + |t^s_{c_1} - t^s_{c_2}| + |t^e_{c_1} - t^e_{c_2}|} \qquad \forall\, c_1, c_2 \in C \qquad (3.3.24)$$

where,

$$\varphi(c_1, c_2) = \begin{cases} 4, & \text{if } r_1 = r_2 \\ 3, & \text{else if } v_1 = v_2 \\ 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, c_1, c_2 \in C \qquad (3.3.25)$$

$$l_{c_1c_2} = \sqrt{\left(x_{c_1} - x_{c_2}\right)^2 + \left(y_{c_1} - y_{c_2}\right)^2} \qquad \forall\, c_1, c_2 \in C \qquad (3.3.26)$$

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

$$\phi(r_1, r_2) = \frac{\left|\sum_{c\in C}\left(q_c z_{cr_1} - q_c z_{cr_2}\right)\right| + \varphi(r_1, r_2)}{l_{r_1r_2} + \left|t^s_{r_1} - t^s_{r_2}\right| + \left|t^e_{r_1} - t^e_{r_1}\right|} \qquad \forall\, r_1, r_2 \in R \qquad (3.3.27)$$

where,

$$\varphi(r_1, r_2) = \begin{cases} 3, & \text{else if } v_1 = v_2 \\ 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, r_1, r_2 \in R \qquad (3.3.28)$$

$$l_{r_1r_2} = \sqrt{\left(\frac{\sum_{c\in C} x_c z_{cr_1}}{\sum_{c\in C} z_{cr_1}} - \frac{\sum_{c\in C} x_c z_{cr_2}}{\sum_{c\in C} z_{cr_2}}\right)^2 + \left(\frac{\sum_{c\in C} y_c z_{cr_1}}{\sum_{c\in C} z_{cr_1}} - \frac{\sum_{c\in C} y_c z_{cr_2}}{\sum_{c\in C} z_{cr_2}}\right)^2} \qquad \forall\, r_1, r_2 \in R \qquad (3.3.29)$$

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

$$\phi(v_1, v_2) = \frac{\left|\sum_{c\in C}\left(\sum_{r\in R_{v_1}} q_c z_{cr} - \sum_{r\in R_{v_2}} q_c z_{cr}\right)\right| + \varphi(v_1, v_2)}{l_{v_1v_2} + \left|t^s_{v_1} - t^s_{v_2}\right| + \left|t^e_{v_1} - t^e_{v_2}\right|} \qquad \forall\, v_1, v_2 \in V \qquad (3.3.30)$$

where,

$$\varphi(v_1, v_2) = \begin{cases} 2, & \text{else if } d_1 = d_2 \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, v_1, v_2 \in V \qquad (3.3.31)$$

$$l_{v_1v_2} = \sqrt{\left(\frac{\sum_{r\in R_{v_1}}\sum_{c\in C} x_c z_{cr}}{\sum_{r\in R_{v_1}}\sum_{c\in C} z_{cr}} - \frac{\sum_{r\in R_{v_2}}\sum_{c\in C} x_c z_{cr}}{\sum_{r\in R_{v_2}}\sum_{c\in C} z_{cr}}\right)^2 + \left(\frac{\sum_{r\in R_{v_1}}\sum_{c\in C} y_c z_{cr}}{\sum_{r\in R_{v_1}}\sum_{c\in C} z_{cr}} - \frac{\sum_{r\in R_{v_2}}\sum_{c\in C} y_c z_{cr}}{\sum_{r\in R_{v_2}}\sum_{c\in C} z_{cr}}\right)^2}$$
$$\forall\, v_1, v_2 \in V \qquad (3.3.32)$$

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

$$\phi(c_o, d_o) = \frac{\varphi(c_o, d_o)}{l_{c_od_o}} \qquad \forall\, c_o \in C; d_o \in D \qquad (3.3.33)$$

where,

$$\varphi(c_o, d_o) = \begin{cases} 2, & \text{if } z_{c_or_o} = 1; r_o \in R_{v_o}, v_o \in V_{d_o} \\ 1, & \text{otherwise} \end{cases} \qquad \forall\, c_o \in C; d_o \in D \qquad (3.3.34)$$

$$l_{c_o d_o} = \sqrt{\left(x_{c_o} - x_{d_o}\right)^2 + \left(y_{c_o} - y_{d_o}\right)^2} \qquad \forall\, c_1, c_2 \in C \qquad (3.3.35)$$

And finally, the worst removal operators operate by removing customer nodes from poorly optimized parts of the solution. To be specific, the *worst-customer* removal operator iteratively removes exactly q customer nodes that render the most increase in the objective function value when included in the solution. However, the *worst-route* removal operator iteratively selects the route with least vehicle capacity utilization and subsequently removes exactly q customer nodes from such routes. Similarly, the *worst-vehicle* removal operator iteratively selects the delivery vehicle with least capacity utilization and consequently iterates through its delivery routes until the solution has at least q customer nodes removed. And likewise, *worst-facility* removal operator iteratively removes the facility with 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 metaheuristic algorithm employs a total of six insertion operators with three distinct principles of insertion, namely, best insertion, greedy insertion, and regret insertion, each with two different measures of insertion.

In particular, the best insertion operators iteratively re-insert a randomly selected customer node at its best position in the solution until all customer nodes are re-inserted into the solution. In this work, the author develops a precise and a perturb version of this insertion method, namely, *best-precise* and *best-perturb*, with the former employing precise values of insertion cost, while the latter perturbs insertion cost by $\pm 20\%$ thus preventing the same solution to recycle 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. Here again, the author develops a precise and a 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 in nature, and thus to cope with this issue, the author employs regret insertion operators which iteratively re-insert the customer node with the highest regret cost at its best position in the solution 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, regret-k cost is the sum of opportunity cost of inserting the customer node at 1st, 2nd, 3rd, …, kth best position instead of its best position. To this end, the algorithm employs *regret-2* and *regret-3* insertion operators.

Local search. After every $n \times j$ iterations, the ALNS metaheuristic algorithm initiates a local search. In doing so, the algorithm further exploits the solution space making small modifications to fine-tune the solution. In this work, the algorithm employs a total of six such local search operators with three distinct principles of local search, namely, 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 moves 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 initiating 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 must choose 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 swaps them into each other's position. In particular, the *swap-customer* local search operator swaps customer nodes, while 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 terminate 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 metaheuristic for LRP. For a comprehensive description of the algorithms and the corresponding Julia code, refer to the GitHub release LML v1.0 (Pahwa, 2022).

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 begin with, this work develops a broad understanding of the impacts of e-commerce on urban goods distribution for the city of LA using the simulation framework. Further, for an e-retailer operating in the city of LA, this study then investigates the impact of key delivery environment parameters on e-commerce goods distribution using the CA framework modeling last-mile distribution operations assuming 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. And finally, considering the dynamic and stochastic nature of customer demand, the author establishes the impact of demand uncertainty on e-commerce goods distribution for this e-retailer using the discrete optimization framework with the LMND problem formulated as DS-2E-C-LRP-TW, addressed with the ALNS metaheuristic algorithm.

This study considers a typical delivery process to begin at the regional distribution facility, wherein, the e-retailer sorts packages for an overnight (off-hours) delivery to specific primary distribution facilities using fleet of 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 via one of the secondary distribution facilities. These secondary 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. Additionally, this work assumes the e-retailer to sufficiently stock both primary and secondary distribution facilities to then cater to the requests

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

Vehicle characteristics	Vehicle type					
Heavy-duty vehicles						
						Class-8 DT
Purchase cost [a] ($)						120k
Capacity (customers per tour)						1800
Range (mi)						1000
Speed on rural network (mph)						50
Speed on urban network (mph)						15
Delivery time at customer (hour)						-
Loading time at facility (hour)						1
Re-fueling time at station (hour)						0.208
Re-fueling time at facility (hour)						0.06
Driver cost [b] ($/hour)						35
Maintenance cost [a] ($/mi)						0.19
Fuel cost [c] ($/gal, $/kWh)						3.86
Fuel con. rate [a] (gal/mi, kWh/mi)						0.125
CO_2 emission rate [d] (g/mi)						1592
CO emission rate [d] (g/mi)						0.81
NO_x emission rate [d] (g/mi)						5.55
PM emission rate [d] (g/mi)						0.09
Vehicle characteristics	**Vehicle type**					
Medium-duty vehicles						
	Class-5 ET	Class-5 DT	Class-4 DT	Class-3 DT	Class-2 DT	Class-1 DT
Purchase cost [a] ($)	150k*	80k	66.67k	53.34k	35.56k	26.67k
Capacity (customers per tour)	360	360	300	240	160	120
Range (mi)	150	500	500	500	500	500
Speed on rural network (mph)	55	55	55	55	55	55
Speed on urban network (mph)	20	20	20	20	20	20
Delivery time at customer (hour)	0.017	0.017	0.017	0.017	0.017	0.017
Loading time at facility (hour)	1.8	1.8	1.5	1.2	0.8	0.6
Re-fueling time at station (hour)	0.800	0.083	0.067	0.056	0.048	0.042
Re-fueling time at facility (hour)	0.800	0.025	0.020	0.016	0.014	0.012
Driver cost [b] ($/hour)	35	35	35	35	35	35
Maintenance cost [a] ($/mi)	0.150	0.200	0.225	0.250	0.275	0.300
Fuel cost [c] ($/gal, $/kWh)	0.12	3.86	3.86	3.86	3.86	3.86
Fuel con. rate [a] (gal/mi, kWh/mi)	0.800	0.100	0.080	0.067	0.057	0.050
CO_2 emission rate [d] (g/mi)	0	1049	799	549	496	335
CO emission rate [d] (g/mi)	0	0.77	0.63	0.50	0.53	0.24
NO_x emission rate [d] (g/mi)	0	4.10	3.28	2.42	2.60	0.12
PM emission rate [d] (g/mi)	0	0.130	0.076	0.021	0.020	0.018

Vehicle characteristics	Vehicle type			
Light-duty vehicles				
	LT	PC	MD	CB
Purchase cost [a] ($)	-	-	-	6.5k
Capacity (customers per tour)	30	20	10	30
Range (mi)	500	500	150	30
Speed on rural network (mph)	60	60	60	10
Speed on urban network (mph)	25	25	25	10
Delivery time at customer (hour)	0.008	0.008	0.008	0.008
Loading time at facility (hour)	0.250	0.167	0.050	0.150
Re-fueling time at station (hour)	0.050	0.020	0.002	0.121
Re-fueling time at facility (hour)	0.050	0.020	0.002	0.604
Driver cost [b] ($/hour)	20	20	20	30
Maintenance cost [a] ($/mi)	-	-	-	0.02
Fuel cost [c] ($/gal, $/kWh)	-	-	-	0.12
Fuel con. rate [a] (gal/mi, kWh/mi)	-	-	-	0.029
CO_2 emission rate [d] (g/mi)	386	303	224	0
CO emission rate [d] (g/mi)	1.77	1.09	20.9	0
NO_x emission rate [d] (g/mi)	0.17	0.08	1.14	0
PM emission rate [d] (g/mi)	0.003	0.002	0.002	0

DT: Diesel Truck, ET: Electric Truck, CB: Cargo Bike, LT: Light-duty Truck, PC: Passenger Car, MD: moped
DT re-fueling rate - 10gal/min at re-fueling station, 35gal/min at facility (Environmental Protection Agency, 1993).
Battery recharging infrastructure - Level 3 DC for electric trucks and Level 1 charger for cargo-bikes (Nicholas, 2019).
[a] Burke and Miller (2020) [b] Caltrans (2016) [c] AAA (2019) [d] California Air Resource Board (2018)
*Charging infrastructure cost excluded
This table includes all vehicle types employed in empirical analysis in this work.

that arrive dynamically during the day for service by the end of the day.

Considering the configuration of the distribution structure, the distribution strategy could encompass a single-echelon distribution structure with door-to-door deliveries directly from primary distribution facilities to the customers' doorstep with a fleet of medium-duty delivery vehicles such as class-X diesel trucks (DD-CXDT), class-X electric trucks (DD-CXET), or a crowdsourced fleet of light-duty delivery vehicles (DD-CSXX) including light-duty trucks (DD-CSLT), passenger cars (DD-CSPC), or mopeds (DD-CSMD). Further, the distribution strategy could include a two-echelon distribution structure wherein the e-retailer delivers some packages directly as described above, while others are delivered via secondary distribution facilities such as micro-hubs coupled with cargo-bikes (MH-CB), or collection-points with customers traveling in their personal cars to collect packages (CP-PC). Refer to Table 1 for a review of a vehicle characteristics of the heavy-, medium-, and light-duty vehicles employed in the distribution structures modeled in this work.

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 fixed cost of distribution facilities, the author employs 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 author estimates 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, additionally, in vehicle purchase cost. In particular, the author assumes the e-retailer to re-fuel the electric truck fleet with Level-3 chargers ($20k per charger) while Level-1 chargers collocated at loading/unloading areas re-fuel the cargo-bikes. If needed, electric trucks can also re-fuel at any of the 100 uniformly located public charging stations equipped with Level-3 chargers. Moreover, the analyses accounts for emission costs from last-mile distribution for CO_2, CO, NO_x, and PM emissions in vehicle operational cost, in addition to driver and maintenance cost, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively (Caltrans, 2017; Marten and Newbold, 2012). And finally, the model assumes a consolidation of 3 deliveries per stop ($\theta = 3$).

5. Empirical Results

In this section, the author presents empirical results exploring the potential of e-commerce to render an economically viable, environmentally efficient, and socially equitable urban goods flow.

5.1. Impact of e-commerce on urban goods distribution

To begin with, in this subsection, the author investigates the impact of e-commerce on urban goods distribution in the city of Los Angeles with a simulation framework founded on consumer shopping behavior thus simulating urban goods flow as discussed previously in the Methodology section.

5.1.1. Description of 2016 ATUS data

Here, the author employs the American Time Use Survey (ATUS), a time use study funded by the US Bureau of Labor Statistics, that logs the place and time of all daily activities for participating individuals, providing information on time spent on more than 400 detailed activities. Although the ATUS includes shopping as one of those daily activities, it does not differentiate between in-store and online shopping. In particular, the "shopping" category in ATUS includes "grocery shopping", "purchasing gas", "purchasing food (not groceries)", "shopping except groceries, food, and gas", "comparison shopping", "shopping, not elsewhere classified (N.E.C.)", "researching purchases, N.E.C.", and "consumer purchases, N.E.C." Thus, to distinguish between in-store and online shopping, the author here defines a *shopping activity* as all of the aforementioned shopping activities except "purchasing gas", and "purchasing food (not groceries)" at any place other than *in-store* including "grocery store," "other store/mall," "post office," "restaurant or bar," and "other place." Thus, *in-store shopping activity* pertains to *shopping activities* performed *in-store,* while *online shopping activity* refers to *shopping activities* performed at any place other than *in-store*. Table 2 further clarifies these descriptions and definitions.

Table 2. Definitions for in-store and online shopping activity for ATUS data

	Activity	**Location**
Shopping activity	Grocery shopping Purchasing food (not groceries) Shopping except groceries, food, and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Anywhere Except purchasing food (not groceries) at any place other than grocery store, other store/mall, post office, restaurant or bar, and other place
In-store shopping activity	Grocery shopping Purchasing food (not groceries) Shopping except groceries, food and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Grocery store Other store/mall Post office Restaurant or bar Other place
Online shopping activity	Grocery shopping Shopping except groceries, food, and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Anywhere other than: Grocery store Other store/mall Post office Restaurant or bar Other place

Note, for each participating individual, the ATUS data contains associated demographic information and weights correcting for under- or over- representation. Thus, with appropriate use of data one help discern the underlying individual behaviors. To this end, the author grouped individuals across different age groups, namely, the *Silent Generation* (born from 1925 – 45), *Baby-Boomers* (born from 1946 – 64), *Generation-X* (born from 1965 – 79), *Millennials* (born from 1980 – 94), and *Generation-Z* (born from 1995 – 2012). Further, this study categorized individuals for education levels, including *graduate-level education*, *secondary level education*, *primary-level* *education,* and *no-education*. This work then grouped individuals for family income into *Poverty Level, Low, Lower-Middle, Median, Middle-Middle, Upper-Middle,* and *High* (Amadeo, 2018). Moreover, the author constructed a binary variable *MSA > 1mill* to indicate if an individual lives in a Metropolitan Statistical Area (MSA) with a population greater than 1 million. And finally, this study developed a household variable, *Family Structure*, to represent the ratio of kids to adults in the household of the individual. Table 3 presents a descriptive analysis of the individuals who participated in the 2016 survey along with a summary of consumer demographics by shopping-channel. This table highlights some salient differences between the different shopping-channels, later tested in this work.

However, the author here acknowledges the limitations of such a dataset to comprehensively understand consumer shopping behavior including the associated complementary, substitution, and induced demand effect. In particular, to develop a robust estimate of these effects it is important to consider each shopping category separately. Generalizing substitution or complementary effects over the entire shopping behavior leads to aggregation impacts. For instance, an individual substituting all of his/her shopping activities in all but one category will still exhibit a complementary effect on aggregate. Since the ATUS data does not categorize different shopping activities in detail, it limits our analyses to general substitution and complementary effects. Further, the ATUS data provides a one-day data window, but it does not include what an individual does the next day or beyond. Nevertheless, this study is a step towards understanding the influence of e-commerce on individual shopping behaviors and consequently urban goods flow. For the purpose of this study, the author considers this individual as the unit of analysis.

Table 3. Descriptive statistics for the 2016 ATUS data

		2016 ATUS Data (10493)	**No Shopping** (6227)	**In-Store** (4038)	**Online** (121)	**Both** (107)
Gender	Male	45%	47%	41%	35%	34%
	Female	55%	53%	59%	65%	66%
Age	Silent Generation [77,97] *	15%	15%	14%	9%	8%
	Baby-Boomer [58,76] *	31%	31%	31%	36%	37%
	Generation-X [43,57] *	27%	25%	29%	26%	35%
	Millennials [28,42] *	21%	21%	21%	23%	17%
	Generation-Z [10,27] *	6%	7%	5%	6%	3%
Education level	No education	0%	0%	0%	0%	0%
	Primary	2%	2%	1%	1%	0%
	Secondary	38%	41%	34%	39%	30%
	Graduate	60%	57%	64%	60%	70%
Employment status	Employed	61%	59%	63%	68%	70%
	Unemployed	3%	3%	4%	1%	3%
	Not in labor force	36%	38%	34%	31%	27%
Family income	Poverty Level	23%	25%	20%	21%	20%
	Low	12%	12%	11%	9%	9%
	Lower-Middle	13%	13%	13%	13%	11%
	Median	18%	17%	19%	24%	17%
	Middle-Middle	12%	11%	13%	10%	14%
	Upper-Middle	12%	11%	13%	10%	12%
	High	10%	10%	10%	13%	17%
Mobility related difficulty	Has no difficulty in mobility	96%	95%	98%	97%	99%
	Has difficulty in mobility	4%	5%	2%	3%	1%
Region	Northeast	16%	16%	17%	14%	18%
	Midwest	23%	24%	22%	20%	21%
	South	39%	39%	39%	44%	32%
	West	22%	22%	22%	22%	29%
MSA size	MSA > 1million	53%	52%	53%	56%	64%
Season	Winter	27%	27%	27%	21%	23%
	Spring	25%	25%	25%	21%	28%
	Summer	24%	25%	24%	21%	21%
	Fall	23%	23%	23%	37%	28%

* Age as of 2022

5.1.2. Multinomial Logit model for consumers' shopping-channel choice

The author models consumer's choice of channel for shopping with a weighted multinomial logit model wherein the alternatives include no-shopping (base choice), shopping exclusively in-store, shopping exclusively online, and shopping both in-store as well as online (Table 4). Note, the coefficient estimates in such a multinomial logit model represent the statistically significant effect of the variables on the log of probability of choosing an alternative relative to the probability of the base alternative, however, the model here retains some statistically non-significant variables that form a significant interaction variable. With this, the author draws some salient insights into consumer shopping behavior discussed below.

