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16. Abstract

In the last decade, e-commerce has grown substantially, increasing business-to-business, business-to-consumer, and consumer-to-consumer transactions. While this has brought prosperity for the e-retailers, the ever-increasing consumer demand has brought more trucks to the residential areas, bringing along externalities such as congestion, air and noise pollution, and energy consumption. To cope with this, different logistics strategies such as the introduction of micro-hubs, alternative delivery points, and use of cargo bikes and zero emission vehicles for the last mile have been introduced and, in some cases, implemented as well. This project, hence, aims to develop an analytical framework to model urban last mile delivery. In particular, this study will build upon the previously developed econometric behavior models that capture e-commerce demand. Then, based on continuous approximation techniques, the authors will model the last-mile delivery operations. And finally, using the cost-based sustainability assessment model (developed in this study), the authors will estimate the economic and environmental impacts of residential deliveries under different city logistics strategies.

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Analytical Modeling Framework to Assess the Economic and Environmental Impacts of Residential Deliveries, and Evaluate Sustainable Last-Mile Strategies

March 2020

A Research Report from the National Center for Sustainable Transportation

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Analytical Modeling Framework to Assess the Economic and Environmental Impacts of Residential Deliveries, and Evaluate Sustainable Last-Mile Strategies

EXECUTIVE SUMMARY

In the last decade, e-commerce has grown substantially, increasing business-to-business, business-to-consumer, and consumer-to-consumer transactions. From being at a lowly 4% in 2009, today e-commerce amounts to about 10% of the total retail sales (U.S. Census Bureau, 2018). As a result, the individual shopping behaviors have undergone considerable transformation, consequently transforming commodity flow and urban goods distribution. It is understood that since delivery trucks optimize their routes, e-commerce has the potential to reduce the negative impacts of shopping on the environment, and therefore is much more sustainable than shopping trips to stores using personal cars. However, in a quest to achieve larger market shares, e-retailers make lucrative offers to its consumers, offering free shipping, free returns, same-day, 1-hr/2-hr expedited (rush) deliveries and more. This has made last-mile ever more demanding, both in terms of economic as well as environmental sustainability. The benefits from shopping online are wiped out by rush deliveries as it compels the e-retailers to ship packages at lower consolidation levels leading to higher amounts of shorter tours, thus, increasing the distances driven, costs and emissions (Tozzi et al., 2013). Free returns is yet another way e-retailers pursue larger market shares. The apparel industry, in particular, witnesses exceptionally high rates of returns. Cullinane et al. (2017) found these return rates to range between 25% and 45%. This results in additional distances driven, additional emissions, and also increases cost of operation for the e-retailer. Hence, in general, one can conclude that such lucrative offers negatively affect the efficacy of last-mile distribution. The increasing customer expectations in terms of lead-time, delivery time and return policy has made the last-mile operators to develop alternate strategies for last-mile distribution. Thus, the purpose of this work is to develop an analytical framework, starting from demand estimation, modeling last-mile operations using Continuous Approximation (CA), and developing a cost-based sustainability model, to assess last-mile sustainability of commonly deployed last-mile strategies.

Impact of Time-windows

The study discusses the impacts of time-windows and facility location, in particular on the cost trade-offs for door-to-door delivery operated with a diesel fleet. Shorter time-windows reduce load utilization factors for the fleet which increases the fleet size, and in-turn the transportation costs. Therefore, to contend with higher transportation costs, the e-retailer requires locating the distribution facility closer to the market, trading off transportation costs for facility location cost. When there are no time-windows constraints, the e-retailer could optimally locate at the edge of the service region. As the time-windows get shorter, there is a need to be even closer to downtown LA (which is assumed to be the center of the service region), with total costs increasing (from the no time-windows case) by 47%, 133% and 297% for the 3hr, 1.5hr and 1hr

time-windows, respectively. These results thus demonstrate the exponential effects of temporal restrictions on last-mile delivery.

Service Comparisons

One of the main objectives of this paper is to understand the efficacy of different last-mile strategies, namely, door-to-door delivery with diesel (D2D - Diesel), electric (D2D - electric) and crowd-sourced fleet (D2D - Crowdsourced), micro-hub based delivery in combination with cargo-bikes (MH - Cargo bikes), and collection point based pickup (CP). Of particular interest are the impacts on total and emission costs. As time-windows got stricter, micro-hubs based delivery and collection point based pick-up outperform conventional truck based delivery, be it diesel or electric fleet. Amongst the two, while electric fleet has a high procurement cost, the lower operating costs over the period of 10 years of operation renders operational as well as external benefits. Back to collection points, as the responsibility of deliveries is transferred from e-retailer to the customer traveling to pick-up at the collection point, the operational cost reduces though at the expense of higher emission cost. On the other hand, the crowd-sourced delivery, due to its lower cost services (lower time-based fee, and no or lower upfront cost), renders significant reductions in shipping costs to the retailer, while at the same time since deliveries are consolidated, emissions could reduce.

To conclude, it could be argued that e-commerce delivery services are logistically efficient and could further be made environmentally sustainable with the ability to consolidate and replace inefficient shopping trips. However, the results of this study show that externality costs increase exponentially as shorter delivery time-windows are introduced. While companies could mitigate increased operational costs by locating closer to their customers (consistent with other facility location studies), delivery time-windows still increase the overall rate of emissions generated to serve the market. There are strategies, such as using cleaner vehicles, alternative delivery modes, or demand consolidation at delivery points, which could mitigate some of these impacts. In fact, the study found significant benefits from out-sourcing delivery, either in the form of customers picking up their packages at the collection points or by crowd-sourcing deliveries. In particular, the results show the benefits (reduced operating costs) of out-sourcing delivery, though these benefits may be realized at the expense of social costs in the form of additional externalities. The results also highlight the importance of considering these freight trends in planning efforts, especially those related to land use. For instance, providing land uses for the location of these facilities near customers will reduce emissions and costs; albeit the increased freight activity may generate negative impacts locally. Today, the retail landscape is changing and delivering goods through multiple channels, many with the consumer as the final destination. All of these changes require fundamental reconsiderations of traditional logistics problems (for researchers) and decisions (for carriers and other logistics agents). The companies are still adapting, whereas the planning process is lagging; this is even more critical at the local level.

I. Introduction and Background

The past couple of decades have witnessed an evolution in individual's commute and goods shipment—the two fundamental facets of transportation. On one hand, shared mobility services render a novel alternative for commute, concomitantly the advent of e-commerce has significantly reshaped our shopping behaviors, thus influencing the latter. The common denominator in both being the Internet. August 11, 1994 marks the day when the first ever internet-based retail transaction took place (Lewis, 1994). With about 90.8% internet penetration in the U.S. today (Clement, 2019a), e-commerce has grown further into the retail sector. From being at a lowly 4% in 2009, today e-commerce amounts to about 10% of the total retail sales (U.S. Census Bureau, 2018). In this last decade, e-commerce sales grew at a steady pace averaging around 15%, while the total retail sales in this time grew at a rate of 4.4% (U.S. Census Bureau, 2018). As a result, the individual shopping behaviors have undergone considerable transformation. A UPS (2017) study found that unlike the traditional way of shopping, wherein a person would search and buy products in a store, today, 36% of one's shopping activities (search and purchase) are conducted via multiple channels, while another 43% are conducted solely online, and only 21% are conducted in stores. To realize this impact on individual shopping behavior, Mokhatarian (2004) developed a conceptual framework. In particular, the study categorized the inter-relation between online and in-store shopping as complementary or substitution effect. A complementary effect occurs when part of an individual's overall shopping activity transpires online and part of it takes place in-store, while a substitution effect occurs when the online shopping activity replaces travel to a store.

A large part of the literature on shopping behavior has rather observed the former—a complementary effect. Rotem-Mindali and Salomon (2007), for instance, suggest that a substitution effect, if evident, is only minor in magnitude; only a handful of studies therefore have found a significant substitution effect. Weltevreden and Rietbergen (2007) is one of such few studies that have documented a substitution effect. This Dutch case study addressed the impacts of online shopping on the frequency and amount of in-store purchases made, both of which reduced substantially for people who made online purchases. However, in yet another Dutch study (Farag et al., 2007), the authors corroborated a complementary relation. The study found a positive effect of product-searching online on both online as well as in-store shopping. Ferrel (2004) and Lee et al. (2017) are some other studies that found a complementary effect of online shopping on in-store shopping. A few studies have also used self-stated surveys to determine the relation between online and in-store shopping. While Zhou and Wang (2014) employed the National Household Travel Survey (NHTS), Jaller and Pahwa (2020) used the 2016 American Time Use Survey (ATUS) to unravel behavioral effects. The former found a complementary effect of online shopping on in-store shopping and a substitution effect the other way, thus suggesting an asymmetric effect. The latter however suggests, "… that substitution and complementary effects must only be discussed for each shopping category separately (for example, grocery shopping or book shopping). Generalizing substitution or complementary effects over the entire shopping behavior leads to aggregation impacts." Other than these two discussed effects of e-commerce, the low cost of acquiring information online can also stimulate demand. Induced demand can transpire either on one's own shopping trips, hence inducing demand under complementary; or online when one purchases products that would not have been bought otherwise, hence inducing demand under substitution (Lee et al., 2017). In general, all of these effects modify, in different ways and forms, the way we shop.