For in-store shopping, the MNL model indicates that in the high-income group, females have a higher propensity of shopping compared to males. Such an observation is consistent with previous studies, such as Srinivasan and Bhat (2005) and Farag et al. (2005). Similarly, for online shopping, the MNL model again finds females to have a higher propensity for shopping online compared to males, in contrast to Farag et al. (2007). However, this gender gap in the context of online shopping diminishes for those individuals living in large metropolitan regions (MSA > 1million). Further, the model shows females to exhibit a stronger complementarity behavior compared to males, shopping in-store as well as online. And unlike with online shopping, this gender gap for complementarity behavior tends to widen for individuals living a metropolitan region. Yet, this gap tends to lessen with income, as males exhibit a stronger complementarity behavior, engaging more in in-store as well as online shopping with more income at disposal.

Nonetheless, with more kids in the household, the proclivity to shop in-store increases for females, while it decreases for males. On the other hand, the propensity to shop online increases equally for both females and males with more kids in the household, particularly for individuals living in a large metropolitan region. This also highlights the trend towards complementarity behavior with kids in the household as individuals engage in both in-store and online shopping.

Consistent with previous work (Cao et al., 2012; Lee et al., 2017), the MNL model shows education level to positively influence the likelihood of shopping in-store with individuals having a graduate degree exhibit a higher propensity for shopping in-store. Living in a metropolitan region further amplifies the likelihood of shopping, in-store or online, for such individuals.

The results also show seasonal variations in shopping behaviors. Reflecting upon the holiday shopping trends, the model indicates a moderate increase in in-store shopping activity but a more significant increase in online shopping activity in the Fall.

As for the regional variations, the model finds Northeasterners and Southerners living in towns (MSA < 1million) to be more likely to shop in-store compared to their fellow Americans, while Westerns in metropolitan regions have a higher propensity to shop online. Black (2007) discussed such differences in shopping behaviors across the regions in the US.

Finally, considering a higher degree of consumer familiarity for conventional in-store shopping, the model shows elder individuals to exhibit a greater proclivity to shop in-store.

The model also understandably indicates mobility issues to hamper the propensity of shopping in-store.

Table 4. Summary of the multinomial logit model modeling consumers' choice of channel for shopping

Multinomial Logit model: consumer shopping-channel choice			
Alternatives	**Frequency**	**Adjusted Mc Fadden R^2**	
No shopping	0.593	Equally likely based	0.459
Exclusively in-store	0.385	Market share based	0.010
Exclusively online	0.012	**Chi-square test w.r.t. market share model**	
Both	0.010	Chi square value	325.5 (p-value = 0)

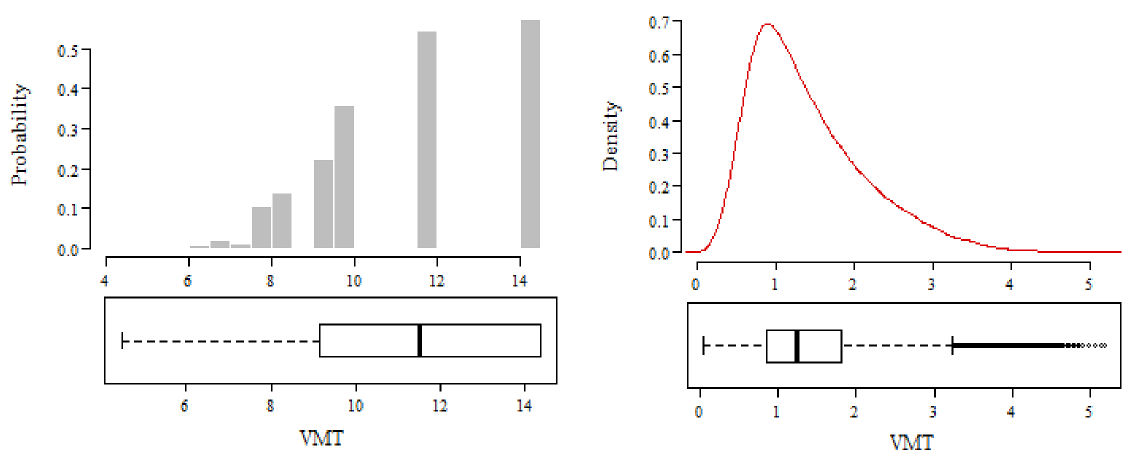
	Estimate, t-values and Significance (respectively)								
Variable	**In-store** (4038)			**Online** (121)			**Both** (107)		
(intercept)	-0.94	(-9.29)	***	-4.93	(-9.52)	***	-6.35	(-9.49)	***
MSA > 1mill	0.07	(0.61)		-0.70	(-1.10)		-0.27	(-0.46)	
Female	0.04	(0.50)		1.09	(2.52)	*	1.40	(2.37)	*
Diff. in Mobility	-0.64	(-5.30)	***	-0.87†	(-1.33)		-2.20†	(-1.75)	.
Family Structure	-0.33	(-1.89)	.	-0.43	(-0.44)		2.54	(3.01)	**
Graduate	0.16	(2.66)	**	-0.39	(-1.33)		-0.31	(-0.96)	
Generation-X	0.17	(3.06)	**	-0.06	(-0.21)		0.70	(2.23)	*
Baby-Boomer	0.20	(3.25)	**	0.44	(1.57)		1.32	(4.04)	***
Silent	0.27	(3.58)	***	0.16	(0.43)		0.82‡	(1.92)	.
Low	-0.18	(-1.54)		0.65	(1.43)		0.92	(1.33)	
Lower-Middle	0.01	(0.08)		0.23	(0.47)		1.05	(1.65)	.
Median	-0.07	(-0.78)		-0.35	(-0.68)		0.34	(0.51)	
Middle-Middle	-0.03	(-0.31)		-1.13	(-1.37)		1.46	(2.58)	**
High	-0.20	(-1.80)	.	-0.37	(-0.66)		1.56	(2.69)	**
Northeast	0.24	(2.32)	*	0.46	(1.02)		-1.58	(-1.56)	
South	0.20	(2.62)	**	0.26	(0.74)		-0.24	(-0.62)	
West	0.10	(1.13)		-0.49	(-0.92)		0.46	(1.14)	
Fall	0.10	(2.06)	*	0.78	(3.93)	***	0.29	(1.31)	
MSA>1mill * Female	0.01	(0.10)		-0.84	(-1.94)	.	0.84	(1.88)	.
MSA>1mill * Fam. Str.	-0.11	(-0.64)		1.77	(2.09)	*	-1.46	(-1.76)	.
MSA>1mill * Graduate	0.20	(2.31)	*	0.84	(2.05)	*	0.57	(1.34)	
MSA>1mill * Northeast	-0.31	(-2.28)	*	-1.06‡	(-1.30)		1.66	(1.53)	
MSA>1mill * South	-0.23	(-2.14)	*	0.69	(1.20)		0.13	(0.24)	
MSA>1mill * West	0.02	(0.14)		1.57	(2.22)	*	-0.33	(-0.59)	
Female * Family Str.	0.69	(3.90)	***	-0.31	(-0.35)		-1.24	(-1.44)	
Female * Low	0.18	(1.24)		-1.67†	(-2.33)	*	-1.1‡	(-1.41)	
Female * Lower-Middle	0.05	(0.38)		-0.58‡	(-0.91)		-2.07‡	(-2.50)	*
Female * Median	0.24	(2.03)	*	0.54	(0.89)		-0.44	(-0.59)	
Female * Middle-Middle	0.18	(1.31)		1.04‡	(1.13)		-1.52‡	(-2.21)	*
Female * High	0.27	(1.81)	.	0.39	(0.54)		-2.04‡	(-2.73)	**

Significant levels: 0% '***' 0.1% '**' 1% '*' 5% '.' 10% ' ' 100%

† Less than 5 observations ‡ Less than 10 observations

5.1.3. Monte-Carlo simulation of shopping-related travel

In this subsection, the author employs the simulation framework to simulate the urban goods flow in the city of LA and establish the impact of e-commerce on urban goods distribution. The simulation framework begins by developing a synthetic population for the city of LA, consistent with the demographics of the region, and consequently deploys the multinomial logit model to identify in-store and online consumers in this synthetic population. For these individuals, the author estimates the shopping-related travel assuming individuals travel in their personal cars to make in-store purchases, while a class-5 diesel truck performs door-to-door delivery to fulfill online purchases. To this end, this work develops typical distance traveled per in-store and online shopping activity (Figure 5) using shopping-travel statistics (Figure 2). With this, the author develops and compares urban goods flow for the traditional retail scenario with only single-channel in-store shopping against the current retail landscape encompassing omni-channel consumer shopping and a potential future retail scenario with only single-channel online shopping. To ensure robust estimates, this work generates 100 replicates for each retail scenario.



a) In-store shopping travel b) Online shopping travel

Figure 5. Distance traveled per in-store and online shopping activity

Table 5 tabulates the results for this Monte-Carlo simulation, while Figure 6 and Figure 7 develop box plots for the same.

Table 5. Impact of e-commerce on externalities in urban goods flow

Externalities	single-channel in-store	omni-channel	single-channel online
VMT	2.804E+07	2.469E+07 (-11.9%)	2.111E+06 (-92.5%)
CO_2	8.495E+09	7.684E+09 (-9.55%)	2.214E+09 (-73.9%)
CO	3.056E+07	2.682E+07 (-12.2%)	1.625E+06 (-94.7%)
NO_x	2.243E+06	3.070E+06 (+36.9%)	8.654E+06 (+286%)
PM	5.607E+04	8.425E+04 (+50.3%)	2.744E+05 (+389%)

To begin with, these results show a substantial decrease in certain externalities in urban goods flow due to e-commerce. In particular, the vehicle-miles traveled in urban goods distribution from point-of-sale to points-of-consumption decrease by about 12% as consolidated delivery trucks fulfilling online purchases replace individual passenger car-travel for in-store purchases. As a consequence, e-commerce also renders a reduction in global greenhouse impact of urban goods flow with a 9.6% reduction in CO_2 emissions. Moreover, with a retail landscape dominated by e-retailers, the vehicle-miles traveled can further reduce by another 80%, thus reducing greenhouse gas emissions by as much as 74%. However, since the trucks are relatively heavy emitters of criteria pollutants, NO_x and PM emissions from urban goods flow increase by 37% and 50% respectively. In fact, such criteria pollutant emissions may undergo a three-fold increase in the future unless tailpipe emissions or truck technologies improve significantly.

While these results showcase potential benefits of e-commerce goods distribution, rush deliveries, an increasingly common service in e-commerce, wipe out any such benefits. As discussed earlier, e-retailers compete with traditional retailers for market share offering lucrative deals to consumers. One of these consumer-focused services includes expedite delivery (e.g.,

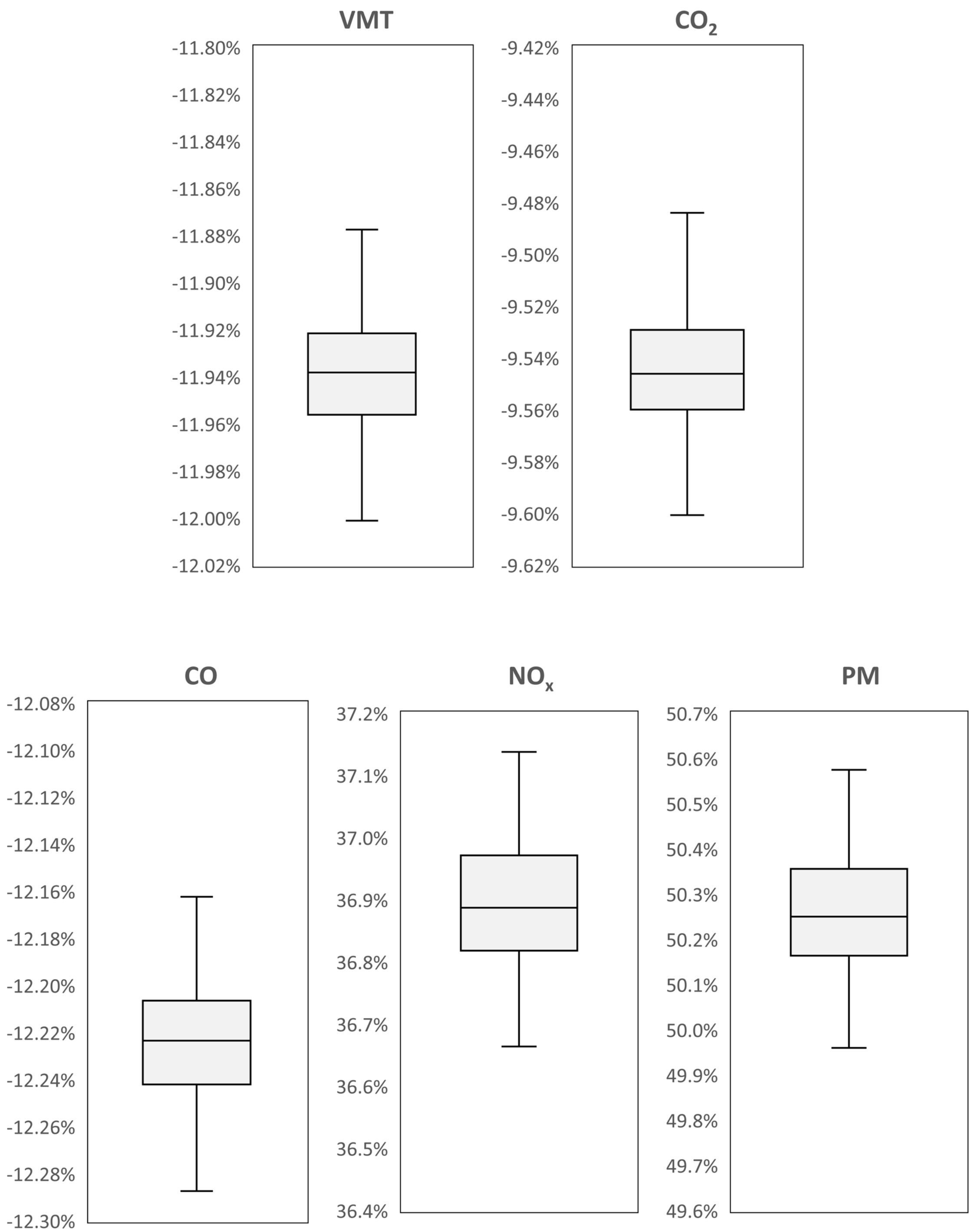


Figure 6. Current impact of e-commerce: omni-channel vs. single-channel in-store

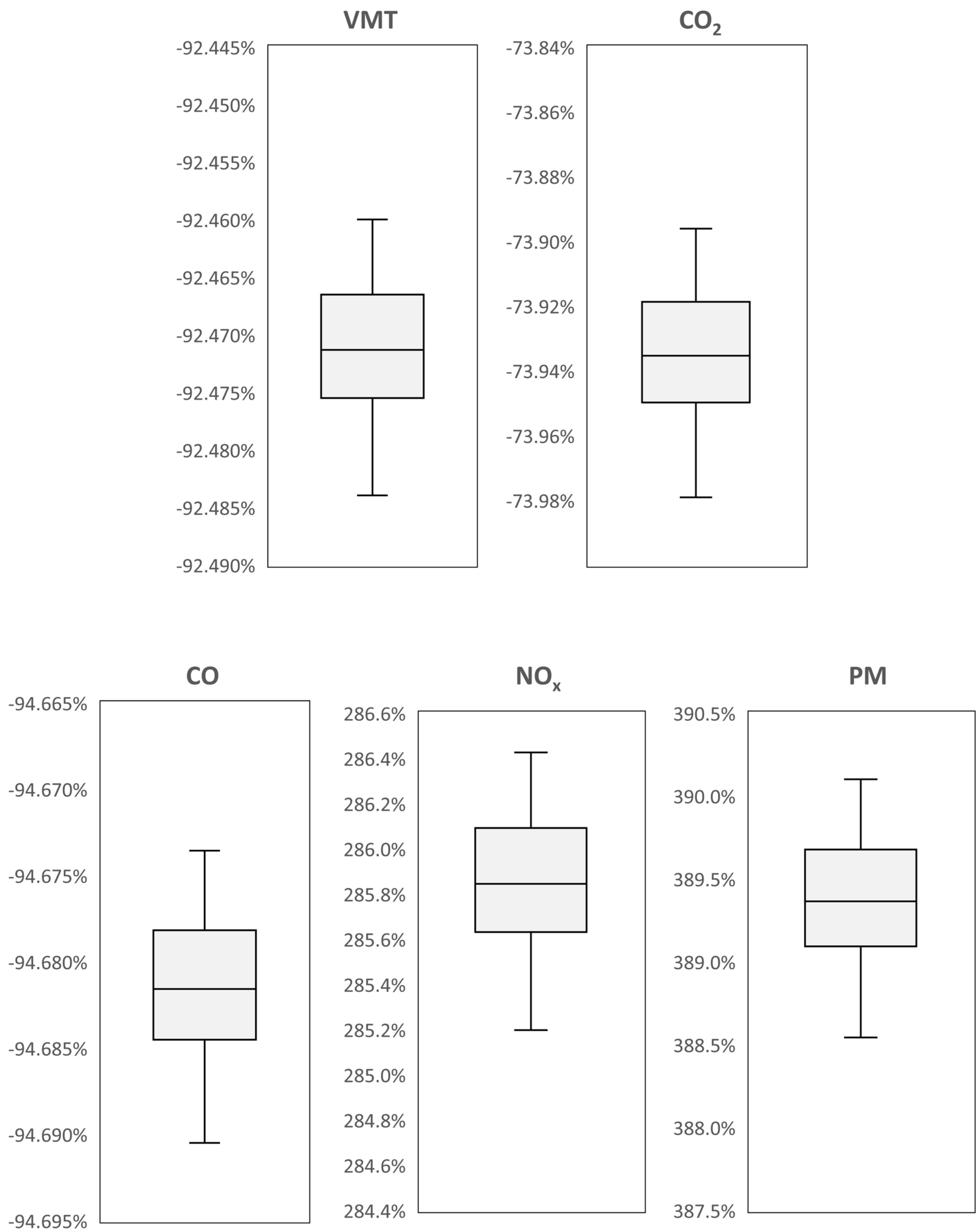


Figure 7. Potential impact of e-commerce: single-channel online vs. single-channel in-store

same day, two-hour, one-hour delivery). Although very complex logistically, some e-retailers have indeed successfully implemented such expedited deliveries for certain products and specific market-segments, with other companies poised to follow. However, expedited delivery services render lower consolidation levels, and therefore increase urban freight flow. Figure 8 presents this increase in freight flow with an exponential increase in freight vehicle-miles traveled as the e-retailer consolidates fewer packages on a delivery truck. However, Lin et al. (2018) test the feasibility of same-day deliveries under different delivery paradigms and suggest that a rise in demand volume could potentially bring down the externalities. Further, the introduction of electric trucks (Bandeira et al., 2019), cargo bikes (Tipagornwong and Figliozzi, 2014b), drones (Goodchild and Toy, 2018) and other zero tailpipe emission vehicles, some of this negative impact from increased last-mile delivery can be mitigated, though other impacts, such as curb-space access requirements, may continue to pose a problem (Allen et al., 2018).

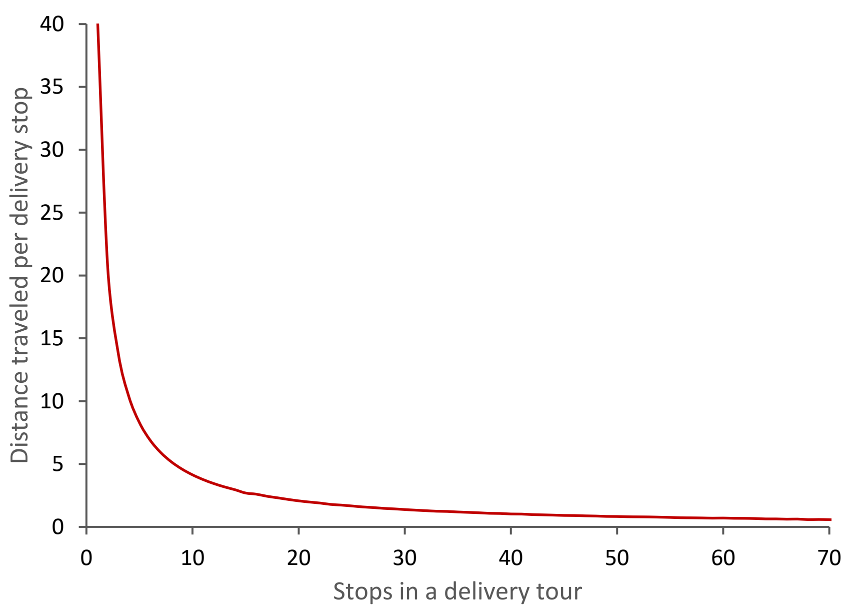


Figure 8. Impact of demand consolidation on delivery tour length

5.2. Impact of key delivery environment parameters on e-commerce goods distribution

In this subsection, the author investigates the impact of key delivery environment parameters on e-commerce goods distribution using the CA framework developed above in the Methodology section.

Without loss of generality, the author here develops analysis for an e-retailer operating in the city of Los Angeles, catering to a market share of 47% of the total 147,849 average daily e-commerce demand from customers located randomly and uniformly across a 475 sq. mi. fairly compact and convex (square) shaped service region, just fitting LA. For this e-retailer, the author considers a variety of distribution strategies including single-echelon distribution structures with door-to-door delivery with a fleet of class-5 diesel trucks (DD-C5DT), class-5 electric trucks (DD-C5ET), and crowdsourced light-duty trucks (DD-CSLT), as well as two-echelon distribution structures employing 15 such micro-hubs located uniformly in the service region coupled with cargo-bikes catering to all the customers (MH-CB), 15 such collection-points located uniformly in the service region with every customer traveling to such collection-points in their personal cars to collect package (CP-PC), and a combination of all with e-retailer delivering 35% of the packages directly from the primary distribution facility to customers' doorstep using a class-5 diesel truck, another 35% using a cargo-bike from 15 such micro-hubs, while the remaining 30% customers collect packages at 15 such collection-points (DDMHCP). Note, in each of these last-mile distribution structures, the author assumes the e-retailer to deploy class-8 diesel trucks to deliver packages from the regional distribution facility to the primary distribution facility.

To begin, the author here presents a subset of optimization results to contextualize the overall discussion in this section. In particular, this section analyzes the sustainability of different last-mile distribution strategies in diverse delivery environments with varying temporal and spatial characteristics of demand. Furthermore, this study develops a detailed sensitivity analysis to establish key factors that affect the efficacy of last-mile delivery for each distribution strategy, including: the impact of service efficiency and vehicle type for a door-to-door last-mile delivery with diesel trucks (DD-CXDT), the impact of battery characteristics on last-mile operations with electric trucks (DD-CXET), the impact of vehicle type and driver wage for crowdsourced delivery (DD-CSXX), and the impact of distribution structure configuration for two-echelon distribution with micro-hubs and/or cargo-bikes (MH-CB, CP-PC, and DDMHCP). In doing so, the author establishes the most suitable delivery environment for each last-mile distribution strategy.

Table 6. Temporal variations through the day

Hour of the day	Market share [a]	Congestion factor [b]
9AM – 10AM	0.0633	0.86
10AM - 11AM	0.0633	0.86
11AM - Noon	0.0633	0.86
Noon - 1PM	0.12	1
1PM - 2PM	0.12	1
2PM - 3PM	0.12	1
3PM - 4PM	0.15	0.82
4PM - 5PM	0.15	0.82
5PM - 6PM	0.15	0.82

Congestion factor reflects speed relative to free flow speed.
[a] UPS (2018) [b] HERE (2019)

For the purpose of analysis, this work considers the 9-hour long working day split into either one 9-hour long time-window, three 3-hour long time-windows, or six 1.5-hour long time-windows. Further, this work assumes temporal variations in the delivery environment through each hour the day (Table 6). Note, the analysis here focuses on per package distribution metrics.

5.2.1. Illustrative results

To contextualize results presented in this section, the author presents here a small subset of optimization results developed in this work. Recall that this work assumes that e-retailers seek to minimize their total distribution cost considering the location of the e-commerce fulfillment facility, delivery vehicle fleet size, number of delivery tours per delivery vehicle, and number of deliveries per delivery tour. Table 7 presents the empirical results with optimal decision variable values for the different last-mile strategies each with delivery within 3-hour long time-windows. Table 8 enlists corresponding outcome values for fixed cost, operational costs, emission cost, and total distribution cost. Similarly, Table 9 shows select externalities, namely, vehicle-miles traveled, CO_2 and NO_x emissions for each distribution strategy with delivery within 3-hour long time-windows. In the following section, the author develops a detailed discussion on each distribution strategy - performance, key factors, and necessary market conditions**.**

5.2.2. Temporal sensitivity analysis

The analysis here establishes sustainability of the different last-mile distribution strategies for varying length of time-window, delivering a total of 69,489 packages in a square shaped-region spanning 475 sq. mi. Figure 9 presents the total distribution cost for each distribution strategy and the corresponding order of best-to-worst distribution strategy across the different delivery time-windows. With emissions monetized, the author develops a similar analysis with emissions cost in Figure 10. Note, these figures showcase single-echelon strategies in shades of blue, with DD-C5DT, DD- C5ET, and DD-CSLT sketched in dark-, normal-, and light- blue respectively; and strategies with a 2nd echelon are in shades of orange, with MH-CB, CP-PC, and DDMHCP sketched

Table 7. Empirical results for decision variables for different last-mile strategies (3-hr time-window)

Last-mile strategy	Location	Fleet size				Tours per vehicle				Load efficiency			
		Tour Type				*Tour Type*				*Tour Type*			
		1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
DD-C5DT	(2.4, 0.0)	22	476	-	-	2	1	-	-	0.87	0.21	-	-
DD-C5ET	(2.8, 0.0)	22	480	-	-	2	1	-	-	0.88	0.21	-	-
DD-CSLT	(4.6, 0.0)	21	1043	-	-	2	1	-	-	0.92	0.99	-	-
MH-CB	(3.2, 0.0)	22	195	522	-	2	1	2	-	0.87	0.51	1	-
CP-PC	(4.2, 0.0)	21	200	-	69489	2	1	-	1	0.91	0.51	-	1
DDMHCP	(2.1, 0.0)	22	311	292	20847	2	1	2	1	0.88	0.32	1	1

Location: primary distribution facility location relative to the center of the service region (coordinates in miles)
Load efficiency: number of customers served in a tour relative to capacity of the vehicle

Table 8. Empirical results for distribution costs for different last-mile strategies (3-hr time-window)

Last-mile strategy	DC	FC				TC				EC			
		Tour Type				*Tour Type*				*Tour Type*			
		1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
DD-C5DT	2.82	0.01	0.71	-	-	0.13	1.75	-	-	0.03	0.18	-	-
DD-C5ET	2.73	0.01	0.92	-	-	0.13	1.63	-	-	0.03	0.00	-	-
DD-CSLT	1.81	0.01	0.50	-	-	0.13	1.11	-	-	0.03	0.03	-	-
MH-CB	3.29	0.01	0.56	0.45	-	0.13	0.70	1.35	-	0.03	0.06	0	-
CP-PC	2.10	0.01	0.54	-	0.42	0.13	0.71	-	-	0.03	0.07	-	0.20
DDMHCP	3.00	0.01	0.66	0.18	0.14	0.13	1.15	0.52	-	0.03	0.12	0	0.06

DC: Distribution Cost, FC: Fixed Cost, TC: Transportation Cost, EC: Emission Cost
Costs in per package terms. Total packages served: 69,489

Table 9. Empirical results for externalities for different last-mile strategies (3-hr time-window)

Last-mile strategy	VMT				CO_2 (g)				NO_x (g)			
	Tour Type				*Tour Type*				*Tour Type*			
	1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
DD-C5DT	0.05	0.38	-	-	84	404	-	-	0.29	1.59	-	-
DD-C5ET	0.05	0.39	-	-	84	0	-	-	0.29	0	-	-
DD-CSLT	0.05	0.85	-	-	80	329	-	-	0.28	0.14	-	-
MH-CB	0.05	0.13	0.31	-	83	140	0	-	0.29	0.55	0	-
CP-PC	0.05	0.14	-	7.14	81	148	-	2166	0.28	0.58	-	0.53
DDMHCP	0.05	0.25	0.35	7.14	85	265	0	2166	0.30	1.04	0	0.53

VMT: Vehicle-miles Traveled
Values in per package terms. Total packages served: 69,489

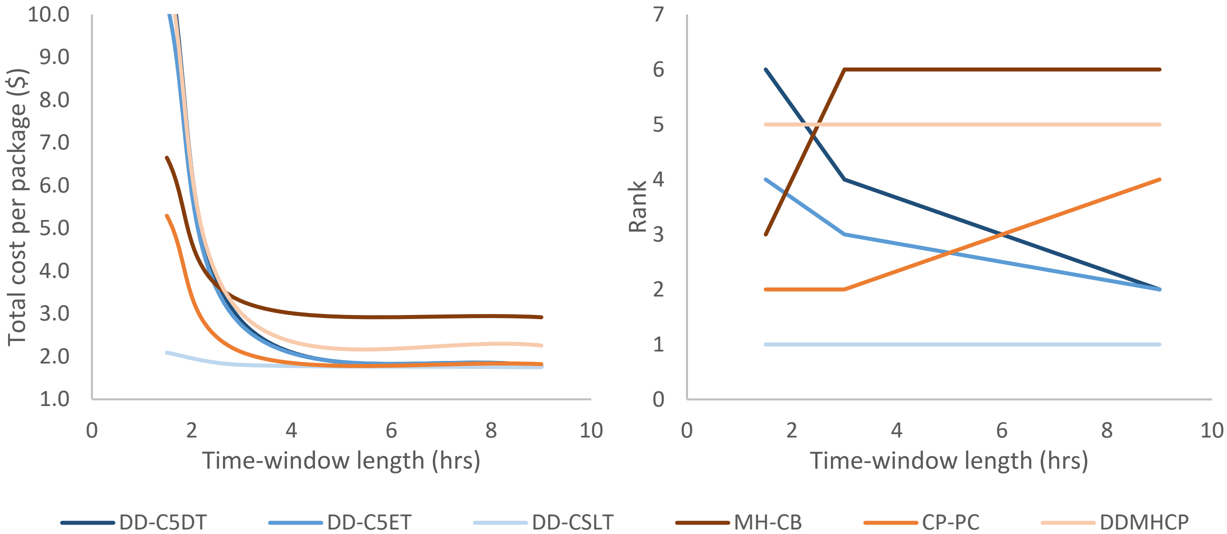


Figure 9. Impact of time-window length on distribution cost

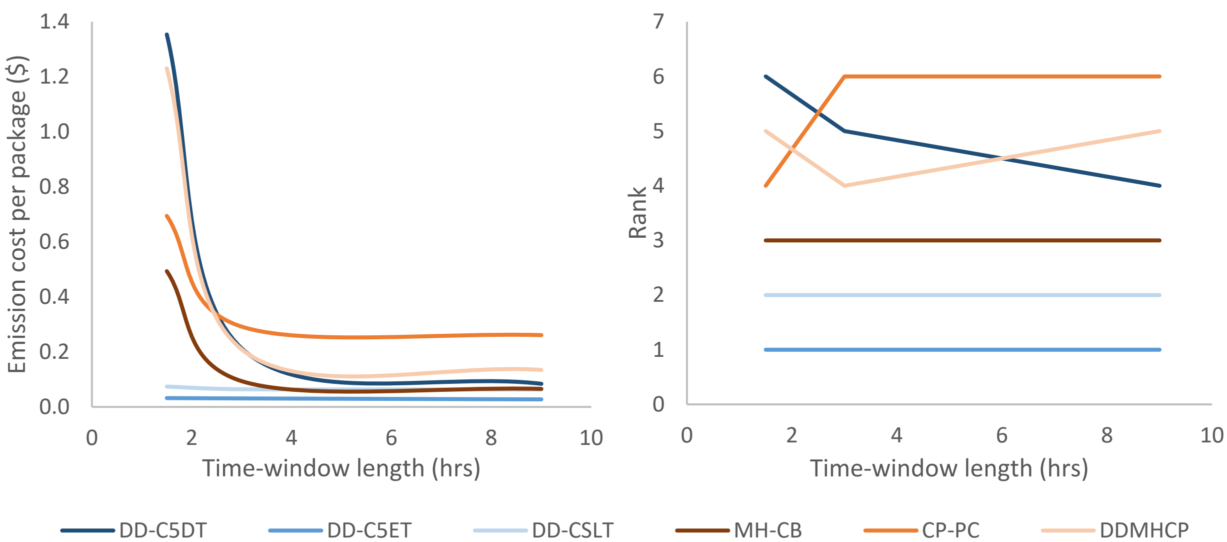


Figure 10. Impact of time-window length on emission cost

in dark-, normal-, and light- orange respectively.

In general, as time-windows get smaller, vehicle consolidation levels drop, leading to an increase in the fleet size and the number of delivery tours required to cater to the demand, and thus the distribution costs per package increase (Figure 9). However, this temporal sensitivity varies significantly across the different last-mile strategies. In particular, crowdsourced delivery with light-duty trucks (DD-CSLT) is least affected as time-windows get shorter, whereas two-echelon distribution strategies (MH-CB and CP-PC) observe a moderate impact, but door-to-door delivery with an e-retailer-owned medium-duty truck fleet (DD-C5DT and DD-C5ET) experience a substantial increase in distribution cost per package. This is because outsourcing last-mile operations either to a crowdsourced fleet with elastic driver availability (DD-CSLT) or to micro-hubs using a low-cost asset like a cargo-bike (MH-CB) or to the customers for collection-point pickup with lenient delivery constraints (CP-PC), adds flexibility to the distribution structure enabling the e-retailer to easily scale up the operations when time-windows get shorter. Finally, DDMHCP consistently performs poorly, however, as this work shows later in the sensitivity analysis, its performance is critical to the configuration of the distribution structure and the share of packages served via micro-hubs and collection-points.

As far as emissions are concerned, since shorter time-windows lead to lower vehicle consolidation, they also render higher delivery emissions per package (Figure 10). This also implies that individuals traveling to a collection-point using their personal vehicles to pick up their packages make for an environmentally inefficient distribution strategy, particularly if the sole purpose of traveling is to collect package. To this end, co-locating these collection-points near major traffic generators, such as customer’s home or workplace can mitigate the need to travel specifically to collect a package. However, some of the more environmentally efficient distribution strategies include those that deploy alternate fuel delivery vehicles to replace conventional diesel truck for last-mile delivery in the service region (MH-CB and DD-C5ET).

Refer to Appendix D for the impact of time-window length on fixed and operational costs.

5.2.3. Spatial sensitivity analysis

The analysis here establishes sustainability of the different last-mile distribution strategies for varying customer density, delivering packages within 3-hour time-windows. Here again, Figure 11 presents the total distribution cost for each distribution strategy and the corresponding order of best-to-worst distribution strategy across the different delivery time-windows. Figure 12, on the other hand, showcases a similar analysis with emissions cost. Again, these figures showcase single-echelon strategies in shades of blue, with DD-C5DT, DD-C5ET, and DD-CSLT sketched in dark-, normal-, and light- blue respectively; and strategies with a 2nd echelon are in shades of orange, with MH-CB, CP-PC, and DDMHCP sketched in dark-, normal-, and light- orange respectively.