These changes in shopping behavior in turn affects the shopping related travel and associated externalities. While the 2016 ATUS data reveals that 14% of all the trips made during the day are shopping trips, it is likely that the number of shopping trips could decrease due to e-commerce. Furthermore, it is understood that since delivery trucks optimize their routes, e-commerce has the potential to reduce the negative impacts of shopping on the environment, and therefore is much more sustainable than shopping trips to stores using personal cars. A number of studies have analyzed these externalities from freight movement in the context of online shopping (Brown and Guiffrida, 2014; Durand and Feliu, 2012; Jaller and Pahwa, 2020; Siikavirta et al., 2003; Wiese et al., 2012; Wygonik and Goodchild, 2016). A study conducted in Helsinki, the capital of Finland, analyzed transportation related externalities from e-commerce, in particular from the e-grocery segment Siikavirta et al. (2003). The study found e-grocery to perform significantly better than making a shopping trip to a grocery store, cutting down driven miles and emissions by at least 54% and 18% respectively. In a similar work, Durand and Feliu (2012) found a potential reduction in VMT by nearly 20% with e-grocery at a market penetration of 50%. These studies suggest that with a sizeable market share, sustainable last-mile operations, and consumers substituting towards online shopping, e-commerce can manifest significant reductions in the negative externalities of freight transportation. Sizeable market share is indeed an essential requirement for e-commerce to function sustainably. And while the 2016 ATUS data shows only 4% of daily shopping activities to be conducted online, the above studies assumed some level of market penetration for e-commerce, thereby exaggerating benefits from e-commerce. Jaller and Pahwa (2020) plugged this very gap in the literature. The authors first modeled the individual shopping behavior and then expanded these shopping behaviors to a macro-level, thus accurately estimating the environmental impacts of changing shopping practices. Unlike the previous studies, the study found a more plausible and realistic potential for e-commerce in reducing shopping related externalities. The authors found 7% reduction in VMT from shopping online compared to shopping in-store, and a potential to further cut it down by 80% if the online platform becomes the dominant choice (as also estimated by other studies at higher penetration levels).

Despite the internet penetration reaching saturation levels, e-commerce is far from being saturated. As discussed above, the 2016 ATUS shows only 4% of all daily shopping activities to be internet based Jaller and Pahwa (2020). This presents a huge scope for e-retailers to further expand. And in a quest to achieve larger market shares, e-retailers make lucrative offers to its consumers, offering free shipping, free returns, same-day, 1-hr/2-hr expedited (rush) deliveries and more. This has made last-mile ever more demanding, both in terms of economic as well as environmental sustainability. The benefits from shopping online are wiped out by rush deliveries as it compels the e-retailers to ship packages at lower consolidation levels leading to higher amounts of shorter tours, thus, increasing the distances driven, costs and emissions (Holguín-Veras et al., 2011; Holguín-Veras et al., 2015; Jaller et al., 2019; Tozzi et al., 2013). Wygonik and Goodchild (2016) corroborated this strong correlation between time-window length and emissions. Pahwa and Jaller (2020) quantified a 180% increment in emissions from shorter time-windows. Free returns is yet another way e-retailers pursue larger market shares. The tendency among the online shoppers to return products is not founded in the functional errors of the products but in lack of satisfaction arising from lack of information about the product. The apparel industry, in particular, witnesses exceptionally high rates of returns. Cullinane et al. (2017) found these return rates to range between 25% and 45%. Due to lack of information on suitability of an apparel, 40% of online shoppers order multiple sizes of the same product and then return all but one (TruleSolutions, 2017). This results in additional distances driven, additional emissions, and also increases cost of operation for the e-retailer. However, not providing free returns to its consumers in the first place puts the retailer under the risk of losing the consumer itself. This therefore compels the e-retailer to provide free returns, face the additional operational cost, only to keep the consumer happy. Hence, in general, one can conclude that such lucrative offers negatively affect the efficacy of last-mile distribution. The above studies therefore highlight the importance of stakeholders. In particular, consumers and e-retailers must consolidate their demand and deliveries respectively, while planners and regulators must manage the urban freight system to foster sustainability.

The increasing customer expectations in terms of lead-time, delivery time and return policy has made the last-mile operators to develop alternate strategies for last-mile distribution. Delivery consolidation at micro-hubs is one of many such alternate strategies. Typically, a micro-hub is coupled with an alternate delivery vehicle which tends to be low-volume low-pollution vehicle, thus limiting the use of long-haul trucks in the residential areas. With recent development in battery technology, electric vans have become increasingly viable option for last-mile service. On the other hand cargo bikes render ease of access and ease of parking, which otherwise (with trucks) would be a trouble, especially in highly dense localities of the city (Choubassi et al., 2016). Testing the effectiveness of electric vans Davis and Figliozzi (2013) and cargo bikes Tipagornwong and Figliozzi (2014) in last-mile distribution, the aforementioned studies developed distribution structure that beckon the use of corresponding alternate fuel vehicle. Tipagornwong and Figliozzi (2014), for instance, found cargo-bikes to be competitive with traditional diesel vehicles when delivery structure is time constrained but not constrained by delivery volume, as is in the case of courier delivery. However, when the temporal constraints become too binding, e-retailers can offer its consumers a collection point alternative at the nearest possible locker or a store. This can significantly reduce the distance driven, the number of failed deliveries, and in turn the operation cost for the e-retailer. Gevaers et al. (2014) established that using a collection point can result in ~16% reduction in delivery costs per package. These potential reductions in operational cost for the e-retailer however come at the expense of increased social cost in terms of the externalities from individual travel to the collection point. Beyond the above discussed last-mile strategies, other strategies include use of robots and drones (Goodchild and Toy, 2018) from a vehicle acting as a mobile consolidation facility, outsourcing delivery through crowdsourcing (Pahwa and Jaller, 2020) and more.

These recent developments in e-commerce and the advancements in information technology has prompted research to analyze last-mile sustainability. The conventional approach to such analysis involved development of complex discrete models, which quickly grew out of the scope of computational capacity as the problems grew in width and depth (e.g., number of facilities, vehicles, demand). Alternatively, Continuous Approximation (CA) techniques modeled parameters and decisions as continuous density functions. This is a sound compromise between accuracy and practicality. In particular, CA-based estimation can be very useful to the e-retailer when making strategic decisions, especially when operating costs may be needed but the precise plan cannot be established. In the context of routing problems, Daganzo (1984b) developed an upper bound for the length of a TSP. Expanding further, Daganzo (1984a, 1984b), developed an upper bound for the distance (total tour length) traveled by a fleet of size m serving N customers from a depot located at a distance ρ from the service region with customer density δ, as shown in Equation 1. The first term of this equation represents the distance traveled from the depot to the service region, or the long-haul, while the second term represents the distance traveled between customers, or the last mile, where k is a constant.

$$TL = 2\rho m \ + \frac{kN}{\sqrt{\delta}} \tag{1}$$

The above equation thus develops an approximation to the Capacitated Vehicle Routing Problem (CVRP) assuming customers are randomly and uniformly distributed within the service region. Breaking free of this assumption, Çavdar and Sokol (2015) developed a distribution-free approximation, accounting for customer dispersion and closeness to the center (of the service region). Many other studies have likewise modified the routing formulation for the purpose of their work and to better approximate the tours. For instance, Figliozzi (2008) modified the last-mile term of Equation 1 by a factor of $(N-m)/m$ to correct for tours with fewer customers served. Using the asymptotic properties of the VRP, Figliozzi (2009) developed an approximation for the VRP with time-windows, sequencing customers within a time-window with some probability. Applications to the original or such modified formulations are abundant and can be broadly categorized by the purpose of use as: Districting, Location, Fleet Composition and Routing problem (Franceschetti et al., 2017). The latter three specifically fall within the context of last-mile distribution. Tipagornwong and Figliozzi (2014), for instance, conducted a CA-based feasibility analysis for last-mile operations, comparing cargo-bike and traditional diesel truck operations for parcel and courier services. Similarly, Davis and Figliozzi (2013) studied the economic feasibility of replacing the conventional diesel fleet with electric fleet, estimating operation costs using CA. Analyzing an alternate last-mile distribution structure, Roca-Riu and Estrada (2012) and Roca-Riu et al. (2016) studied the feasibility of consolidation facilities. In particular, Estrada and Roca-Riu (2017) modeled delivery tours from consolidation facilities using CA, and then developed conditions in terms of customer density and consolidation facility capabilities that could generate profits for stakeholders when implementing a carrier-led consolidation strategy within the service region. In another study, Tozzi et al. (2013) adopted the above-mentioned tour length model to assess the time-sensitivity of last-mile distribution in terms of additional tours needed under various delivery time-windows. The authors concluded that stricter constraints and congestion forces the carrier to operate at lower efficiency and with lower fleet utilization. For a complete overview of the advancements in CA models for transportation logistics, refer to source, Ansari et al. (2018).