In general, as customer density reduces, customer-to-customer distances increase, leading to an increase in the operational costs, and thus the distribution costs per package increase (Figure 11). However, this spatial sensitivity varies significantly across the different last-mile strategies. Contrary to temporal sensitivity, door-to-door delivery strategies with e-retailer-owned medium-duty truck fleet (DD-C5DT and DD-C5ET) are amongst the least affected as the customer density reduces, while micro-hub-based strategies, namely, DDMHCP and MH-CB, are the most affected. This poor performance of micro-hub-based strategies is due to slow vehicle

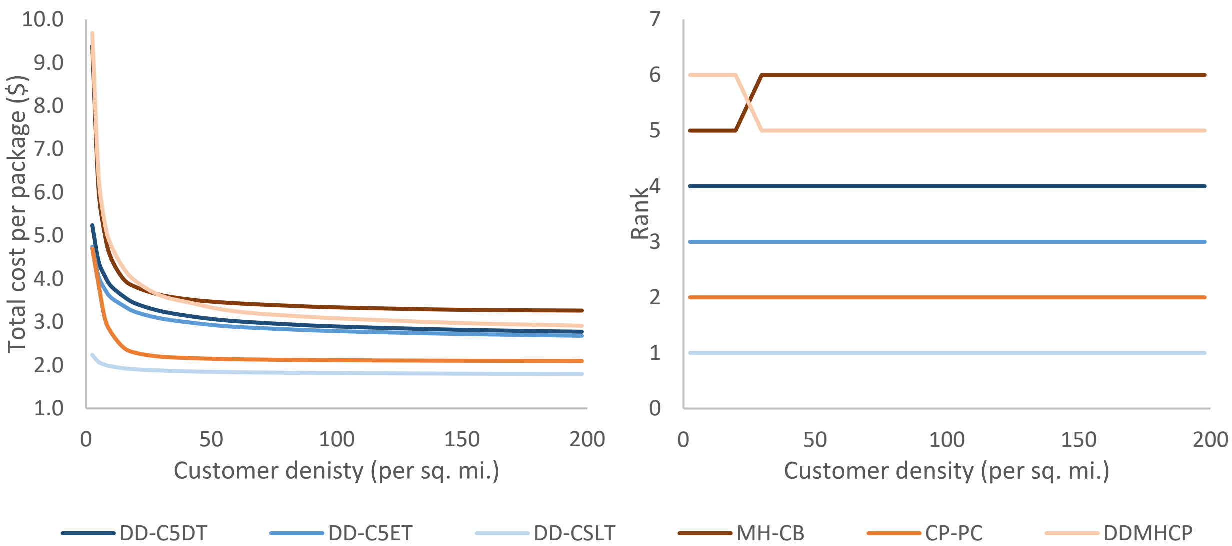


Figure 11. Impact of customer density on distribution cost

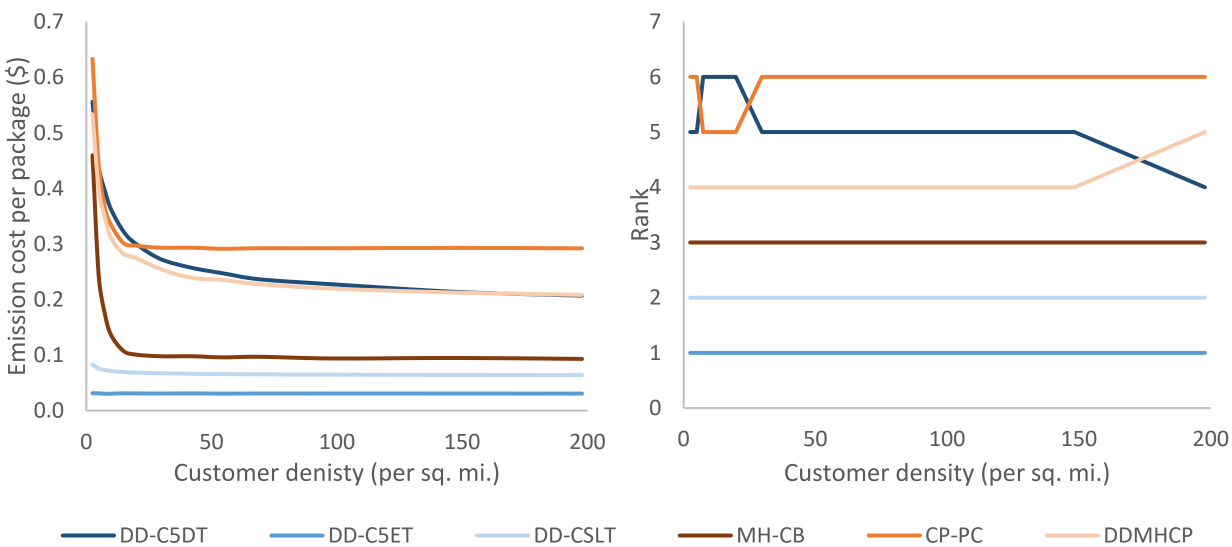


Figure 12. Impact of customer density in emission cost

speed for cargo-bikes. Thus, as customers locate sparsely, cargo-bike delivery tour travel time increases more significantly, resulting in a much more significant increase in costs compared to other distribution strategies.

As for the delivery emissions, since a reduction in customer density increases customer-to-customer distances, the per package delivery emissions for delivery vehicles with non-zero/significant tailpipe emissions increase (Figure 12). Comparison across different last-mile strategies for emissions per package however is largely consistent with observations made in the previous sub-sections.

These results from temporal and spatial sensitivity analysis have significant implication for e-retailers, particularly for those with small market size, or for traditional retailers planning for omni-channel distribution. Considering the results, the author suggests such e-retailers to rather not set up a traditional last-mile distribution strategy, but to instead crowdsource deliveries initially, reacting to the demand as it appears. Of course, as demand increases, the fleet requirements would grow as well, and it could be difficult to find enough drivers willing to crowdship packages. Thus, once the e-retailer can ensure a sizeable and stable demand, the author recommends the e-retailer to then own a dedicated fleet for last-mile delivery. With further growth, the e-retailer could also offer higher levels of service including expedited delivery and product return by operating through collection-point or micro-hubs.

Refer to Appendix E for the impact of customer density on fixed and operational costs.

5.2.4. General sensitivity and breakeven analysis

In this subsection, the study further explores key factors affecting efficacy of last-mile delivery for the different distribution strategies. To this end, the author here A) develop cost sensitivity for each last-mile distribution strategy to certain strategy-specific distribution parameters, and B) develop breakeven costs and in doing so, compares alternate last-mile distribution strategies with the conventional door-to-door delivery using diesel trucks (DD-C5DT). In particular, the analysis here explores A) the impact of service efficiency and vehicle type for a door-to-door last-mile delivery with diesel trucks (DD-CXDT), B) the impact of battery characteristics on last-mile operations with electric trucks (DD-CXET), C) the impact of vehicle type and driver wage for crowdsourced delivery (DD-CSXX), and D) the impact of distribution structure configuration for two-echelon distribution with micro-hubs and/or cargo-bikes (MH-CB, CP-PC, and DDMHCP). Note, the sensitivity analysis examines the last-mile performance for delivery with 9-hr and 3-hr time-windows.

DD-CXDT. In terms of service efficiency, vehicle speed inside the service region and service time at the customer can have a substantial impact on distribution costs, particularly if the customers demand the e-retailer to make deliveries within short time-windows (Figure 13). For instance, threefold increase in service time per customer, from 1 min to 3 mins, nearly doubles the distribution costs for the e-retailer. On the other hand, congested urban network rendering a 50% reduction in average vehicle speed, from 30mph to 15mph, results in about 60% higher distribution costs for the e-retailer. These results thus reinforce the general arguments made earlier, that temporal restrictions have significant impacts on last-mile delivery efficacy. In addition, these results bode well for light-duty delivery vehicles such as electric vans, cargo-bikes, UAVs, and ADRs. In particular, last-mile deliveries into dense urban areas such as downtowns can be susceptible to congestion (affecting vehicle speed) and access unavailability (affecting service

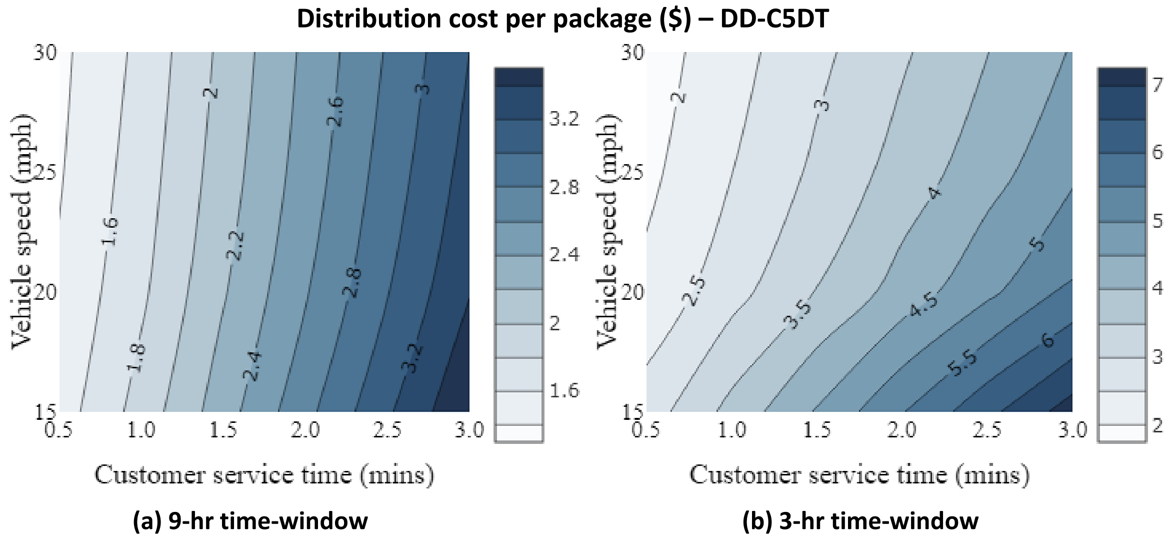


Figure 13. Impact of service efficiency door-to-door delivery with diesel trucks

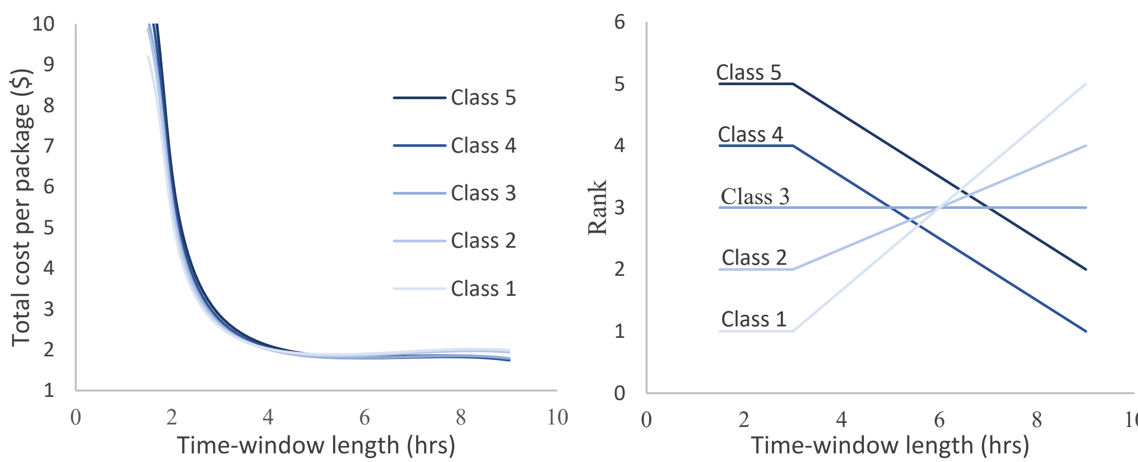


Figure 14. Temporal sensitivity of door-to-door delivery with diesel trucks of different classes

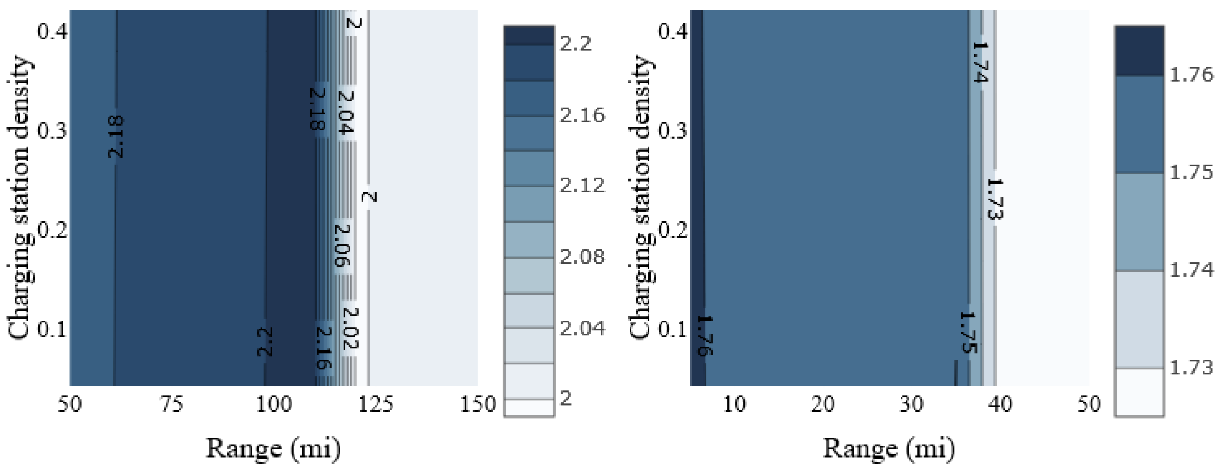
time). Thus, light-duty delivery vehicles, with appropriate infrastructure enabling ease of access, can flourish under such delivery conditions.

Beyond service efficiency impacts, this work also evaluates the impact of vehicle type on last-mile delivery using different class of diesel trucks, ranging from smaller and cheaper class-1 diesel trucks (DD-C1DT) to larger and more expensive class-5 diesel trucks (DD-C5DT) (U.S. Department of Energy, 2020). While the analysis here (Figure 14) finds only minor differences between different truck class operations, yet it sheds light onto the optimal selection of diesel trucks for different time-window lengths. For instance, the e-retailer must deploy a small fleet of medium-duty diesel trucks to consolidate as much demand for delivery within longer time-window, and in doing so, keep distribution costs low. Conversely, the e-retailer must deploy a large fleet of light-duty diesel trucks to have as many delivery vehicles at disposal for delivery within shorter time-window allows, and in doing so, keep distribution costs low. Thus, depending on the delivery lead-time and the length of the time-window, different truck sizes may suit for optimal last-mile delivery operations. However, it is important to note that a large light-duty diesel truck fleet renders higher vehicle-miles traveled and potentially higher tailpipe emissions than a small medium-duty truck fleet. These results and inferences hold true not only for DD-CX-DT, but also across other last-mile distribution strategies.

DD-CXET. The analysis here evaluates short-term and long-term implications for an e-retailer switching to an electric truck fleet in terms of its ability to carry out day-to-day last-mile operations, considering the battery characteristics of the electric truck and available charging infrastructure. In particular, in the short term, the analysis assumes the e-retailer to locate the primary distribution facility furthest from downtown LA, while in the long-term, the analysis assumes the e-retailer to re-optimize and relocate to a location that results in least distribution cost. The author first evaluates the impact of vehicle range and charging station density on efficacy of last-mile delivery with electric fleet (Figure 15). To this end, the author varies electric truck range and consequently its purchase cost by varying the battery size given the battery efficiency. With a 150-mile range electric truck priced at $150k, for every mile of reduction in vehicle range, the analysis assumes the purchase cost of the vehicle to drop by $500 (equivalent to battery retail price of $400/kWh and 0.8mile/kWh battery efficiency) (Burke and Miller, 2020). Thereafter, the author evaluates the impact of battery characteristics on efficacy of last-mile delivery with electric fleet. In particular the author tests the impact of battery efficiency and re-charging rate, keeping vehicle range, and therefore vehicle purchase cost fixed (Figure 16).

To begin with, it is evident that the density of chargers does not have a significant impact on last-mile operations in the long-term, as the facility can re-locate closer to the customers and thus the vehicle range would suffice for a typical delivery tour. However, in the short-term, i.e., if the facility cannot relocate at all or sufficiently close to customers, insufficient vehicle range (less than 125 miles) can cause disruptions in last-mile operations, as delivery vehicles need to de-tour and re-charge at a charging station. And while electric trucks have been consistently improving in the past few years in terms of battery capacity, vehicle range, and re-charging rates, such issues may still create a deterrence for the successful transformation from fossil fuel to electric truck-based last-mile delivery, especially in the short run. These results highlight the need for improvement in battery efficiency and electric truck range at the cost of a minimal increase in purchase price for low-cost zero-emission last-mile distribution. Note, the analysis here finds a fast-charging economical battery to reduce total costs by as much as 25%. However, it is worth

Distribution cost per package ($) – DD-C5ET

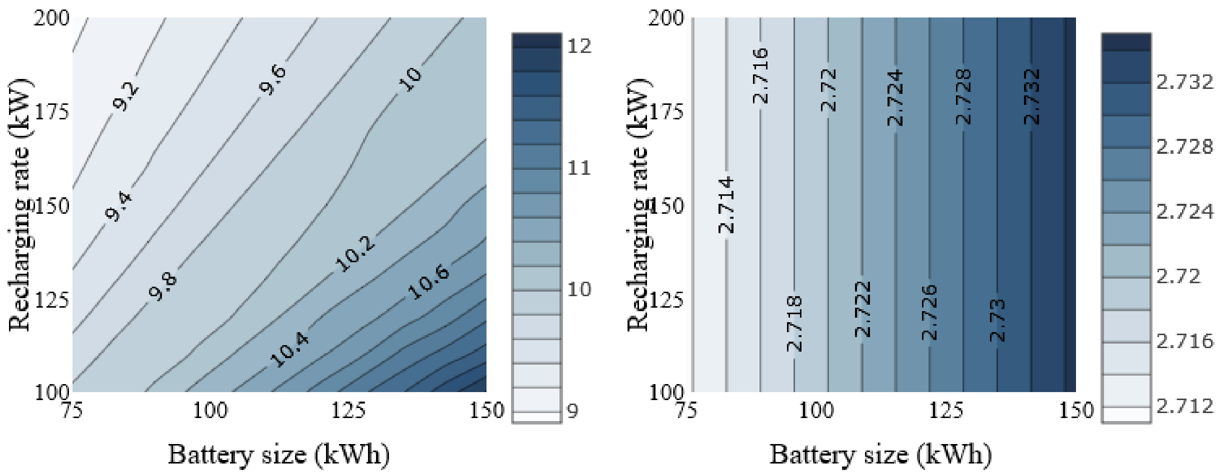


(a) Facility location - 49 miles (Short term)
DD-C5DT distribution cost per package: $2.3

(b) Facility location at optimal (Long term)
DD-C5DT distribution cost per package: $1.8

Figure 15. Impact of vehicle range on last-mile delivery with electric fleet (9-hr time-window)

Distribution cost per package ($) – DD-C5ET



(a) Facility location - 25 miles
DD-C5DT distribution cost per package: $10.02

(b) Facility location - 2.78 miles
DD-C5DT distribution cost per package: $2.8

Figure 16. Impact of battery characteristics on last-mile delivery with electric truck (3-hr time window)

noting that even with the current battery technology and market prices, this work finds last-mile delivery with electric fleet to render lower distribution costs per package compared to conventional door-to-door delivery with diesel trucks. In fact, even with smaller electric vehicles such as the Mercedes electric Sprinter ($50k purchase price, 90mile range, 55kWh battery, and a capacity of 160 customers), commonly deployed for last-mile deliveries, the distribution costs fall to $2.2 per package in contrast to $2.73 with class-5 electric trucks, and $2.83 with class-5 diesel trucks, for delivery within 3-hr time-windows.

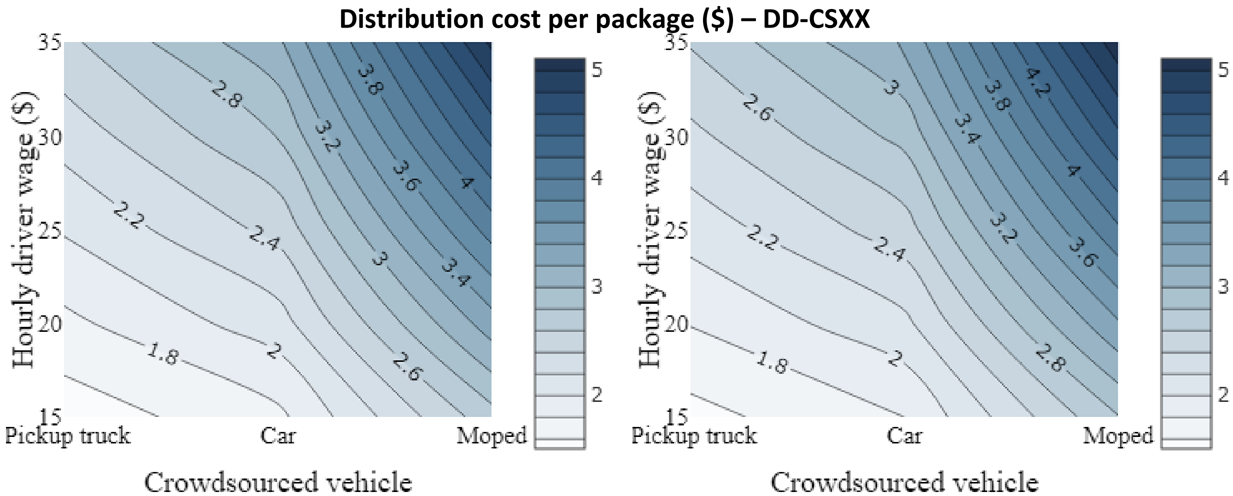
DD-CSXX. In the general case, the analysis assumes the crowdsourced vehicle to be a medium-sized light-duty vehicle (pickup truck or sport utility vehicle) with a driver wage of $20/hour. In this section, the analysis expands crowdsourced delivery operations, deploying alternate delivery vehicles, such as a car or moped. While cars and pickup trucks are more common delivery vehicles in the US, mopeds are typical delivery vehicles in metropolitan European and Asian cities, especially in the e-grocery and food delivery segment of e-commerce. In addition, the sensitivity analysis varies driver wages from a minimum wage of $15/hour to a typical truck driver wage of $35/hour.

Considering the results of this sensitivity analysis (Figure 17), it is evident that pickup trucks have an advantage due to their larger capacity, so much so that offering high driver wages ($35/hour) to a pickup truck driver renders an equivalent distribution costs per package as offering minimum wage ($15/hour) to a moped driver. In fact, crowdsourcing pickup trucks for delivery, particularly at low driver wages, can render a lower distribution cost than the conventional door-to-door delivery with diesel trucks (DD-C5DT). Whereas a moped-based crowdsourced delivery at low driver wages and under shorter time-windows can just about compete with DD-C5DT.

As far as externalities are concerned, pickup trucks render a lower vehicle-miles traveled, but owing to the differences in emission rates across the different delivery vehicles, last-mile delivery with crowdsourced fleet of drivers using personal cars produce the fewest distribution emissions in crowdsourced operations. On the other hand, a crowdsourced fleet of mopeds renders the most vehicle-miles traveled as well as the highest emissions but amount the least to congestion individually.

MH-CB. To further develop a comprehensive understanding of micro-hub-based last-mile deliveries, this study carries out a sensitivity analysis varying the number of micro-hub facilities and the share of packages delivered via such facilities (Figure 18). Note, the packages that do not go through micro-hubs go directly from the primary distribution facility to the customer's doorstep on e-retailer's fleet of class-5 diesel trucks.

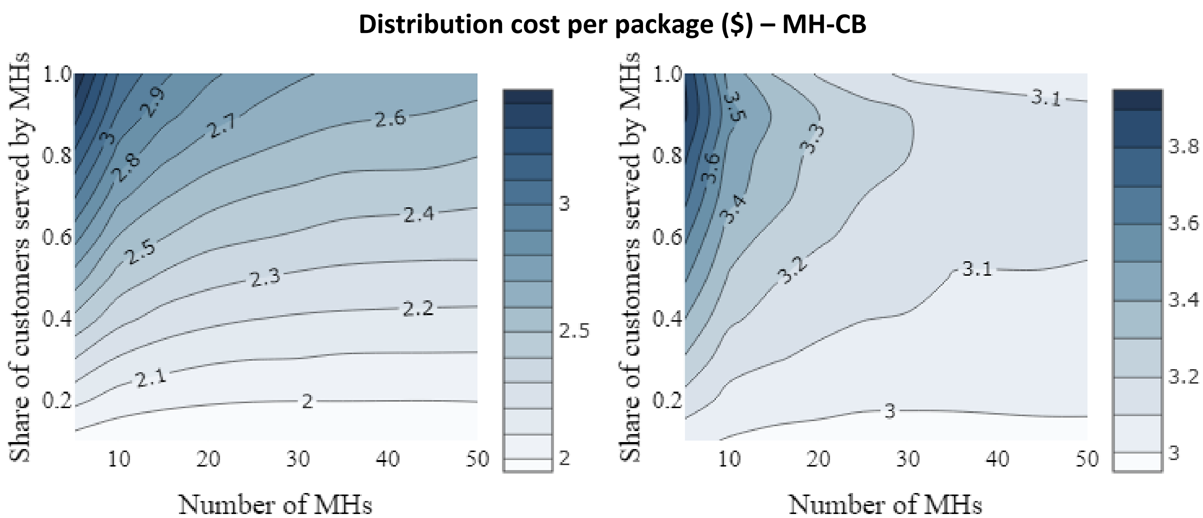
To begin with, the analysis shows the distribution costs to increase more significantly as the e-retailer delivers an increasing share of packages from fewer micro-hubs. However, as the e-retailer sets up more micro-hubs in the service region it requires fewer cargo-bikes each with shorter delivery tours to cater to its customers. And thus, for every additional micro-hub set up for service, the distribution costs for the e-retailer reduce by 0.8% on average. Nonetheless, increasing the number of micro-hubs also increases the fixed costs, thus it is important to note that the benefit of adding another micro-hub is diminishing. Further, consistent with the previous discussion in the subsection developing temporal sensitivity for last-mile distribution strategies, conventional door-to-door delivery with diesel trucks (DD-C5DT) renders lower distribution costs than micro-hub-based last-mile delivery (MH-CB). Figure 18 offers this direct cost comparison



(a) 9-hr time-window
DD-C5DT distribution cost per package: $1.8

(b) 3-hr time-window
DD-C5DT distribution cost per package: $2.8

Figure 17. Impact of crowdshipping agent on DD-CS-XX



(a) 9-hr time-window
DD-C5DT distribution cost per package: $1.8

(b) 3-hr time-window
DD-C5DT distribution cost per package: $2.8

Figure 18. Impact of distribution structure on MH-CB

between MH-CB and DD-C5DT, with the $1.8 and the $2.8 contour line representing the DD-C5DT distribution cost per package for delivery within the 9-hr and 3-hr time-windows, respectively. However, reiterating previous discussions, it is important to note that cargo-bikes can flourish in dense urban environments, where deliveries are susceptible to access unavailability, congestion, and stringent time-windows. Moreover, replacing diesel trucks with cargo-bikes for last-mile deliveries can reduce emissions by 0.62%, vehicle-miles traveled by 0.63%, as well as traffic accidents by 0.72%, on average for every additional % of packages delivered using a cargo-bike.

CP-PC. Here again, the study develops sensitivity analysis varying the number of collection-points and the share of customers collecting packages at collection-points (Figure 19). Note, the packages that do not go through collection-points go directly from the primary distribution facility to the customer's doorstep on e-retailer's class-5 diesel trucks.

The analysis here again shows the distribution costs to vary more significantly as an increasing share of customers collect packages from fewer collection-points. Thus, adding more collection-points in the service region improves the coverage of the service region, reducing the distance traveled by the customer and related emissions by 1.75% on average. However, increasing the number of collection-points also increases the fixed cost, and hence the marginal benefit of adding another collection-point is diminishing.

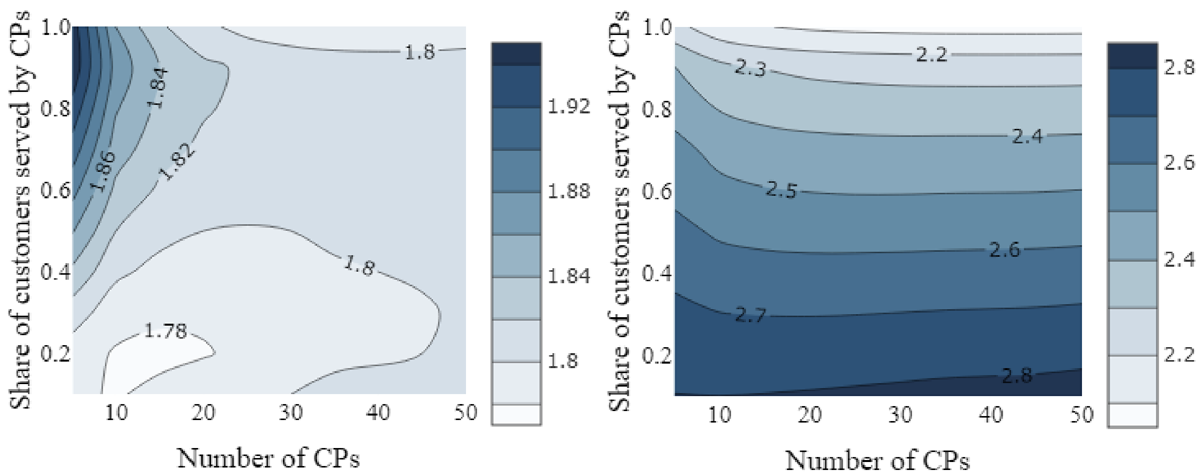
Again, consistent with the results from temporal sensitivity analysis, conventional door-to-door delivery with diesel trucks (DD-C5DT) is an economically viable strategy for delivery within the longer 9-hr time-window, while having customers collect packages at collection-points renders a lower distribution cost if service is constrained by shorter 3-hr time-windows. Figure 19 offers this direct cost comparison between CP-PC and DD-C5DT, with the $1.76 and the $2.8

contour line representing the DD-C5DT cost per package for delivery within the 9-hr and 3-hr time-windows, respectively. Nonetheless, it is important to note that for every additional % of packages self-collected, the vehicle-miles traveled and emissions increase by 1.73% and 8.37%, on average, respectively.

DDMHCP. The author develops sensitivity analysis for a distribution structure with multiple delivery options including door-to-door delivery, delivery via micro-hubs, and self-collection at collection-points. In particular, the analysis varies the share of packages the e-retailer delivers through micro-hubs and collection-points (Figure 20). Note, the packages that do not go through either micro-hubs or collection-points go directly from the primary distribution facility to the customer's doorstep on one of the e-retailer's class-5 diesel trucks.

The discussion here specifically focuses on the collaboration between micro-hubs and collection- points. For delivery within the longer 9-hr time-window, it is best for the e-retailer to deliver directly to the customer without routing packages from a 2nd echelon. Yet, for delivery within the shorter 3-hr time-window, having a 2nd echelon with both collection-points and micro-hubs can result in a lower distribution cost per package than conventional door-to-door delivery with diesel trucks (DD-C5DT). This is evident from the $2.8 contour line representing DD-C5DT distribution cost per package in the corresponding figure. In fact, the e-retailer would prefer to operate solely through collection-points as it renders an even lower distribution cost. This though would come at the cost of high emissions from individuals traveling to the collection-point. At this point, routing some deliveries via micro-hubs using cargo-bikes while having some customers collect packages at collection-points may render both - a lower distribution costs as well as lower emissions in comparison to conventional last-mile delivery.

Distribution cost per package ($) – CP-PC

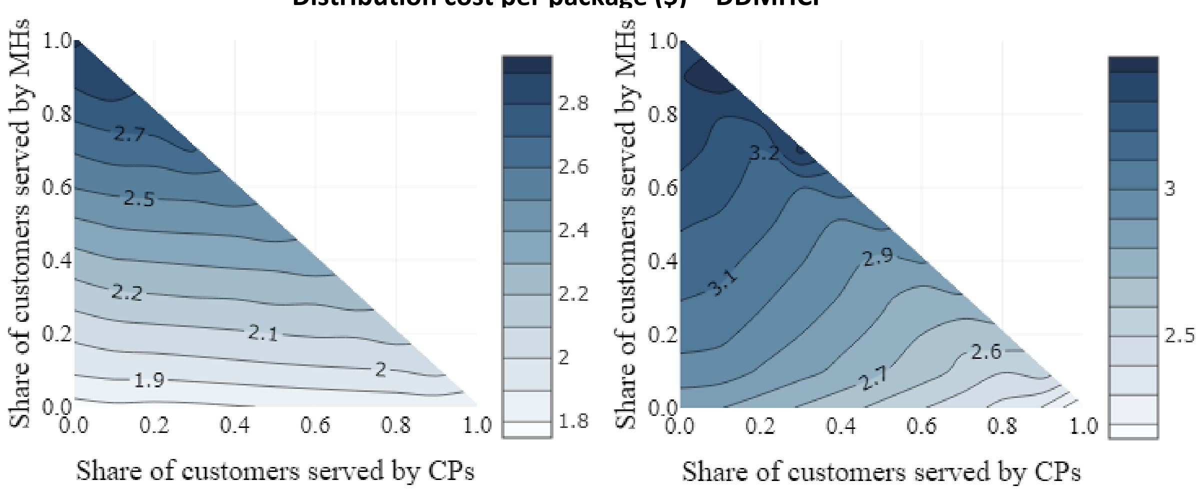


(a) 9-hr time-window
DD-C5DT distribution cost per package: $1.76

(b) 3-hr time-window
DD-C5DT distribution cost per package: $2.8

Figure 19. Impact of distribution structure on CP-PC

Distribution cost per package ($) – DDMHCP



(a) 9-hr time-window
DD-C5DT distribution cost per package: $1.8

(b) 3-hr time-window
DD-C5DT distribution cost per package: $2.8

Figure 20. Impact of distribution structure on DDMHCP

5.3. Impact of demand uncertainty on e-commerce goods distribution

In this subsection, the author develops the impact of demand uncertainty on e-commerce goods distribution using the discrete optimization framework developed in this work, wherein the author formulates the LMND problem for the e-retailer as a DS-2E-C-LRP-TW, addressed using the ALNS metaheuristic algorithm, as discussed above in the Methodology section.

Without loss of generality, the author presents the empirical results for an e-retailer with a 1% market share, operating in the city of Los Angeles, catering to the dynamic-stochastic customer demand in the region (Figure 22) with a last-mile distribution structure encompassing a regional distribution facility located 50 miles east of downtown LA, potential primary distribution facility locations, and potential secondary distribution facilities including micro-hubs and collection-points (Figure 21). Thus, 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 22a) and additionally service of dynamic customer demand arriving through the day (Figure 22b).

For this e-retailer, the author investigates the opportunities and challenges associated with the different last-mile distribution strategies to cope with daily dynamic-stochastic total customer demand (Figure 22c and 22d). To this end, the author models this e-retailer's strategic, tactical, and operational decision-making process encompassing the LMND problem with the DS-2E-C-LRP-TW formulation.

In particular, the author begins with the strategic decision-making process wherein the e-retailer establishes the type, number, and location for the primary and secondary distribution

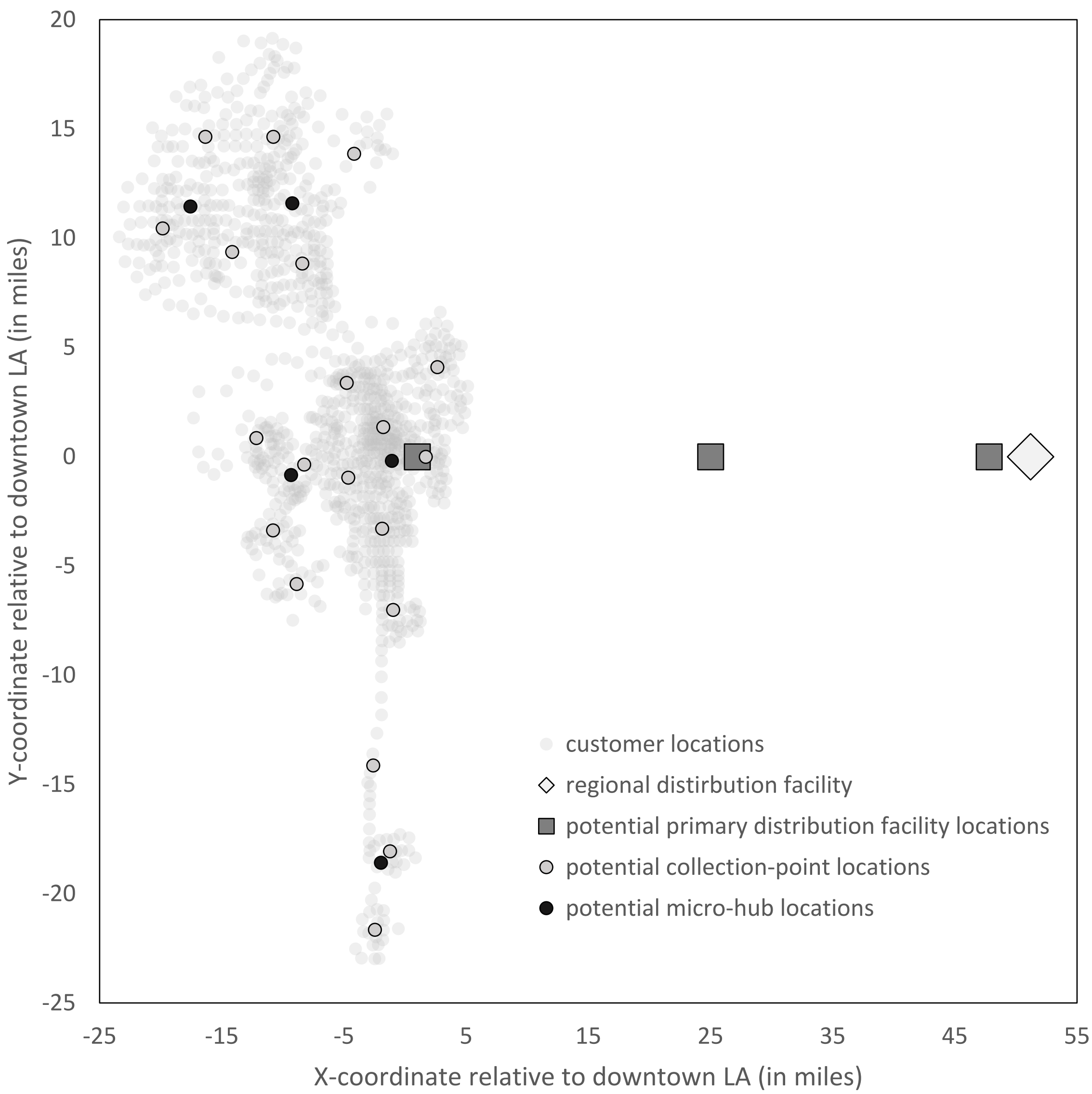
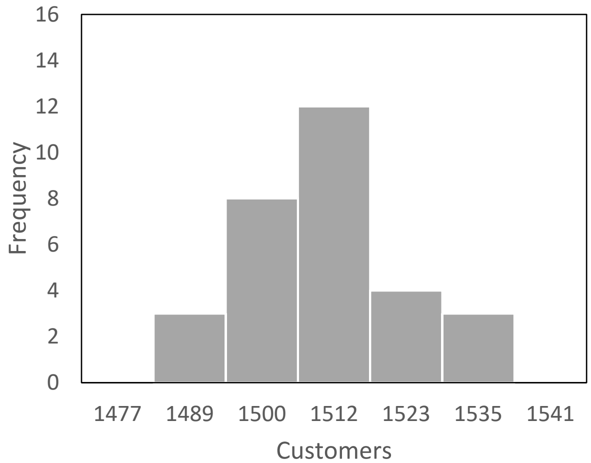
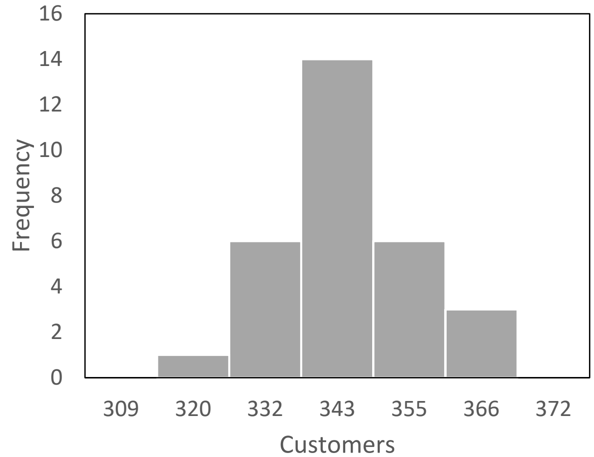