As can be noted from the vast number of studies discussed in this section, there is a plethora of literature on different last-mile strategies and operations. However, the results can be ambiguous and case-study specific. To some extent, Estrada and Roca-Riu (2017) developed conditions in terms of customer density and consolidation facility capabilities which could generate profits to stakeholders when implementing a consolidation strategy. Similarly, Arnold et al. (2017) tested the efficacy of different last-mile distribution strategies (home delivery, collection point and cargo bikes) for Antwerp, Belgium. However, a holistic knowledge of the efficacy of different last-mile strategies is missing. Thus, the purpose of this work is to develop an analytical framework, starting from demand estimation, modeling last-mile operations using Continuous Approximation (CA), and developing a cost-based sustainability model, to assess last-mile sustainability of commonly deployed last-mile strategies.

II. Methodology

Developing Demand for E-Commerce

A sophisticated e-commerce demand model is fundamental to a comprehensive analytical framework for urban last-mile delivery. To develop this demand model, in Jaller and Pahwa (2020), the authors analyzed the individual shopping behaviors using the 2016 American Time Use Survey (ATUS). ATUS, a time use study funded by the US Bureau of Labor Statistics (BLS), logs the place and time of all daily activities for participating individuals, providing information on time spent on more than 400 detailed activities. Additionally, the data contains key demographic variables and weights assigned to each respondent (to account for under- or over-representation), which can help discern the underlying behaviors. Hence, the authors modeled the shopping behaviors as a Multinomial Logit (MNL) model with the alternatives being: to not shop at all (No Shopping); to shop exclusively in-store (In-store); to shop exclusively online (Online); and to shop in-store as well as online (Both) (see choices in Figure 1). Table 1 shows the weighted MNL model, correcting for under/over representation, with the base choice being not shopping at all, i.e., No Shopping. The estimates represent the effect of the variables on the log of probability of choosing the alternative relative to the probability of the base alternative. Some statistically non-significant independent variables are in the model because they are included as part of interaction terms.

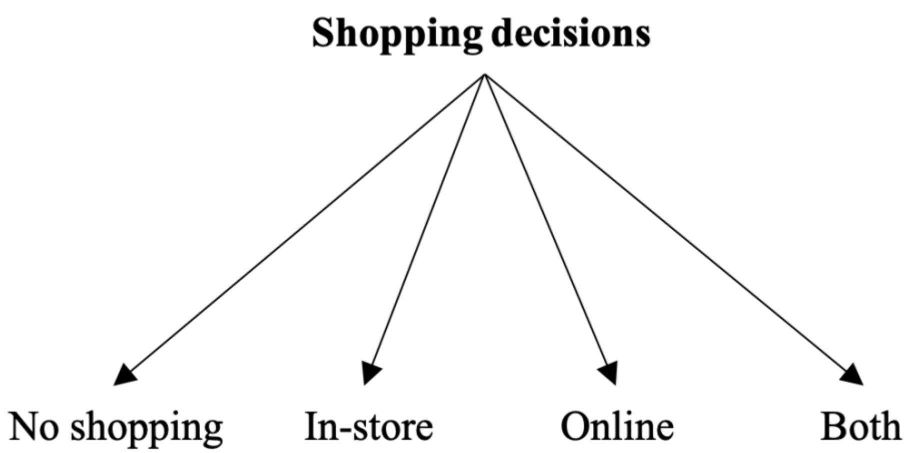

Figure 1. Alternatives in the multinomial shopping choice logit model

Now, to develop demand for e-commerce, the authors generated a synthetic population using the 2010 Census Data, replicating the inhabitants for each census tract for the two cities. This process reconstructed each individual attribute, such as gender, age, income level etc., assuming a Categorical distribution (Bernoulli/Multinoulli distribution). For each individual, the authors then implemented the behavioral multinomial choice model described above. From the resulting probabilities and subsequently assuming a Multinoulli distribution for channel choice, the study determined who would shop in-store, online, or engage in both channels. This entire process, starting from analysis of individual shopping behavior at the micro level, expands to develop the total e-commerce demand for a region.

Table 1. Shopping choice model

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)	
Gen 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

MSA>1mill implies that the individual lives in MSA with population greater than 1 million

Family structure is the ratio of kids to adults in a household

Modeling Last-Mile Delivery Operations

Facility location impacts in the VRP CA formulation

Without loss of generality, a delivery tour begins from a facility located at ρ_x, ρ_y relative to the center of the service region of size A, wherein the operator loads the packages onto the fleet. Each vehicle then travels the first leg of the tour, i.e., from the facility to the first customer in the tour, known as the long-haul (LH).

Since in this study we focus on a one-to-many structure of distribution, i.e., one facility serving N customers, the vehicles complete the last-mile (LM) by visiting each customer in the tour, delivering their respective packages. Finally, the vehicles return to the facility completing a delivery tour. Since facility location impacts are central to the model formulation here, it is important to note that, as such, there is no "long-haul" for the facility located inside the service region. However, to keep consistency irrespective of the location of the facility, we call the first leg of the tour as the long-haul, wherein the first leg is the distance traveled by a vehicle from the facility to the first customer in the tour. This study therefore builds a generic delivery tour of length L serving C customers per tour as follows,

$$L = 2\rho \ + \frac{kC}{\sqrt{\delta}} \tag{2}$$

where ρ represents the long-haul distance, dependent on the facility location (ρ_x, ρ_y).

This study bifurcates the location relative to the service region as "far" and "inside". Consider ρ as the average distance of the facility from the customers. Hence, when a facility is located far from the service region it is essentially,

$$\rho_{far} = \sqrt{\rho_x^2 + \rho_y^2} \tag{3}$$

If the facility is located inside the service area, the average distance from facility to customers is given as,

$$\rho_{inside} = \frac{1}{A}\int_{-\sqrt{A}/2}^{\sqrt{A}/2}\int_{-\sqrt{A}/2}^{\sqrt{A}/2}\sqrt{(x-\rho_x)^2 + \left(y-\rho_y\right)^2}\,dydx \tag{4}$$

To develop a closed form equation, the authors regressed multiple values of ρ_{inside} with $\sqrt{\lambda A}$. Here, λ is the expansion factor relative to the corner of the square shaped service region furthest from the facility, equivalent to the ratio of the shaded region (P'Q'R'S) to the area of the service region (PQRS) in Figure 2. The motivation behind this regression rests in the mathematical principle of homothecy, which is an affine transformation applied on space relative to the homothetic center (in this case, the furthest corner from the facility), although the exact concept does not apply here.

Regressing for multiple values of ρ_{inside} against $\sqrt{\lambda A}$, renders $\rho_{inside} = 0.722\sqrt{\lambda A}$ (R2 = 0.996). Where λ is the expansion factor relative to the corner of the square shaped service region furthest from the facility, equivalent to the ratio of the shaded region (P'Q'R'S) to the area of the service region (PQRS) in Figure 2, expressed as,

$$\lambda = (0.5 + \frac{\rho_x}{\sqrt{A}})(0.5 + \frac{\rho_y}{\sqrt{A}}) \tag{5}$$