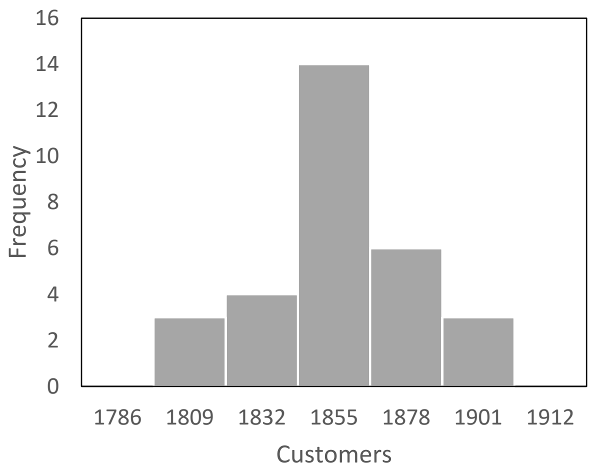
Figure 21. Last-mile distribution structure of the e-retailer



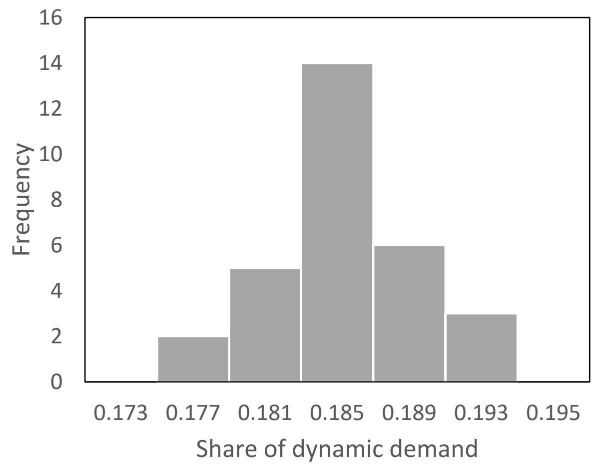
a) Daily static-stochastic customer demand



b) Daily dynamic-stochastic customer demand



c) Daily dynamic-stochastic total customer demand



d) Degree of Dynamism

Figure 22. Daily customer demand

Table 10. 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-C5ET	$1.96	1.13%	$0.11
DD-CSLT	$1.87	0.70%	$0.12
MH-CB	$2.80	3.22%	$0.21
CP-PC	$1.85	1.53%	$0.13
DDMHCP	$2.37	1.23%	$0.10

facilities, as well as the size and composition of the associated delivery fleet, to serve the expected customer demand over a planning horizon spanning a period of 10 years.

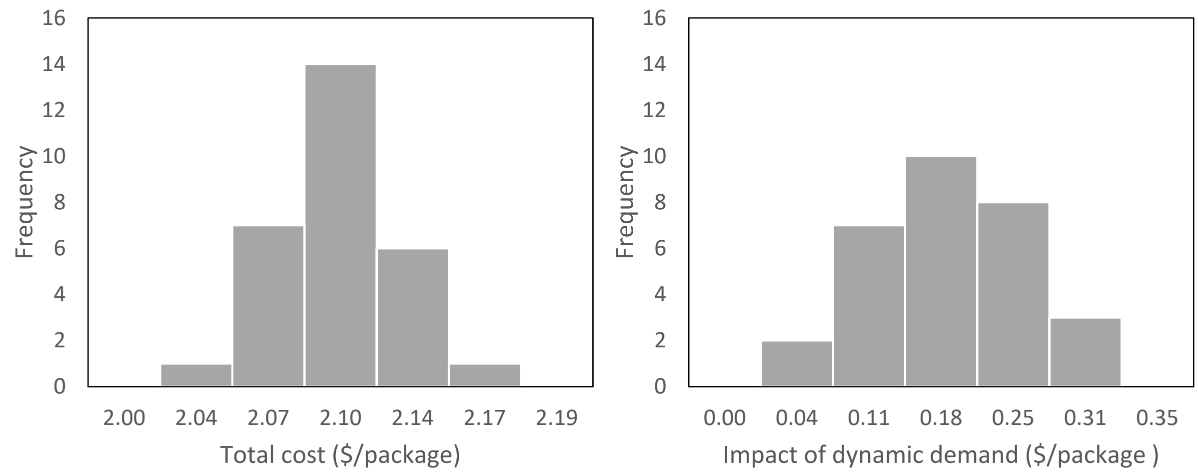
This study then replicates the tactical decisions with the e-retailer defining the order of customer visits for each day of a month sampled from the planning horizon to meet the daily stochastic customer demand, given the primary and secondary distribution facilities and the associated delivery vehicle fleet.

And finally, this work replicates the operational decision-making process wherein the e-retailer fine-tunes the last-mile delivery in every hourlong time-slot in the day considering the dynamic arrival of certain customer requests requiring service by the end of this day. Here, the author assumes the e-retailer to delay route commitments until the last-feasible time-slot to accumulate customer requests and consequently assign them to an uncommitted delivery route. At the end of every time-slot then, the e-retailer integrates the new customer requests by inserting these customer nodes into such uncommitted delivery routes in a manner that results in least increase in distribution cost keeping the customer-distribution facility allocation fixed.

With this, the author develops the impact of demand uncertainty on last-mile distribution for this e-retailer (Table 10). In particular, for each distribution structure, the analysis here establishes expected distribution cost with a counterfactual scenario assuming the e-retailer has complete knowledge of the delivery environment. Further, this work develops operational variance metric, estimating coefficient of variance of total cost, to assess the impact of stochastic customer demand. And to investigate the impact of dynamic customer demand, this study develops value of information metric, comparing counterfactual scenario with the actual scenario wherein customers arrive dynamically through the day.

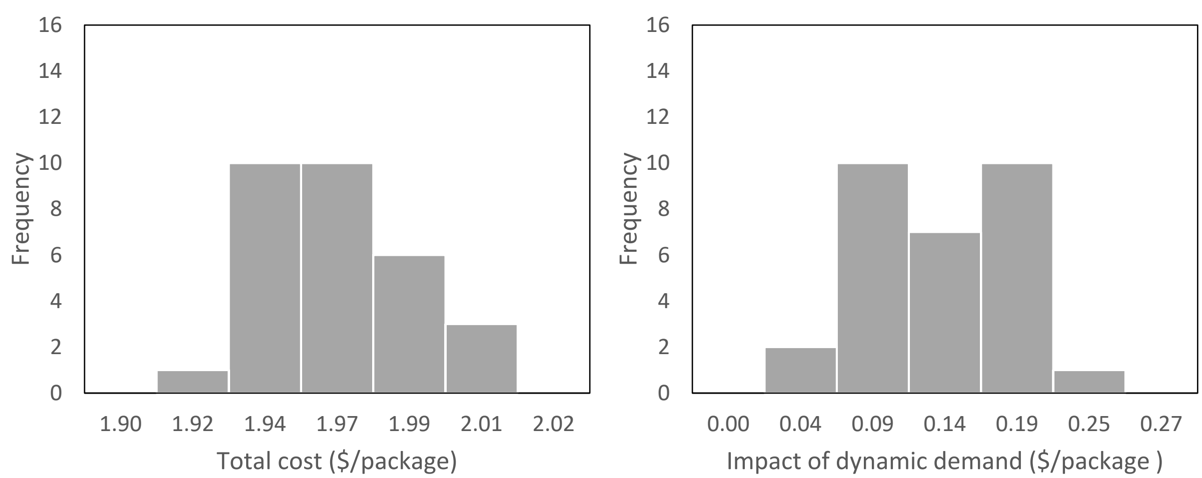
DD-C5DT. Here, the e-retailer establishes a single-echelon distribution structure with direct delivery using a fleet of class-5 diesel trucks operating from a primary distribution facility fulfilled by the regional distribution facility located in San Bernardino with a fleet of class-8 diesel trucks (Figure 23). To cater to the expected demand over the planning horizon, 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. 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 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.

DD-C5ET. Unlike with the DD-C5DT, here the e-retailer establishes direct delivery using a fleet of class-5 electric trucks instead, each with an operating range of 150 miles, operating from a primary distribution facility fulfilled by the regional distribution facility with a fleet of class-8 diesel trucks (Figure 24). 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



a) Total cost per package b) Value of Information

Figure 23. Direct delivery with class-5 diesel trucks (DD-C5DT)



a) Total cost per package b) Value of Information

Figure 24. Direct delivery with class-5 electric trucks (DD-C5ET)

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. Owing to these operational improvements, the stochastic and dynamic uncertainties in daily customer demand renders only as much as 1.13% in daily operational variance and $0.11 in additional distribution cost, respectively. Nonetheless, outsourcing additional electric trucks to cater to this dynamic-stochastic customer demand can significantly affect viability of last-mile distribution owing to the high rental fee associated with electric trucks.

DD-CSLT. Here, the e-retailer establishes door-to-door delivery with a fleet of crowdsourced drivers using light-duty trucks to perform last-mile operations operating from a primary distribution facility (Figure 25). Like with 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 located 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) and therefore the e-retailer remunerates these crowdsourced drivers only for their labor at $20/hour while saving upon costs pertaining to vehicle maintenance and fuel. Considering this incentive structure, the authors here assume the crowdsourced drivers to 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 operating from the primary distribution facility located a mile away 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 that for last-mile delivery with e-retailer owned fleet. Further, owing to the flexible nature of crowdsourced delivery, the stochastic and dynamic uncertainties in daily customer demand renders 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 last-mile delivery renders inefficient flow of goods with every package necessitating 1.1miles of vehicle-travel resulting in 477g of CO_2, 1.8g of CO, 0.5g of NO_x, 0.008g of PM tailpipe emissions.

MH-CB. Unlike in the above discussed last-mile distribution strategies, here the e-retailer establishes a two-echelon distribution structure with the additional layer encompassing micro-hubs each with a fleet of cargo-bikes (Figure 26). Note, the regional distribution facility fulfills the primary distribution facility using class-8 diesel trucks and the primary distribution facility in-turn fulfills the micro-hub facilities with class-5 diesel trucks. Here, the e-retailer groups the expected customer demand and appropriately locates 5 micro-hub facilities. Thus, with this distribution structure, the e-retailer can cater to daily total customer demand with some customers receiving packages via one of the 3 class-5 diesel trucks directly from the primary distribution facility located a mile east of downtown LA, while 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. In fact, fine-tuning last-mile operations to serve the customers arriving dynamically through the day results in 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

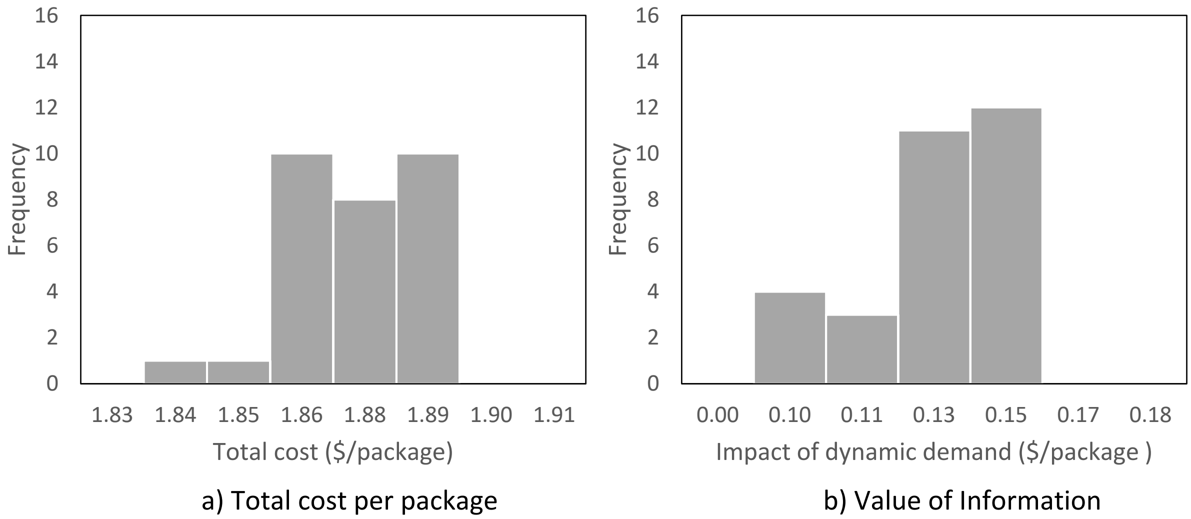


Figure 25. Direct delivery with crowdsourced fleet of light-duty trucks (DD-CSLT)

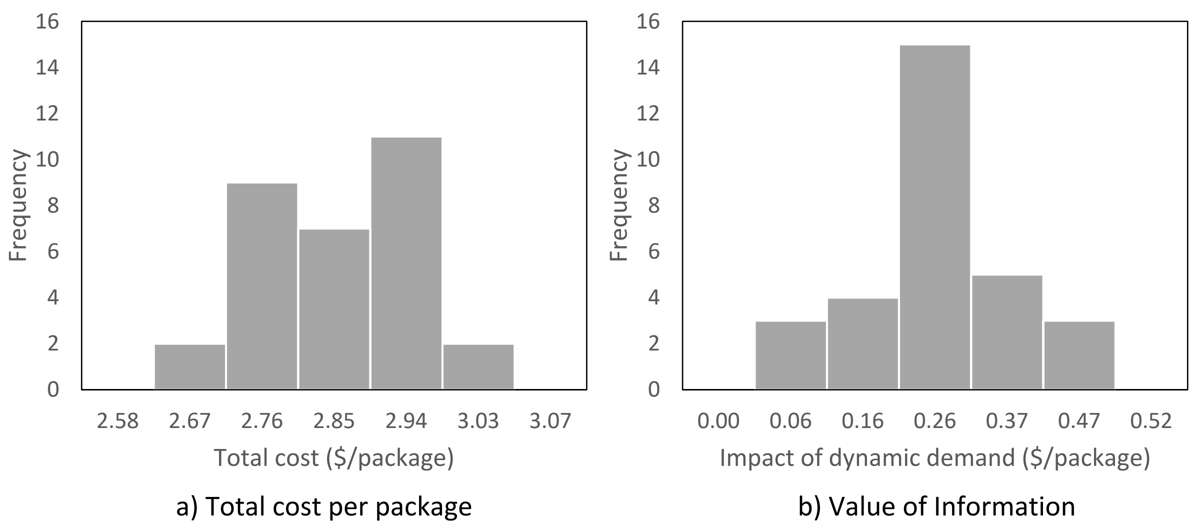
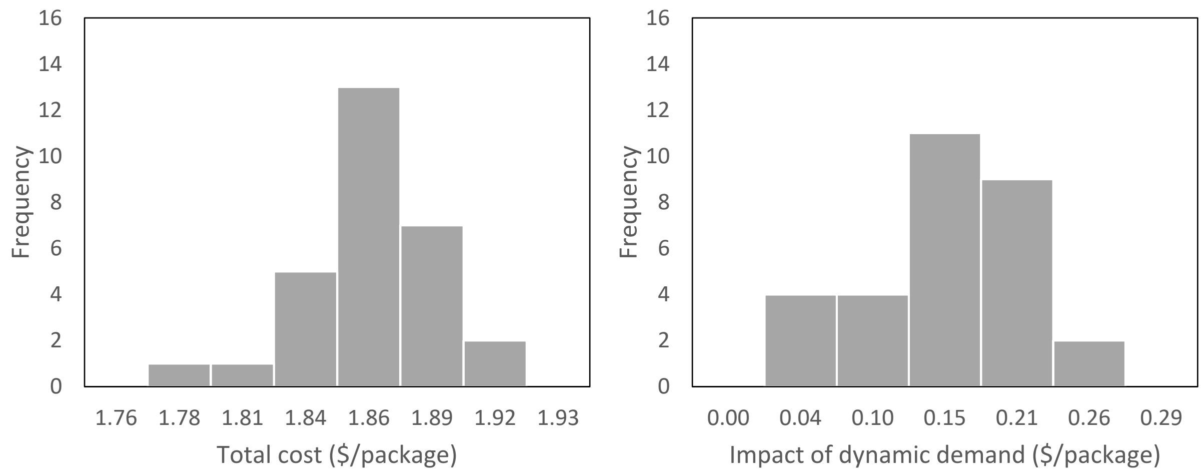


Figure 26. Delivery via micro-hubs using cargo-bikes (MH-CB)

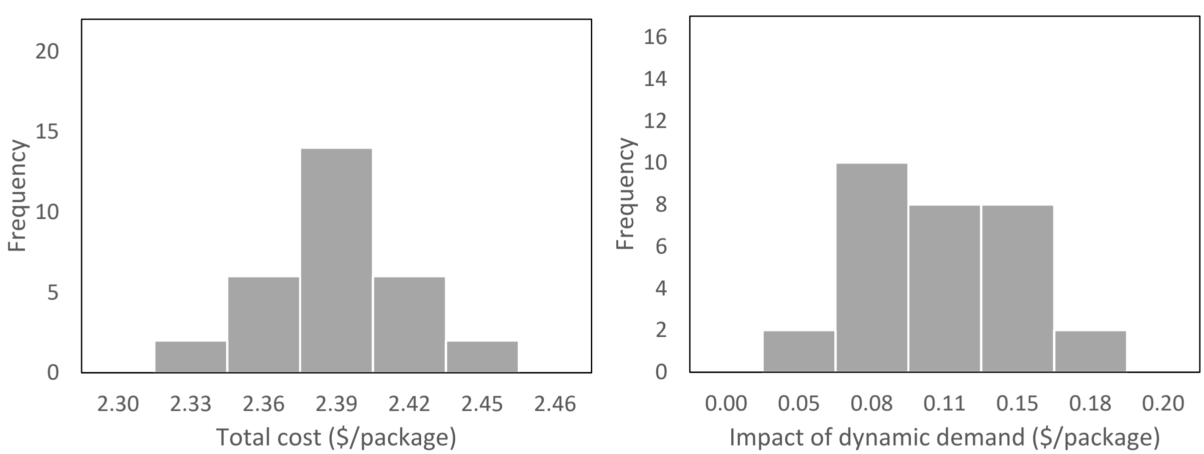
distribution structure, each package generates 0.55 vehicle-miles traveled, substantially higher in comparison to a single-echelon distribution structure. Nonetheless, owing to use of cargo-bikes for last-mile delivery, the tailpipe emissions in such a distribution structure amount to \$0.14 per package.

CP-PC. Here 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 27). To this end, the e-retailer groups the expected customer demand and appropriately operates 15 of the potential 20 collection-point facilities. Note, the author here assumes the customers to travel at most 5 miles to self-collect packages. Thus, with this distribution structure, the e-retailer can cater to the daily total customer demand such that some packages travel directly via one of the 3 class-5 diesel trucks operating from the primary distribution facility located near downtown LA, while other customers self-collect package driving to collection-points. With this, the e-retailer can effectively outsource a segment of the last-mile to the customer and can 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 therefore reduces the impact of demand uncertainty (in contrast to DD-C5DT), with stochastic customer demand rendering 1.5% operational variance in distribution cost, while dynamic customer demand resulting in additional \$0.13 per package. Nonetheless, considering that individuals travel in their personal cars to collect packages, collection-point pickup renders 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.



a) Total cost per package b) Value of Information

Figure 27. Delivery via collection-points with customer pickup (CP-PC)



a) Total cost per package b) Value of Information

Figure 28. Direct delivery with class-5 diesel trucks in addition to delivery via micro-hubs and collection-points (DDMHCP)

DDMHCP. And finally, the e-retailer establishes a two-echelon distribution structure with the additional layer including all 5 micro-hub facilities and 16 of the potential 20 collection-point facilities (Figure 28). Thus, with this distribution structure, some customers receive packages directly from the primary distribution facility on a class-5 diesel truck, some receive packages via micro-hubs on a cargo-bike, while the remaining customers travel to a collection-point to self-collect. Note, the e-retailer fulfills the second echelon facilities from the regional distribution facility via the primary distribution facility. Such a diverse distribution structure encapsulates the opportunities and challenges associated with each individual distribution structure, and thus renders a distribution cost of $2.37 per package to cater to the daily total customer demand. Owing to the stochastic nature of this customer demand, the e-retailer may observe an operational variance of 1.23% in distribution costs, while the dynamic arrival of customers further increase this distribution cost by $0.1 per package.

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 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 thus affecting those living close to logistics clusters. Hence, such consumer-focused trends in e-commerce render economically unviable, environmentally inefficient, and socially inequitable urban goods flow. In this context, a number of studies have investigated the sustainability of e-commerce last-mile distribution. However, several of these studies develop poor estimates of the potential impacts of e-commerce owing to use of crude frameworks modeling the delivery environment. To this end, this study modeled the delivery environment with a robust multinomial logit model establishing the demand-side, and sophisticated continuous approximation and discrete optimization frameworks establishing the supply-side. And with this, the author explored potential opportunities and challenges associated with urban freight in light of the increasingly consumer-focused e-commerce goods distribution.

In particular, considering the current retail landscape, the author found that with consolidated and optimized deliveries, e-commerce can render urban goods flow a 12% reduction in vehicle-miles traveled and a 10% reduction in greenhouse gas emissions. Moreover, this study established a further 80% reduction in vehicle-miles traveled and additional 64% reduction in associated greenhouse gas emissions from urban goods distribution for a potential future landscape with e-retail dominating the traditional retail. However, this work found criteria pollutant emissions to increase substantially as a consequence of increased truck flow from e-commerce goods distribution. Nonetheless, with appropriate improvements in fuel and engine technology, the author believes that e-commerce has the potential to render efficient flow of goods from point-of-sale to point-of-consumption.

Yet, the author here raises relevant concerns pertaining to sustainability of urban goods flow owing to the increasingly consumer-focused services offered by e-retailers competing for a larger market share. In particular, the study found the recent consumer-focused trends in e-commerce to reduce demand consolidation and consequently render frequent less-than-truckload deliveries, thus resulting in increased cost, distances driven, and tailpipe emissions from urban goods distribution. To address these concerns, the study suggests the use of alternate system-level strategies with use of electric delivery vehicles for last-mile operations, or 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. To this end, this study provides relevant insights for large size e-retailers planning to offer higher levels of service and to diversify their operations, as well as for small size e-retailers and traditional retailers planning for omni-channel distribution.

Yet, in general, the author suggests e-retailers to develop a conventional distribution strategy with a dedicated fleet to ensure reliable last-mile service. However, certain delivery environments necessitate use of alternate distribution strategies to ensure sustainable last-mile service. For instance, for a small size e-retailer with sparsely spread customers, deploying a fleet of crowdsourced drivers for last-mile delivery could render a more viable option. Yet, for large size e-retailers, the author suggests establishing a hybrid distribution structure with a dedicated fleet of medium-duty trucks making last-mile delivery coupled with a crowdsourced fleet that caters to customers arriving dynamically through the day. In doing so, the e-retailer can establish a cost-effective and flexible last-mile distribution structure resistant to demand uncertainty. Nonetheless, it is important to note that the use on independent contractors may result in less reliable performance compared to e-retailer-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 mitigate these negative impacts of urban goods flow, this large size e-retailer can deploy a dedicated fleet of medium-duty electric trucks instead of conventional diesel trucks. In fact, it is worth noting that this work found delivery with an electric fleet to be equally competitive if not better than delivery with diesel fleet (total cost per package $2.2 with electric van, $2.73 with electric truck, and $2.83 with diesel truck fleet, for the 3-hr time-window case). However, it is worth considering the potential barriers to the adoption of 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. Further, the author here raises concerns pertaining to the short-term implications of adopting an all-electric fleet which are subject to battery characteristics, vehicle range, and the availability as well as the quality of public charging infrastructure. Nonetheless, since electric trucks have consistently been improving in the past few years, the author believes that it is possible that in coming years the opportunity cost of owning an electric fleet will diminish.

Alternatively, the e-retailer can deploy a fleet of light-duty delivery vehicles to make the last-mile deliveries from micro-hubs located within the service region. In fact, this study found cargo-bikes to flourish in the dense residential/commercial parts of the city owing to their ease of access and parking which otherwise could be a limitation with a delivery truck, thereby improving service efficiency and in turn reducing distribution costs for the e-retailer, as well as reducing delivery emissions, congestion, and traffic accidents. However, this work found such multi-echelon distribution strategies to be less cost-effective and less resistant to demand uncertainty than other single-echelon distribution strategies due to the additional handling and transportation required to move packages between the micro-hubs and the final delivery location. Nonetheless, to cope with additional handling and transportation cost, the e-retailer can outsource a segment of last-mile and have customers collect packages at collection-points, albeit at the expense of additional vehicle-travel and negative externalities from individual customers traveling to these collection-points.

Thus, a last-mile distribution structure with collection-points co-located near major traffic generators and micro-hubs located in dense neighborhood presents a viable middle ground for the e-retailer, rendering an economically viable, environmentally efficient, and socially equitable multi-echelon distribution structure that is resistant to demand uncertainty.

Overall, the conclusions developed in this work are in general consistent with the literature, with this study providing further insight on the: importance of service efficiency, short-term/long-term implications of electric truck use, range of crowdsourcing options, design of micro-hubs and/or collection-point based distribution structures, and more. Importantly this work allows for consistent comparison across different last-mile strategies in terms of total costs per package, vehicle miles traveled, and emissions, thereby enabling consistent decision-making for the e-retailer as well as other stakeholders Hence, this work highlights the need to manage the urban freight system in general, and delivery operations and services in particular, to foster a more sustainable urban environment, in light of the growing consumer-focused trends in e-commerce distribution.

7. Conclusions

Considering the potential of e-commerce to render economically viable, environmentally efficient, and socially equitable urban goods flow, it is pertinent to understand the opportunities and challenges associated with urban freight in light of the increasingly consumer-focused e-commerce distribution. To this end, the author developed the impact of e-commerce on urban goods distribution, with a simulation framework founded on consumer shopping behavior simulating urban goods flow; the impact of key delivery environment parameters on e-commerce goods distribution, with a continuous approximation (CA) framework modeling last-mile distribution operation for an e-retailer; the impact of demand uncertainty on e-commerce goods distribution, with a discrete optimization framework formulating 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 algorithm.

In doing so, the author established a comprehensive analysis investigating the sustainability of e-commerce goods distribution, 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 costs of distribution. The parameter values employed in this analysis is reflective of the industry structures, regulations, geographies, urban forms, and consumer behaviors in the Los Angeles region.

However, future work must address the limitations of this work to further develop a robust understanding of the sustainability of last-mile distribution. In particular, future work must consider intra-route re-fueling for delivery vehicles to comprehensively model last-mile operations. Further, future work must model 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 willingness of customers to collect package accounting for customers' value-of-time. Importantly, any future work must consider synchronization between the different echelons to thoroughly model the last-mile operations in a multi-echelon distribution structure. Further, considering that this work assessed sustainability of last-mile distribution accounting for high-probability low-severity fluctuations in the delivery environment, future work can extend this analysis to additionally 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 urban freight in light of the recent consumer-focused trends in e-commerce.

Appendix A.

Estimating long-haul for a delivery vehicle operating from a primary distribution facility

A. I Long-haul travel distance

For the continuous approximation framework, the author estimates long-haul for a delivery vehicle operating from a primary distribution facility as the average distance from this primary facility located at ρ_x, ρ_y relative to the center of the service region, to the customers located randomly and uniformly in the service region. Thus,

$$\rho = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} |\rho_x - x| \, dx + \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} |\rho_y - y| \, dy \qquad (A.1)$$

To this end, the author computes,

$$z = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} |\rho_t - t| \, dt \qquad (\mathrm{A.2})$$

Hence, if $\rho_t \geq a/2$,

$$z = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} (\rho_t - t) \, dt \qquad (\mathrm{A.3})$$

$$z = \rho_t \qquad (\mathrm{A.4})$$

else if $-a/2 < \rho_t < a/2$,

$$z = \frac{1}{a}\int_{-\frac{a}{2}}^{\rho_t} (\rho_t - t) \, dt + \frac{1}{a}\int_{\rho_t}^{\frac{a}{2}} (t - \rho_t) \, dt \qquad (\mathrm{A.5})$$

$$z = \frac{\rho_t^2}{a} + \frac{a}{4} \tag{A.6}$$

$$z = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} (t - \rho_t)\, dt \tag{A.7}$$

$$z = -\rho_t \tag{A.8}$$

else if $-a/2 < \rho_t < a/2$,

$$z = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} (t - \rho_t)\, dt \tag{A.9}$$

$$z = -\rho_t \tag{A.10}$$

Thus,

$$z = \begin{cases} |\rho_t| \quad , & \text{if } |\rho_t| \geq a/2 \\ \rho_t^2/a + a/4\,, & \text{else if } |\rho_t| < a/2 \end{cases} \tag{A.11}$$

And therefore, the long-haul distance traveled by a delivery vehicle operating from a primary distribution facility is,

$$\rho = \begin{cases} |\rho_x| + |\rho_y| \quad , & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| \geq a/2 \\ |\rho_x| + \frac{\rho_y^2}{a} + \frac{a}{4}, & \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| < a/2 \\ \frac{\rho_x^2}{a} + |\rho_y| + \frac{a}{4}, & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| \geq a/2 \\ \frac{\rho_x^2 + \rho_y^2}{a} + \frac{a}{2}\ , & \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| < a/2 \end{cases} \tag{A.12}$$

A. II Long-haul travel time

Considering the long-haul distance traveled by a delivery vehicle operating at the primary distribution facility, the long-haul travel time for this delivery vehicle with speed v^r and v^u on a rural and urban network respectively is,

$$\lambda = \begin{cases} \dfrac{|\rho_x| + |\rho_y|}{v^r} + a\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right) &, \quad \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| \geq a/2 \\ \dfrac{|\rho_x|}{v^r} + \dfrac{\left(\dfrac{\rho_y^2}{a} + \dfrac{a}{4}\right)}{v^u} + \dfrac{a}{2}\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right), & \quad \text{if } |\rho_x| \geq a/2 \text{ and } |\rho_y| < a/2 \\ \dfrac{\left(\dfrac{\rho_x^2}{a} + \dfrac{a}{4}\right)}{v^u} + \dfrac{|\rho_y|}{v^r} + \dfrac{a}{2}\left(\dfrac{1}{v^u} - \dfrac{1}{v^r}\right), & \quad \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| \geq a/2 \\ \dfrac{\left(\dfrac{\rho_x^2 + \rho_y^2}{a} + \dfrac{a}{2}\right)}{v^u} &, \quad \text{if } |\rho_x| < a/2 \text{ and } |\rho_y| < a/2 \end{cases} \tag{A.13}$$

Wherein,

if the primary distribution facility is located inside the service region, i.e., if $|\rho_x| < a/2$ and $|\rho_y| < a/2$, the delivery vehicle travels the entire length of the long-haul within the service region, and hence the long-haul travel time is,

$$\lambda = \left(\frac{\rho_x^2 + \rho_y^2}{a} + \frac{a}{2}\right)/v^u \tag{A.14}$$

else if the primary distribution facility is located such that $|\rho_x| < a/2$ and $|\rho_y| < a/2$, then the delivery vehicle traverses $\left(|\rho_x| - a/2 + |\rho_y| - a/2\right)$ outside the service region, traveling towards the boundary of the service region, and $(a/2 + a/2)$ within the service region, thus resulting in a long-haul trave time that is,

$$\lambda = \frac{|\rho_x| + |\rho_y|}{v^r} + a\left(\frac{1}{v^u} - \frac{1}{v^r}\right) \tag{A. 15}$$

else if the primary facility is located such that $|\rho_x| \geq a/2$ and $|\rho_y| < a/2$, then the vehicle travels $(|\rho_x| - a/2)$ segment of the long-haul outside the service region, and travels $\left(\left(\rho_y^2/a + a/4\right) + a/2\right)$ inside the service region rendering a long-haul travel time of,

$$\lambda = \frac{\left(\frac{\rho_x^2}{a} + \frac{a}{4}\right)}{v^u} + \frac{|\rho_y|}{v^r} + \frac{a}{2}\left(\frac{1}{v^u} - \frac{1}{v^r}\right) \tag{A. 16}$$

And likewise, if the facility is located such that $|\rho_x| < a/2$ and $|\rho_y| \geq a/2$, then the vehicle traverses a distance of $\left(|\rho_y| - a/2\right)$ outside the service region, and completes $\left(\left(\rho_x^2/a + a/4\right) + a/2\right)$ inside

$$\lambda = \frac{|\rho_x|}{v^r} + \frac{\left(\frac{\rho_y^2}{a} + \frac{a}{4}\right)}{v^u} + \frac{a}{2}\left(\frac{1}{v^u} - \frac{1}{v^r}\right) \tag{A. 17}$$

Appendix B.

Estimating long-haul for a delivery vehicle operating from a secondary distribution facility

For the continuous approximation framework, the author estimates long-haul for a delivery vehicle operating from a secondary distribution facility as the average distance from this secondary facility to the customers located randomly and uniformly in the service region. Thus, for a secondary facility located at ρ_x, ρ_y relative to the center of the service region, this distance is,

$$\rho = \frac{\rho_x^2 + \rho_y^2}{a} + \frac{a}{2} \qquad (B.1)$$

Considering randomly and uniformly located secondary distribution facilities, the average long-haul distance is,

$$\bar{\rho} = \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} \left(\frac{\rho_x^2}{a} + \frac{a}{4}\right) d\rho_x + \frac{1}{a}\int_{-\frac{a}{2}}^{\frac{a}{2}} \left(\frac{\rho_y^2}{a} + \frac{a}{4}\right) d\rho_y \qquad (\mathrm{B.2})$$

$$\bar{\rho} = 2\int_{-\frac{a}{2}}^{\frac{a}{2}} \left(\frac{u^2}{a^2} + \frac{1}{4}\right) du \qquad (\mathrm{B.3})$$

$$\bar{\rho} = \frac{2a}{3} \qquad (\mathrm{B.4})$$

This work further assumes each micro-hub to only serve a smaller sub-region of size a^2/n^{MH}, thus the author modifies the average long-haul distance to, $\bar{\rho} = 2a/3\sqrt{n^{MH}}$. Considering that the delivery vehicle traverses this distance inside the service region, the long-haul travel time is $\bar{\rho}/v^u$.

Appendix C.

Validating delivery tour length estimation for the model developed in this work

The author here validates the delivery tour length estimation of the continuous approximation framework developed in this work. In this validation process (Table 11), the author not only develops a general understanding of the estimation error of the proposed model, but also carries out analysis to evaluate the impact of certain parameters on model estimation error, much like Winkenbach et al. (2016). These parameters include, n - number of customers to serve, a^2 - size of the service region, (ρ_x, ρ_y) - primary distribution facility location (in miles) relative to the center of the service region, and q_c - capacity of the delivery vehicle. Note, l_o, l_e, and ϵ represent the optimal delivery tour length, model estimation of the delivery tour length, and the estimation error, respectively.