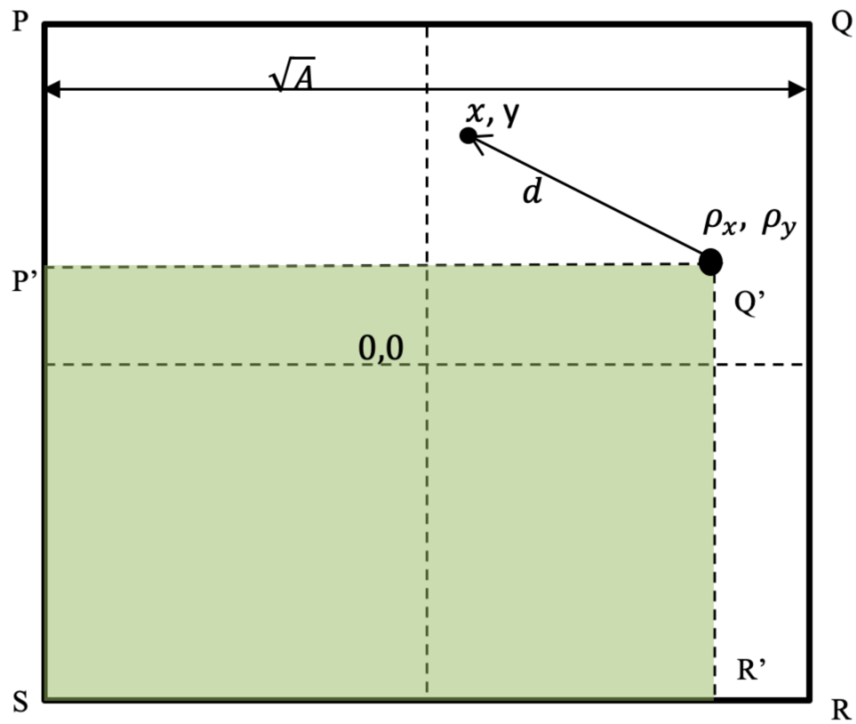

Figure 2. Visualizing expansion factor

This render ρ_{inside} as $0.722\sqrt{\lambda A}$ (R^2 = 0.996). Note, the error at the transition point, i.e., at the service region boundary, in assuming that the facility is located "far" rather than inside the service region is about 2%. This error can be further brought down by introducing a transitional space at the periphery of the service region, wherein a facility can be said to be near the service region (see Appendix). However, for the sake of simplicity, the study ignores this transitional space. Thus, on consolidating the model, one can express the long-haul distance as,

$$\rho = \begin{cases} \sqrt{\rho_x^2 + \rho_y^2} & \text{if facility is located far} \\ 0.722\sqrt{\lambda A} & \text{if facility is located inside} \end{cases} \tag{6}$$

$$\text{Facility location} = \begin{cases} \text{Far if } \rho_x \textit{ or } \rho_y > 0.5\sqrt{A} \\ \text{Inside if } \rho_x \textit{ and } \rho_y \leq 0.5\sqrt{A} \end{cases} \tag{7}$$

Furthermore, assuming v_{LH} and v_{LM} as the long-haul and last-mile vehicle speeds, respectively, the time taken to traverse the long-haul can then be given as,

$$t_{LH} = \begin{cases} \frac{\rho - \frac{\sqrt{A}}{2}}{v_{LH}} + \frac{\frac{\sqrt{A}}{2}}{v_{LM}} & \text{if facility is located far} \\ \frac{\rho}{v_{LM}} & \text{if the facility is located inside} \end{cases} \tag{8}$$

Hence, if the service time at customer and at the depot are τ_C and τ_F respectively, then the total tour travel time is,

$$T = C\tau_F + 2t_{LH} + \left(\frac{k}{v_{LM}\sqrt{\delta}} + \tau_C\right) C \tag{9}$$

With this we have a comprehensive CA based model that can account for facility location impacts on the last-mile operations. In order to validate the model, the authors compared the estimates of this newly proposed model with various VRP instances from the literature. The model estimates the length of the VRP within a range of -6% to 13% of the calculated VRP length (Table 2). Not accounting for the impact of facility location on model formulation, as in the original formulation renders heavily underestimated tour lengths. Thus, the model developed here provides a robust platform to understand the impacts of, and tradeoffs between, facility location, fleet characteristics and time-windows on a one-to-many last-mile delivery structure.

Table 2. Model comparison with VRP instances

TSP instance	Source	Market size	Service region size	Depot location	VRP length Cited	VRP length Estimated	Error
Experiment I	(Daganzo, 1984a)	32	100	0, 0	64	61	-4.5%
Experiment II		32	100	0, 0	96	90	-6.2%
Experiment III		111	72.5	0, 0	174	168	-3.6%
Experiment IV		111	72.5	0, 0	119	119	0.0%
A-n32-k5	(Augerat, 1995)	31	10,000	32, 26	784	887	13.2%
A-n44-k6		43	10,000	36, 18	937	1036	10.6%
A-n53-k7		42	10,000	26, 13	1,010	969	-4.1%
A-n60-k9		59	10,000	23, 43	1,354	1,509	11.4%
A-n69-k9		68	10,000	9, 6	1,159	1,217	5.0%
A-n80-k10		79	10,000	42, 42	1,763	1,835	4.1%
X-n209-k16	(Uchoa et al., 2017)	208	1000000	500, 500	30,656	31,325	2.2%
X-n322-k28		321	1000000	0, 0	29,834	30,428	2.0%
X-n429-k61		428	1000000	262, 54	65,843	69,023	4.8%
X-n524-k154		523	1000000	191, 229	154,593	153,443	-0.7%
X-n599-k92		598	1000000	216, 333	108,489	116,536	7.4%
X-n733-k159		732	1000000	0, 0	136,250	130,220	-4.4%
X-n801-k40		800	1000000	500, 500	73,331	73,882	0.8%
X-n895-k37		894	1000000	206, 363	53,946	58,747	8.9%
X-n1001-k43		1000	1000000	498, 357	72,402	75,449	4.2%

Comprehensive last-mile delivery model

At this point, the model developed above only supports one-to-many structure of last-mile operations, wherein the service region is served by one facility. This form of last-mile structure is evident for certain retailers serving LA, specifically Target and Sam's Club, each of which has one e-commerce fulfillment center. Walmart similarly has two e-commerce fulfillment centers, both of which are located east of downtown LA, 12 miles apart. These companies also conduct e-fulfillment (deliveries or click-n-collect) from their stores under an omni-channel distribution strategy. Table 3 provides a comparison between the number of facilities for Amazon, Walmart, and Target in the study region. Moreover, it shows the different types of facilities for their distribution structure (stores are not included, except Whole Foods). Notably, the data provide insights about the hierarchy of the different facilities, and the differences in size and the relative location with respect to the customers. For Amazon, the Prime Hub Now, for instance, are smaller and locate very close to the customers to distribute in short time windows.

Now, to expand from a single echelon structure to a multi-echelon structure, as is the case with Amazon in LA, this study develops an analytical model for a last-mile delivery service provider, serving N customers in a service region of size A in n_t periods of time-window of length T_{TW} from a depot located at a distance of ρ_x and ρ_y from the center of the service region. This depot—an e-commerce fulfillment—center is serviced from a larger regional fulfillment center located at a distance of ρ_x', ρ_y' from the center of the service region. In addition, there are N_F randomly and uniformly distributed facilities within the service region, of which N_{MH} operate as micro-hubs (consolidation facilities or MHs) and N_{CP} are collection point pick-up facilities, serving a market share of p_{MH} and p_{CP}, respectively. The vehicles departing from the distribution facility serve the $N(1 - p_{MH} - p_{CP})$ customers directly and/or the other facilities (i.e., collection points, micro-hubs) as well, and the vehicles departing from micro-hubs serve the market, while customers drive to the collection-points to pick-up their packages.

For the objectives of this work, the authors assume the case of an e-retailer distributing from a facility or multiple facilities with fixed, aggregated size acting as a single facility, irrespective of its location. This facility serves as a fulfillment center, with the associated logistics (e.g., inventory, transportation) and management costs. This facility locates "far" (under the previous considerations) from the urban core; based on Table 3, about 50 miles from Downtown LA. To serve the market under specific time-windows, the e-retailer evaluates the use of additional local distribution levels, such as an e-commerce fulfillment facility in combination with micro-hubs and/or collection points, closer to the customers, as well as use of alternate fuel vehicles such as electric vehicles and cargo-bikes. Because this new facilities have a fast throughput, inventory costs could be ignored (i.e., already accounted for at the fulfillment center), and the analyses therefore concentrate on the costs of the facility, the transport fleet, the transport to fulfill this facility (inbound cost from the fulfillment center), and the last mile distribution costs. Moreover, the authors evaluate the impacts of time-windows in the logistics decisions.

Table 3. Logistics facilities around LA*

E-retailer/Type of facility	# of facilities	Sq. Ft.	Distance (mi) from DLA	Description
Amazon				
Inbound Cross Dock	2	684,650	57.1	International shipments
Regional Sortation Center	1	514,600	56.1	Outbound shipments to USPS
Fulfillment Center	14	862,269	52.1	Specific purpose shipments
Delivery Stations	3	150,033	40.7	Outbound shipments to customers
Prime Hub Now	3	51,400	16.8	Amazon Prime shipments
Pantry and Fresh	1	121,000	4.2	Grocery shipments
Whole Foods Retail	1	128,000	3.1	Whole food shipments
Walmart				
General Merchandise DC	1	1,340,000	71.26	All-purpose shipments
Perishables DC	1	520,000	52.48	Grocery and perishables shipments
Import DC	4	687,550	40.01	International shipments
E-commerce FC	2	919,750	39.58	E-commerce shipments
Center Point DC	3	277,997	35.91	Domestic shipments
Sam's Club DC	1	60,000	35.16	Sam's Club related shipments
Target				
Import Warehouse	1	1,530,000	47.89	International shipments
Food DC	1	500,000	47.25	Grocery and perishables shipments
Regional DC	2	1,636,500	45.92	All-purpose shipments
E-commerce FC	1	725,000	38.7	E-commerce shipments

*Aggregated data from MWPVL International Inc. (n.d.), DC – Distribution Center, FC – Fulfillment center

For the purpose of the analysis, this study divides the distribution structure into three echelons (see Figure 3). The first echelon comprises of fulfillment trips between the regional fulfilment center and the e-commerce fulfilment center. The second echelon on the other hand pertains to the tours from this e-commerce fulfillment center to different locations (customers, micro-hubs, collection points) in the service region. And finally, the third echelon encompasses tours from the micro-hubs to the customers, and the customers traveling to the collection points to pick up their packages. To begin with, we define generic variables for the model as, X_i - variable X in i^{th} time-period; X^j - variable X for tour type j; ${}^kX$ - variable X associated with vehicle type k and X_i^j - variable X in i^{th} time-period for tour type j. Below we develop tour length L^j and tour time T^j for each echelon with other essential variables explained as they come by.

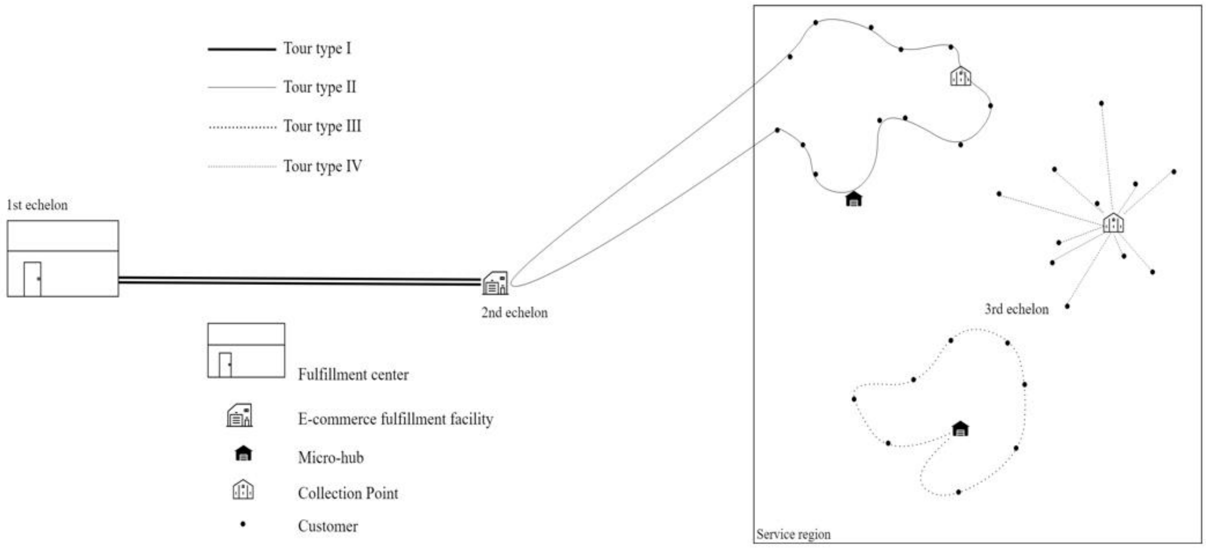

Figure 3. Distribution structure

1st echelon (Tour type I)

The vehicles travel to-and-fro between the two facilities in the first echelon. Accordingly, the tour time can be established as service time at the two facilities plus the travel time.

$$L^I = 2\sqrt{(\rho_x' - \rho_x)^2 + (\rho_y' - \rho_y)^2} \tag{10}$$

$$T^I = 2C_c^{I\,k}\tau_F + \frac{1}{\bar{\varphi}}\begin{cases} \dfrac{L^I}{{}^k v_{LH}} & \text{if depot is outside the service region} \\ \dfrac{L^I}{1+\alpha}\left(\dfrac{1}{{}^k v_{LM}} + \dfrac{\alpha}{{}^k v_{LH}}\right) & \text{if depot is inside the service region} \end{cases} \tag{11}$$

$$\alpha = \frac{\rho_x' - \frac{\sqrt{A}}{2}}{\frac{\sqrt{A}}{2} - \rho_x} \tag{12}$$

Given W working hours, the total number of such trips per vehicle are

$$m^I = \frac{W}{T^I} \tag{13}$$

Assuming that vehicles operate full-load, the fleet size can be given as

$$f^I = \frac{N}{VC^I m^I} \tag{14}$$

2nd echelon (Tour type II)

Analogous to Daganzo's tour length equation, the tour length in the 2nd echelon is sum of the long-haul distance, the last-mile distance which is proportional to the number of stops, here, number of micro-hubs, collection points and customers served (θ customers are assumed to be consolidated per stop), and the detour taken for re-fueling/re-charging purpose (represented by the last term). This detour length is proportional to the number of visits to the re-fueling/re-charging station required, Ω_i^j, and inversely proportional to the root of number of such re-fueling/re-charging facilities. Thus, as the number of re-charging facilities increase, the amount of detour reduces. Accordingly, then the tour time is established as the sum of service time at the facility, Λ_i^j, long-haul travel time, and the time spent in the last-mile traveling between the stops, serving the customers, loading/unloading at the facilities and re-fueling time. The long-haul distance and the long-haul travel time here are established based on the formulation developed in the previous sub-section. The number of stops, vehicle tours and fleet size are determined based on the latter three equations.

$$L_i^{II} = 2\rho^{II} + \frac{k\left(C_{MH,i}+C_{CP,i}+\frac{C_{C,i}^{II}}{\theta}\right)}{\sqrt{\delta_F+\frac{\delta_{C,i}}{\theta}(1-p_{MH}-p_{CP})}} + \frac{\varphi_{L,i}^{II}\Omega_i^{II}}{\sqrt{\delta_{CS}}} \tag{15}$$

$$T_i^{II} = \Lambda_i^{II} + 2t_{LH,i}^{II} + \frac{k\left(C_{MH,i}+C_{CP,i}+\frac{C_{C,i}^{II}}{\theta}\right)}{{}^{k}v_{LM}\varphi_i\sqrt{\delta_F+\frac{\delta_{C,i}}{\theta}(1-p_{MH}-p_{CP})}} + C_{C,i}^{II}\,{}^{k}\tau_C + \left(\frac{C_{MH,i}N_i p_{MH}}{N_{MH}} + \frac{C_{CP,i}N_i p_{CP}}{N_{CP}}\right){}^{k}\tau_F + \varphi_{L,i}^{II}\left(\frac{\Omega_i^{II}}{{}^{k}v_{LM}\varphi_i\sqrt{\delta_{CS}}} + t_{rfP,i}^{II}\right) \tag{16}$$

$$C_{MH,i}m_i^{II}f_i^{II} = N_{MH} \tag{17}$$

$$C_{CP,i}m_i^{II}f_i^{II} = N_{PF} \tag{18}$$

$$C_{C,i}^{II}m_i^{II}f_i^{II} = N_i(1-p_{MH}-p_{CP}) \tag{19}$$

3rd echelon – Tours emanating from micro-hubs (Tour type III)

Similar to the second echelon, the tour length for tours emanating from the micro-hubs is given by the sum of the long-haul distance, the last-mile distance and the detour length for re-fueling/re-charging. The long-haul here has been established assuming it is the distance traveled by vehicles from the micro-hub to the nearest customer. Accordingly, the tour time is then established as the sum of facility service time, long-haul travel time, and the time spent traveling between the stops, serving the customers, and re-fueling time.

$$L_i^{III} = 2\rho^{III} + \frac{\frac{kC_{C,i}^{III}}{\theta}}{\sqrt{\frac{\delta_{C,i}}{\theta}p_{CF}}} + \frac{\varphi_{L,i}^{III}\Omega_i^{III}}{\sqrt{\delta_{CS}}} \tag{20}$$

$$T_i^{III} = \Lambda_i^{III} + 2t_{LH}^{III} + \left(\frac{\frac{k}{\theta}}{{}^{k}v_{LM}\varphi_i\sqrt{\frac{\delta_{C,i}}{\theta}p_{CF}}} + {}^{k}\tau_C\right)C_{C,i}^{III} + \varphi_{L,i}^{III}\left(\frac{\Omega_i^{III}}{{}^{k}v_{LM}\varphi_i\sqrt{\delta_{CS}}} + t_{rfP,i}^{III}\right) \tag{21}$$

$$\rho^{III} = 0.361\sqrt{\frac{A}{N_{MH}}} \tag{22}$$

$$t_{LH}^{III} = \frac{\rho^{III}}{k_{v_{LM}}\varphi_i} \tag{23}$$

$$C_{C,i}^{III} m_i^{III} f_i^{III} = N_i p_{MH} \tag{24}$$

3rd echelon – Personal vehicle trip to collection point pick-up (Tour type IV)

It is assumed that a customer requests for collection point pickup at the nearest possible location. The corresponding travel is assumed to be a trip from customer's residence to this pick-up location.

$$L^{IV} = 2\rho^{IV} \tag{25}$$

$$\rho^{IV} = 0.361\sqrt{\frac{A}{N_{CP}}} \tag{26}$$

$$f^{IV} = N p_{CP} \tag{27}$$

The remainder of this section deals with vehicle re-charging and time spent at depot for tour type II and III.