Table 11. Continuous Approximation model validation

VRP instance	n	a^2	ρ_x	ρ_y	q_c	l_o	l_e	ϵ
Set I instances								
A-n33-k5	32	7125	37.5	47.5	100	841.6	822.8	-2.23%
A-n32-k5	31	9215	48.5	47.5	100	998.2	1071.7	7.36%
A-n33-k6	32	8455	44.5	47.5	100	944.7	981.3	3.87%
A-n34-k5	33	8832	48.0	46.0	100	990.6	935.7	-5.54%
A-n36-k5	35	8648	46.0	47.0	100	1017.3	1054.2	3.63%
A-n37-k5	36	8460	45.0	47.0	100	851.8	868.2	1.92%
A-n37-k6	36	9108	49.5	46.0	100	1208.3	1230.6	1.84%
A-n38-k5	37	8256	48.0	43.0	100	929.5	950.3	2.25%
A-n39-k5	38	9216	48.0	48.0	100	1046.6	1088.0	3.96%
A-n39-k6	38	8832	46.0	48.0	100	1058.1	1100.4	4.00%
A-n44-k6	43	9409	48.5	48.5	100	1193.0	1240.6	3.99%
A-n45-k6	44	9215	48.5	47.5	100	1201.9	1160.4	-3.46%
A-n45-k7	44	8272	44.0	47.0	100	1459.1	1531.2	4.94%
A-n46-k7	45	9024	47.0	48.0	100	1163.7	1252.9	7.66%
A-n48-k7	47	9408	48.0	49.0	100	1366.2	1444.0	5.69%
A-n53-k7	52	9215	48.5	47.5	100	1286.0	1299.9	1.08%
A-n54-k7	53	8648	47.0	46.0	100	1485.9	1427.8	-3.91%

VRP instance	n	a^2	ρ_x	ρ_y	q_c	l_o	l_e	ϵ
A-n55-k9	54	9312	48.0	48.5	100	1366.2	1457.8	6.71%
A-n60-k9	59	8648	47.0	46.0	100	1724.0	1863.3	8.08%
A-n61-k9	60	9216	48.0	48.0	100	1316.5	1461.2	10.99%
A-n62-k8	61	9408	48.0	49.0	100	1639.9	1678.2	2.33%
A-n63-k9	62	9604	49.0	49.0	100	2057.6	2124.9	3.27%
A-n63-k10	62	9900	49.5	50.0	100	1673.0	1833.7	9.60%
A-n64-k9	63	8648	46.0	47.0	100	1783.8	1913.2	7.26%
A-n65-k9	64	9216	48.0	48.0	100	1494.8	1525.5	2.06%
A-n69-k9	68	9408	48.0	49.0	100	1475.7	1483.9	0.56%
A-n80-k10	79	9800	50.0	49.0	100	2244.7	2362.2	5.23%
Set II instances								
P-n16-k8	15	1470	17.5	21.0	35	573.0	631.0	10.13%
P-n19-k2	18	1512	18.0	21.0	160	269.9	250.1	-7.33%
P-n20-k2	19	1512	18.0	21.0	160	275.0	253.4	-7.84%
P-n21-k2	20	1512	18.0	21.0	160	268.7	256.7	-4.46%
P-n22-k2	21	1512	18.0	21.0	160	275.0	259.8	-5.54%
P-n23-k8	22	1512	18.0	21.0	40	673.5	652.0	-3.20%
P-n40-k5	39	3422	29.0	29.5	140	583.1	578.2	-0.85%
P-n45-k5	44	3654	29.0	31.5	150	649.4	607.1	-6.51%
P-n50-k7	49	3894	29.5	33.0	150	705.4	791.4	12.20%
P-n50-k8	49	3894	29.5	33.0	120	803.4	858.9	6.91%
P-n50-k10	49	3894	29.5	33.0	100	886.2	993.9	12.16%
P-n51-k10	50	3654	29.0	31.5	80	943.5	940.7	-0.29%
P-n55-k7	54	3960	30.0	33.0	170	723.2	811.2	12.17%
P-n55-k8	54	3960	30.0	33.0	160	748.7	811.2	8.36%
P-n55-k10	54	3960	30.0	33.0	115	883.6	1014.2	14.78%
P-n55-k15	54	3960	30.0	33.0	70	1259.2	1352.5	7.41%
P-n60-k10	59	4392	30.5	36.0	120	947.3	1066.4	12.57%
P-n60-k15	59	4224	32.0	33.0	80	1232.5	1391.5	12.90%
P-n65-k10	64	4608	32.0	36.0	130	1008.4	1098.8	8.97%
P-n70-k10	69	4608	32.0	36.0	135	1053.0	1114.0	5.80%
P-n76-k4	75	4608	32.0	36.0	350	755.0	710.1	-5.95%
P-n76-k5	75	4608	32.0	36.0	280	798.3	780.3	-2.25%
P-n101-k4	100	4810	32.5	37.0	400	867.1	784.9	-9.48%
Set III instances								
Christofides_1	50	3654	29.0	31.5	160	668.0	626.4	-6.22%
Christofides_2	75	4608	32.0	36.0	140	1063.5	1131.5	6.40%
Christofides_3	100	4810	32.5	37.0	200	1051.9	1063.5	1.10%
Christofides_4	150	4810	32.5	37.0	200	1309.4	1455.9	11.18%
Christofides_5	199	4810	32.5	37.0	200	1644.1	1828.6	11.22%
Christofides_6	50	3654	29.0	31.5	160	707.2	626.4	-11.43%

VRP instance	n	a^2	ρ_x	ρ_y	q_c	l_o	l_e	ϵ
Christofides_7	75	4608	32.0	36.0	140	1158.2	1131.5	-2.30%
Christofides_8	100	4810	32.5	37.0	200	1102.5	1063.5	-3.54%
Christofides_9	150	4810	32.5	37.0	200	1480.2	1455.9	-1.64%
Christofides_10	199	4810	32.5	37.0	200	1777.3	1828.6	2.89%
Set IV instances								
E-n51-k5	50	3654	29	31.5	160	663.4	626.4	-5.57%
E-n76-k7	75	4608	32	36	220	868.3	920.8	6.04%
E-n76-k8	75	4608	32	36	180	935.8	991.1	5.90%
E-n76-k10	75	4608	32	36	140	1056.8	1131.5	7.07%
E-n76-k14	75	4608	32	36	100	1300.0	1412.5	8.66%
E-n101-k8	100	4810	32.5	37	200	1040.2	1063.5	2.23%
E-n101-k14	100	4810	32.5	37	112	1363.6	1481.4	8.63%
Set V instances								
M-n151-k12	150	4810	32.5	37	200	1340.7	1455.9	8.59%
M-n200-k17	199	4810	32.5	37	200	1748.2	1828.6	4.60%

Table 12. Continuous Approximation model error descriptive statistics

Statistic	Value
Min	-11.43%
1st Quartile	-2.23%
Mean	3.15%
Median	3.96%
3rd Quartile	7.66%
Maximum	14.78%

Table 13. Impact of certain relevant parameters on Continuous Approximation model estimation error

Parameter	Coefficient	Std. error	t Stat	P-value	Lower 95%	Upper 95%
n	0.07%	0.02%	3.426	0.001	0.03%	0.11%
a^2	0.00%	0.00%	-0.057	0.955	0.00%	0.00%
ρ_x	0.06%	0.08%	0.743	0.460	-0.09%	0.20%
ρ_y	-0.07%	0.07%	-1.058	0.294	-0.20%	0.06%
q_c	-0.06%	0.01%	-4.306	0.000	-0.08%	-0.03%

Results developed using regression analysis. Adjusted R^2: 23.8%, Intercept coefficient: 6.81%, p-value: 0.018.

This validation process renders model estimation error averaging at 3.15% with a maximum error of 14.77%, and the three quartiles at -2.23%, 3.96%, and 7.66%, respectively, shown in Table 12 and depicted in Figure 29. And finally, assessing the impact of the relevant parameters on estimation error, the author found only number of customers and vehicle capacity to have statistically significant influence on model error albeit negligible (Table 13).

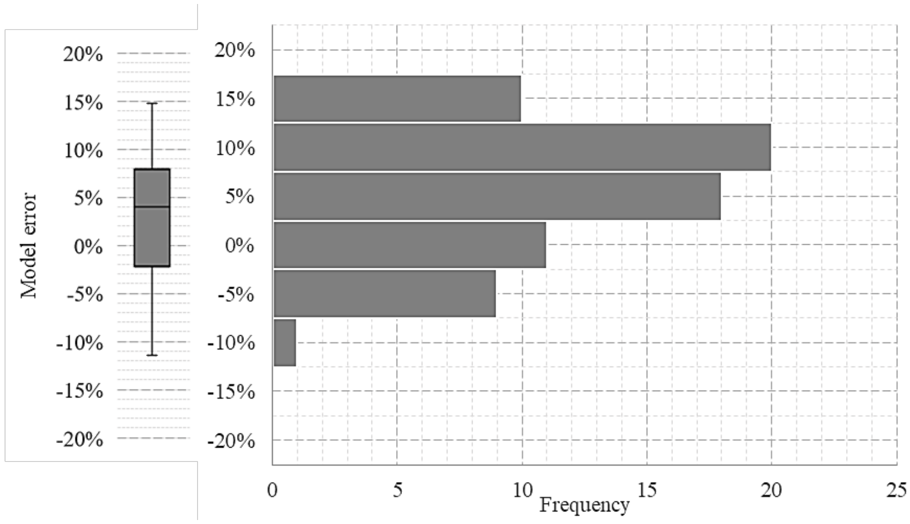


Figure 29. Continuous Approximation model error histogram and box plot

It is important to note that the instances tested here belong to single-echelon capacitated vehicle routing problem. These instances do not account for a multi-echelon distribution structure, temporal constraints, vehicle recharging, and the other operational details modeled in this work. Nonetheless, the validation process carried out here assesses the underlying capacitated vehicle routing problem in the multi-echelon distribution structure developed in this work. Moreover, with the mathematical proofs established wherever needed, the author believes that model developed in this study is robust and sound.

Appendix D.

Temporal sensitivity of last-mile distribution strategies

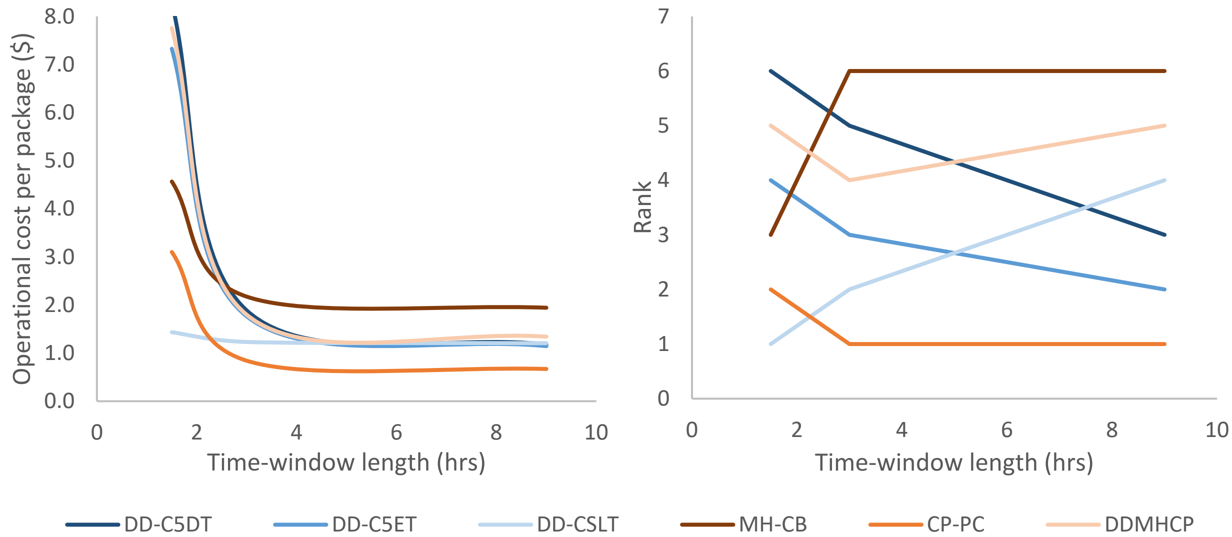


Figure 30. Impact if time-window length on fixed cost

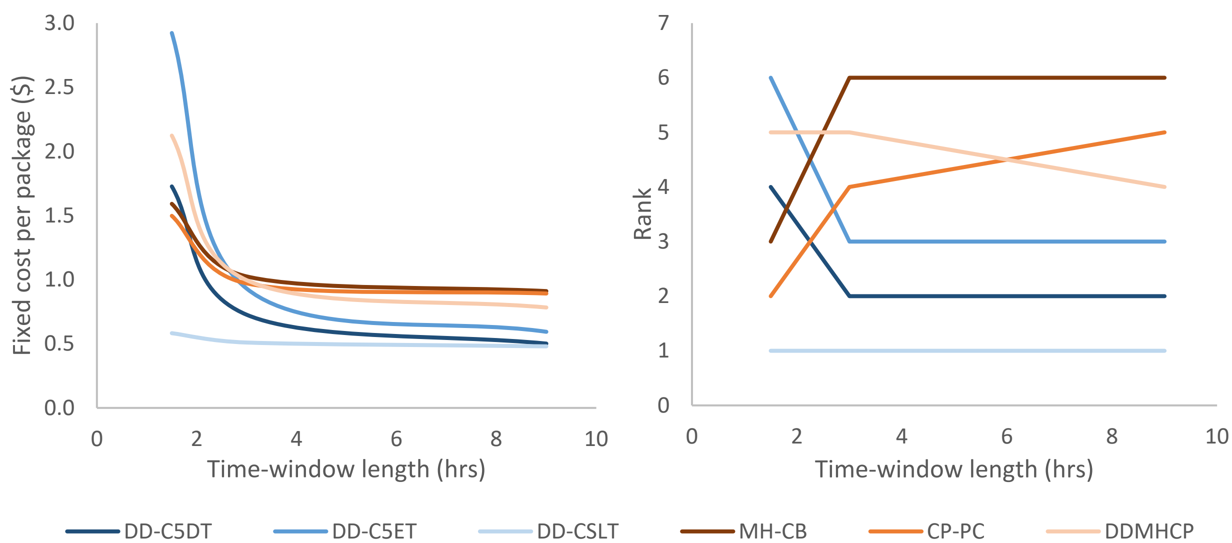


Figure 31. Impact of time-window length on transportation cost

Appendix E.

Spatial sensitivity of last-mile distribution strategies

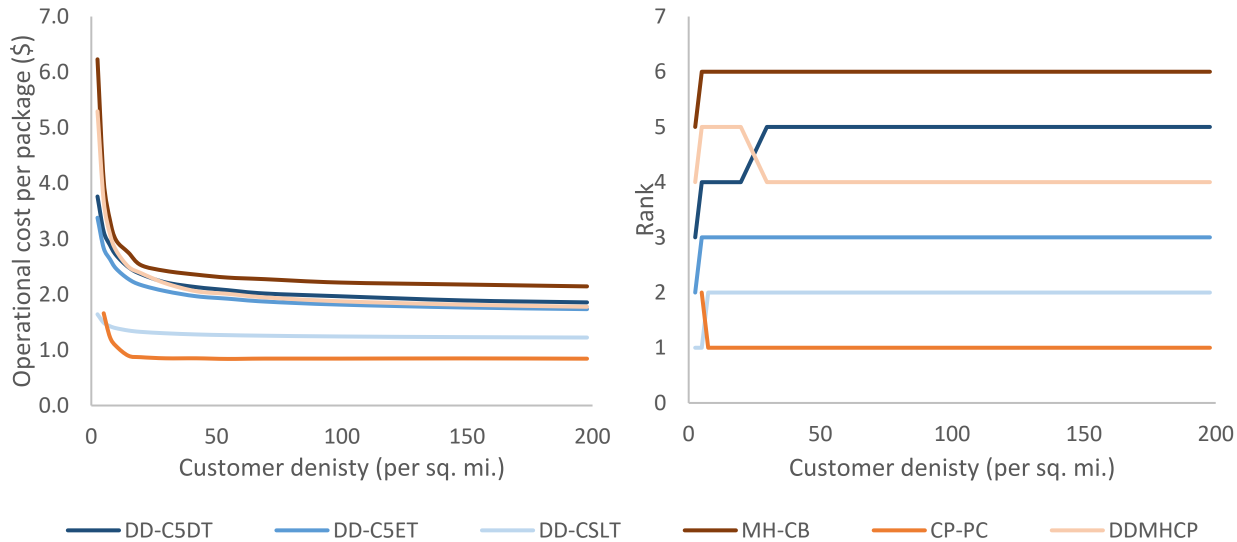


Figure 32. Impact if customer density on fixed cost

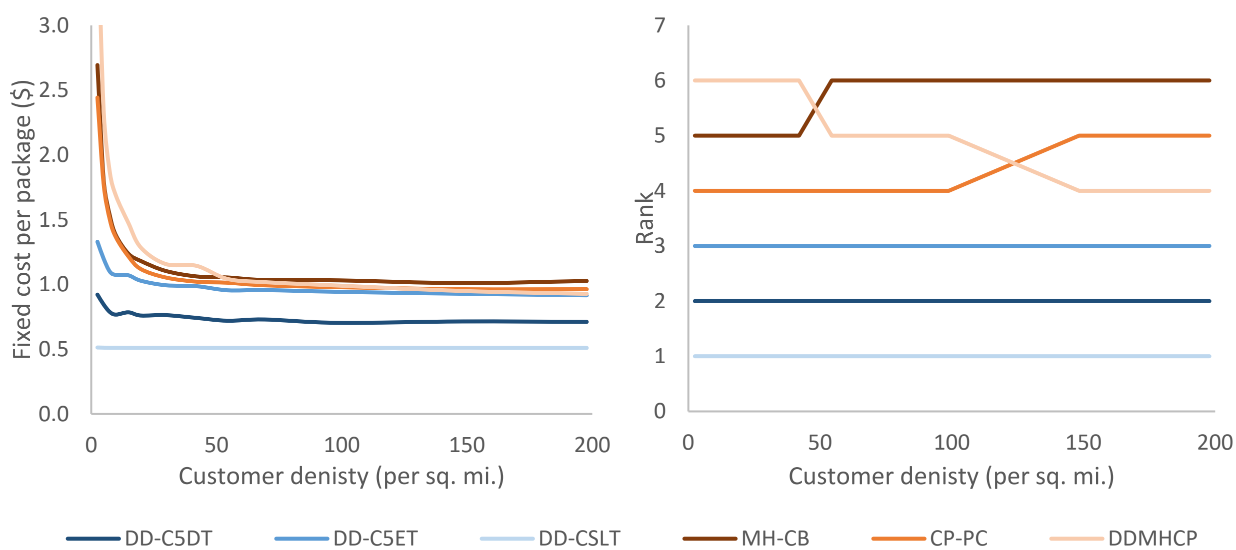


Figure 33. Impact of time-window length on transportation cost

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