Since re-charging at the station renders an opportunity cost, it is assumed that the battery levels are only restored to the point that the vehicle can just return to the depot, and hence the re-charging time at the station is given as,

$$t_{rfP,i}^{j} = \frac{L_i^j - k_R}{k_R} k_{\tau_{rf}^{CS}} \tag{28}$$

It is assumed that facilities have re-fueling/re-charging capabilities, and hence the re-fueling time at the facility is proportional to the ratio of deficit in the range relative to total distance traversed by a delivery vehicle and the vehicle range

$$t_{rfT}^{j} = \frac{\left(\sum_i L_i^j m_i^j - k_R\right)}{k_R} k_{\tau_{rf}^{F}} \tag{29}$$

As discussed previously, the frequency of visits to re-fueling/re-charging station is given by Ω_i^j which essentially depends on how large the delivery tour length is relative to the vehicle range, and hence is given as,

$$\Omega_i^j = \left[\frac{L_i^j - k_R}{k_R}\right]^+ \tag{30}$$

The service time at the facility, hence, must be enough to load/unload the packages and re-fuel/re-charge as required. While the loading/unloading times depend on the number of customer served in the tour and the efficiency in performing the loading/unloading operations, the re-charging time would depend upon whether all the tours or a tour can be completed within the vehicle range. This is expressed in the binary variables φ_T^j and $\varphi_{L,i}^j$ respectively. Note, $\varphi_{L,i}^j = 1$ is a stronger condition, and when $\varphi_{L,i}^j = 1$, $\varphi_T^j = 1$ as well. If the vehicle range is insufficient to carry out even a single tour, then the vehicle recharges full tank at the facility, however if the multiple but not all tours can be carried out under the vehicle range, then at the end of each tour vehicle recharges proportionally such that at the end of the day, the tank is empty. The authors acknowledge that the latter recharging strategy is an optimal one and often the last-mile operator may not know precise re-charging plan due to the inherent uncertainties in the last-mile.

$$\Lambda_{1,i}^{j} = \max\left(C_i^{j\,k}\tau_F, \varphi_T^{j}\frac{t_{rfT}^{j}}{\sum_i m_i^{j}}\right) \tag{31}$$

$$\Lambda_{2,i}^{j} = \max\left(C_i^{j\,k}\tau_F, \varphi_{L,i}^{j\,k}\tau_{rf}^{F}\right) \tag{32}$$

$$\Lambda_i^{j} = \left(1 - \varphi_{L,i}^{j}\right)\Lambda_{1,i}^{j} + \varphi_{L,i}^{j}\Lambda_{2,i}^{j} \tag{33}$$

Wherein,

$$C_i^{j} = \begin{cases} \frac{C_{MH,i}N_i p_{MH}}{N_{MH}} + \frac{C_{CP,i}N_i p_{CP}}{N_{CP}} + C_{C,i}^{II}, & j = II \\ C_{C,i}^{III}, & j = III \end{cases} \tag{34}$$

$$\varphi_{L,i}^{j} = \begin{cases} 1 & L_i^{j} > {}^kR \\ 0 & otherwise \end{cases} \tag{35}$$

$$\varphi_T^{j} = \begin{cases} 1 & \sum_i L_i^{j} m_i^{j} > {}^kR \\ 0 & otherwise \end{cases} \tag{36}$$

$\forall \quad i,$

$\forall \quad j \in II, III$

All the above tours and echelons are subject to capacity, time-window and working hours constraints express below,

$$C_{C,i}^{j} \le {}^kVC \tag{37}$$

$$T_i^{j} m_i^{j} - t_{LH}^{j} \le T_{TW} \tag{38}$$

$$\sum_{i=1}^{n_t} T_i^{j} m_i^{j} \le W \tag{39}$$

$\forall \quad i, j$

Cost-based Sustainability Assessment Model

The total cost, TC, for providing the service considers facility costs (only building/land because equipment and construction is assumed constant regardless of location), fleet purchase costs, operational costs (except facility operations because they are assumed to remain constant for the various locations), and the cost of externalities (GHGs and criteria pollutants). The operational costs encompass driver, maintenance, fuel and facility operational costs. Facility operational costs are assumed constant regardless of location, thus, ignored in the sub-sequent analyses.

The objective of the e-retailer is to minimize total costs (Equation 40) subject to driver working hour constraints, as represented in Equation 39; tour capacity constraints represented by the number of customers served in a tour by Equation 37; customers served constraint–Equations 17-19, 24 and 27; and the time-window constraints in Equation 38. The decision variables for the e-retailer are the fleet size - f_i, and the number of tours per vehicle - m_i, which this study assumes to be integer. In the case of no time-windows, the study assumes a single delivery period with a time-window as large as the available working hours

$$TC = Fixed\ Cost + (Operation\ Cost + Externalities\ Cost).\frac{d\left(1-(1+r)^{-Y}\right)}{r} \tag{40}$$

$$Fixed\ Cost = Facility\ fixed\ cost + Fleet\ Ownership\ Cost \tag{41}$$

$$Facility\ fixed\ cost = \sum_j F_{fc}^j \tag{42}$$

$$Fleet\ Ownership\ Cost = \sum_j {}^kPCf^j \tag{43}$$

$$Operation\ Cost = Driver\ Cost + Maintenance\ Cost + Fuel\ Cost + Facility\ Operation\ Cost \tag{44}$$

$$Driver\ Cost = \sum_{j,j\neq IV} \sum_i T_i^j m_i^j f_i^j {}^kC_d \tag{45}$$

$$Maintenance\ Cost = \sum_{j,j\neq IV} \sum_i L_i^j m_i^j f_i^j {}^kC_m \tag{46}$$

$$Fuel\ Cost = \sum_{j,j\neq IV} \sum_i L_i^j m_i^j f_i^j {}^kr_f {}^kC_f \tag{47}$$

$$Facility\ Operation\ Cost = F_{oc} \tag{48}$$

$$Externalities\ Cost = \sum_j \sum_i L_i^j m_i^j f_i^j \left(\sum_e {}^kr_e C_e\right) \tag{49}$$

The notations for the above developed last-mile delivery model and the cost model are summarized below.

Sets

e: Pollutant type
i: Time-period
j: Tour type (I, II, III, IV)
k: Vehicle type

Objective function

TC: Total cost

Decision Variables

m_i^j: Number of tours per vehicle in time period i for tour type j

f_i^j: Fleet size in time period i for tour type j

Parameters

N: Number of customers to be served in a day

N_{MH}: Number of micro-hubs

N_{CP}: Number of collection points

A: Size of the service region

ρ_x, ρ_y: Facility location (e-commerce fulfillment facility)

ρ'_x, ρ'_y: Location of the regional fulfillment center

θ: Number of customers served at one vehicle stop

p_{MH}: Share of customers served through micro-hubs

p_{CP}: Share of customers that collect the packages at a collection point

N_i: Number of customers to be served in time-period i

φ_i: Congestion factor in time-period i

F_{fc}^j: Facility fixed cost for facility responsible for tour type j

F_{oc}: Facility operation cost

${}^kPC$: Vehicle purchase cost of vehicle type k

${}^kVC$: Vehicle capacity of vehicle type k

${}^kR$: Range of vehicle of vehicle type k

${}^kv_{LH}$: Free flow vehicle speed in the long-haul for vehicle type k

${}^kv_{LM}$: Free flow vehicle speed in the last-mile for vehicle type k

${}^k\tau_C$: Service time per customer at a stop for vehicle type k

${}^k\tau_F$: Service time at facility in per customer basis for vehicle type k

${}^kr_f$: Rate of fuel consumption of vehicle type k

${}^kr_e$: Rate of emissions of vehicle type k

${}^kC_d$: Driver cost for vehicle type k

${}^kC_m$: Maintenance cost of vehicle type k

${}^kC_f$: Fuel cost for vehicle type k

C_e: Emission cost of pollutant e

n_t: Number of time-periods

Y: Number of years of operation

d: Number of working days in a week

r: Rate of return

W: Working hours in a day

Variables

λ: Expansion factor

T_{TW}: Length of time-period (time-window)

$C_{C,i}$: Customers served per tour in time-period i

$C_{MH,i}$: Number of micro-hubs visited per tour in time-period i

$C_{CP,i}$: Number of collection points visited per tour in time-period i

$\delta_{C,i}$:	Customer density in time-period i
δ_F:	Facility density (micro-hubs and collection points)
δ_{CS}:	Density of charging stations
ρ^j:	Length of the long-haul for tour type j
f^j:	Total fleet size for tour type j
Λ_i^j:	Time spent at the facility loading/unloading or recharging
$t_{LH,i}^j$:	Long-haul travel time in time-period i for tour type j
$t_{rfP,i}^j$:	Time spent re-charging at a charging station in a delivery tour
t_{rfT}^j:	Total time spent charging at the facility during the day
Ω_i^j:	Frequency of visits to the charging station in a delivery tour
$\varphi_{L,i}^j$:	Binary variable ($= 1$ if delivery tour length exceeds vehicle range)
$\varphi_{T,i}^j$:	Binary variable ($= 1$ if total vehicle tour length exceeds vehicle range)
L_i^j:	Tour length (distance) in time-period i for tour type j
T_i^j:	Tour length (time) in time-period i for tour type j

III. Case Study

The authors analyzed the potential e-retailer's last mile service in Southern California, specifically for a defined area in the city of Los Angeles. Using the behavioral shopping models developed in Jaller and Pahwa (2020), and discussed above, the authors estimate total demand for e-commerce, in a typical day, at the census tract level within the study area. Although this study does not model a particular e-retailer or operator, the work analyzes various types of services following the operations of a company such as Amazon. This is because Amazon is responsible for almost 50% of the demand (47% market share) (Clement, 2019b), and has been offering shorter time-windows, with other retailers poised to follow. In particular, this work tests the efficacy for an e-retailer providing door-to-door service with a) diesel fleet, b) electric fleet and c) crowd-sourced fleet. The study also examines the sustainability of an additional echelon/level of facility in the form of micro-hubs, which are essentially consolidation facilities, and collection points where customers can pick their packages from. Additionally, the study assumes a consolidation of 3 deliveries per vehicle stop, which are randomly and uniformly distributed in a service region centered in downtown Los Angeles (Figure 4). The service operates during a 9-hr workday, and to scale up the costs, the work considers a time horizon of 10 years of operation, with 330 working days in a year.

To understand the fixed and operational cost trade-off, the authors developed a facility (building) cost model (Figure 4) using the Co-Star sales and lease 2018 data for industrial (e.g., warehouses, manufacturing) facilities in Southern California (Jaller et al., 2020). The light blue circles in Figure 4 are actual observations for warehouse sales plotted as sales prices against location of depot relative to downtown Los Angeles, while the dark blue dashed line is the best fit for these observations. This model estimates the square footage price as a function of distance from Downtown LA.

For the analyses about the impacts of time-windows, the authors developed four scenarios: no time-window ($n_t = 1, T_{TW} = W = 9$); three 3-hr long time-windows (one for morning, afternoon and evening each) ($n_t = 3, T_{TW} = 3$); six 1.5-hr long time-windows (early/late morning, afternoon and evening)($n_t = 6, T_{TW} = 1.5$); and nine 1-hr long time-windows ($n_t = 9, T_{TW} = 1$). For illustration purposes, the study assumes a demand distribution of 0.19, 0.36 and 0.45 (UPS, 2018), and congestion factors (relative speeds) of 0.86, 1, and 0.82, developed using HERE real-time speed data (HERE, 2019), for the morning, afternoon and evening time-periods, respectively. The study assumes static and known demand (no real-time demand considered), and predefined time-windows (e.g., e-grocery deliveries with customer chosen time-windows). Table 4, Table 5, Table 6, Table 7 and Table 8 shows the various parameters and summarizes the assumptions discussed above. Note, only tailpipe emissions are considered for vehicle emission rates in Table 6. The authors estimate a per-day per-customer cost metric to facilitate the comparison of results. Further, the study conducts sensitivity (for some of the parameters) and breakeven analyses comparing location and activity. The data for the analyses and the optimization tool is available on Dryad: https://doi.org/10.25338/B82K67.

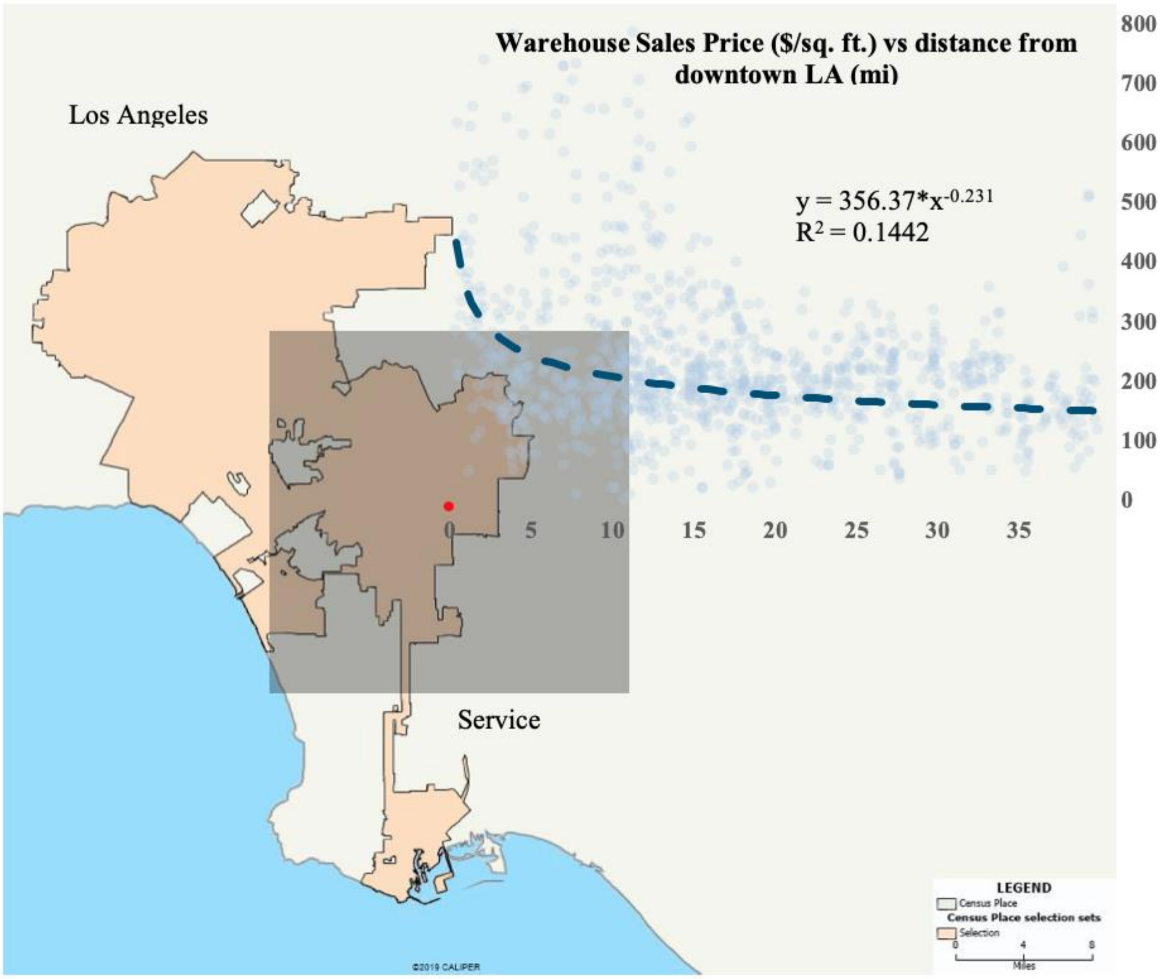

Figure 4. Service region for Los Angeles, centered in Downtown LA. Note: Light blue markers represent the price per sq. ft. for transactions in 2018.

Table 4. Service region and operator characteristics

Service region characteristics		
Market size		147849 customers (49283 delivery stops)
Service region size	$\sqrt{A}$	21.8 mi
Operator characteristics		
Warehouse purchase price per sq. ft. [a]	F_{fc}	$\$356.37\left(\rho_x^2 + \rho_y^2\right)^{-0.115}$
Working hours in a day	W	9 hours
Days of working in a year	d	330 days
Time horizon of operation	Y	10 years

[a] CoStar (2019)

Table 5. Time-window characteristics

Time-window characteristics	
Market share [a]	
No time-window	1
Three 3-hr long time-window	0.19, 0.36, 0.45 morning, afternoon, evening respectively
Six 1.5-hr long time-windows	0.095, 0.18, 0.225 early/ late morning, afternoon and evening respectively
Nine 1-hr long time-window	0.0633, 0.12, 0.15 in the first, next and the last three hours
Congestion [b]	
No time-window	0.893
Three 3-hr long time-window	0.86, 1, 0.82 morning, afternoon and evening respectively
Six 1.5-hr long time-windows	0.86, 1, 0.82 early/late morning, afternoon and evening respectively
Nine 1-hr long time-window	0.86, 1, 0.82 in the first, next and last three hours respectively

[a] UPS (2018) [b] HERE (2019)

Table 6. Vehicle characteristics

Vehicle characteristics		Class 8 DT	Class 5 DT	Class 5 ET	ECB	LDT	PC
Purchase cost [a]($)	${}^{k}PC$	120k	80k	150k*	6.5k*	-	-
Vehicle capacity (customers per tour)	${}^{k}VC$	1800	360	360	30	30	-
Long-haul speed (mph)	${}^{k}v_{LH}$	50	50	50	10	60	60
Last-mile speed (mph)	${}^{k}v_{LM}$	15	15	15	10	25	25
Service time at customer (mins)	${}^{k}\tau_{s}^{C}$	-	1	1	0.5	0.5	-
Service time at facility (s per customer)	${}^{k}\tau_{s}^{D}$	2	18	18	18	30	-
Driver cost [b] ($/hour)	${}^{k}C_{d}$	35	35	35	30	20	-
Vehicle maintenance cost [b] ($/mi)	${}^{k}C_{m}$	0.19	0.20	0.15	0.02	-	-
Fuel cost [c] ($/gal, $/kWh)	${}^{k}C_{f}$	3.86	3.86	0.12	0.12	-	-
Fuel consumption rate [a] (mpg, mpkWh)	${}^{k}r_{f}$	0.125	0.1	0.8	0.29	-	-
Range (mi)	${}^{k}R$	-	-	150	30	-	-
CO_2 emission rate [d] (g/mi)	${}^{k}r_{CO_2}$	1592	1049.38	0	0	386.1	303
CO emission rate [d] (g/mi)	${}^{k}r_{CO}$	0.81	0.77	0	0	1.77	1.09
NO_x emission rate [d] (g/mi)	${}^{k}r_{NO_x}$	5.55	4.1	0	0	0.17	0.08
PM emission rate [d]	${}^{k}r_{PM}$	0.09	0.132	0	0	0.0026	0.002

DT – Diesel Truck, ET – Electric Truck, ECB – Electric Cargo Bike, LDT – Light Duty Truck (crowd-sourcing vehicle), PC – Passenger Car

[a] Jaller et al. (2018) [b] Caltrans (2016) [c] AAA (2019) [d] California Air Resource Board (2018) *Charging infrastructure cost to be added over it

Table 7. Emission costs

Emissions cost ($/kg)		
CO_2 cost [a]	C_{CO_2}	0.1996
CO cost [b]	C_{CO}	0.1763
NO_x cost [b]	C_{NO_x}	70.43
PM cost [b]	C_{PM}	576.84

[a] California Air Resources Board (CARB) (2008)

[b] Caltrans (2016)

Table 8. Charging infrastructure cost

Charging Levels	Power (kW)	Price ($)
Level 1	1.44	1000
Level 2	7.2	3000
Level 3 (DC)	150	20000

IV. Empirical Results

This section discusses the results of the model implementation in the study region. The analyses focus on cost-trade off, impact of time-windows, efficacy of different last-mile strategies and emissions.

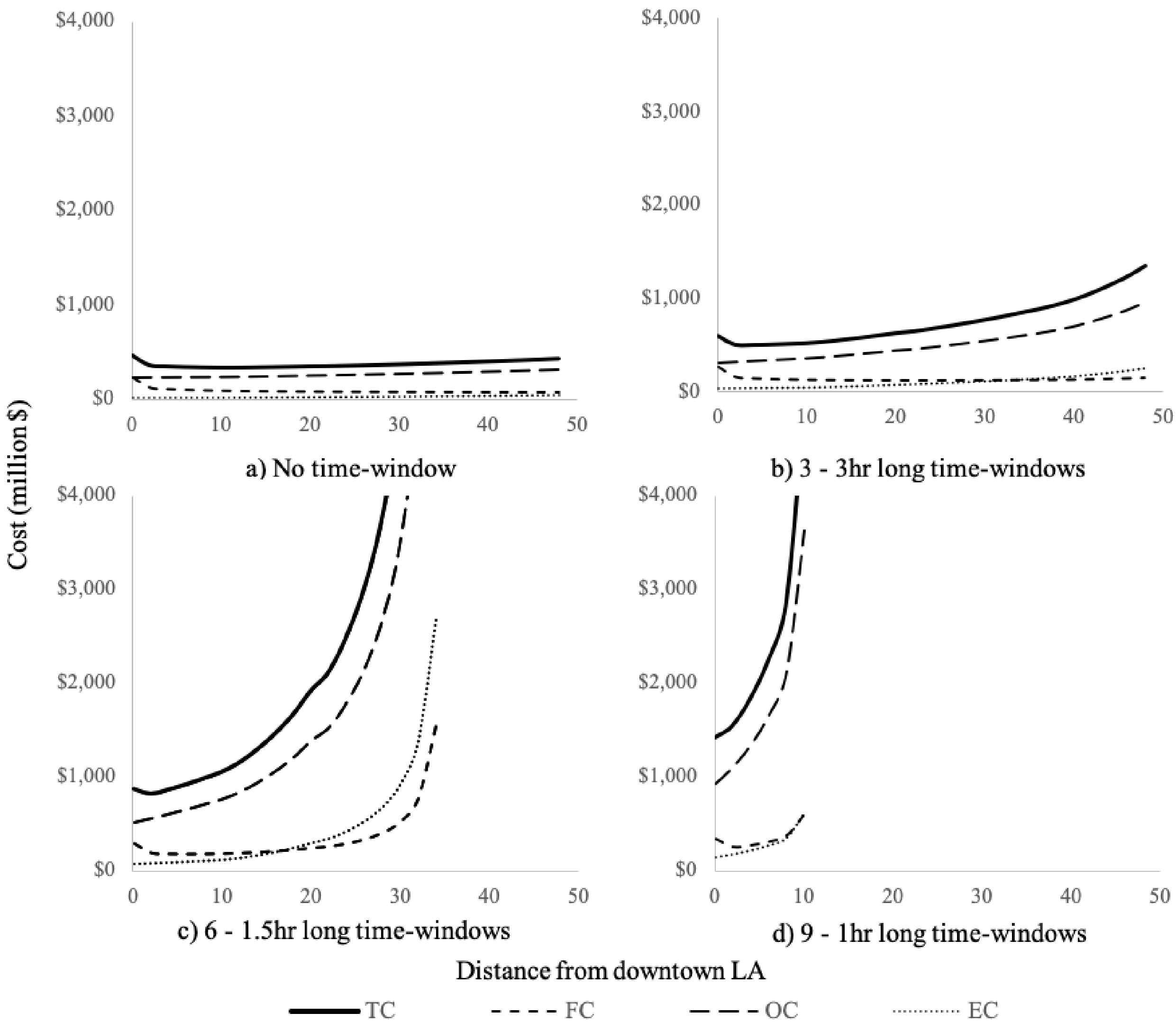

Figure 5. The cost trade-offs and impacts of time-windows

The Cost Trade-offs

In this particular sub-section, the study discusses the impacts of time-windows and facility location, in particular on the cost trade-offs for door-to-door delivery operated with a diesel fleet. Figure 5 illustrates the impact of facility location on fixed, operational, externality and total costs. Recalling that the fixed costs includes both facility and fleet ownership costs, and that while the former decreases, the latter increases as the facility locates further from the center of the market region. The results show evidence of the effect of time-windows in last-mile operations. Shorter time-windows reduce load utilization factors for the fleet (shown later in this section) which increases the fleet size, and in-turn the transportation costs. Therefore, to contend with higher transportation costs, the e-retailer requires locating the distribution facility closer to the market, trading off transportation costs for facility location cost.

For the study market, when there are no time-windows constraints, the e-retailer could optimally locate at the edge of the service region. As the time-windows get shorter, there is a need to be even closer to downtown LA (which is assumed to be the center of the service region), with total costs increasing (from the no time-windows case) by 47%, 133% and 297% for the 3hr, 1.5hr and 1hr time-windows, respectively. The impact of time-windows, in fact, extends beyond just the increase in costs. The study found no feasible solution for facilities locating beyond 32 miles from downtown LA for the 1.5hr time-window, and beyond 10 miles from city center for the 1hr time-window cases. This is because, under the speeds and service time assumptions, the facility could not serve the region without violating the time-window constraints. These results thus demonstrate the exponential effects of temporal restrictions on last-mile delivery.

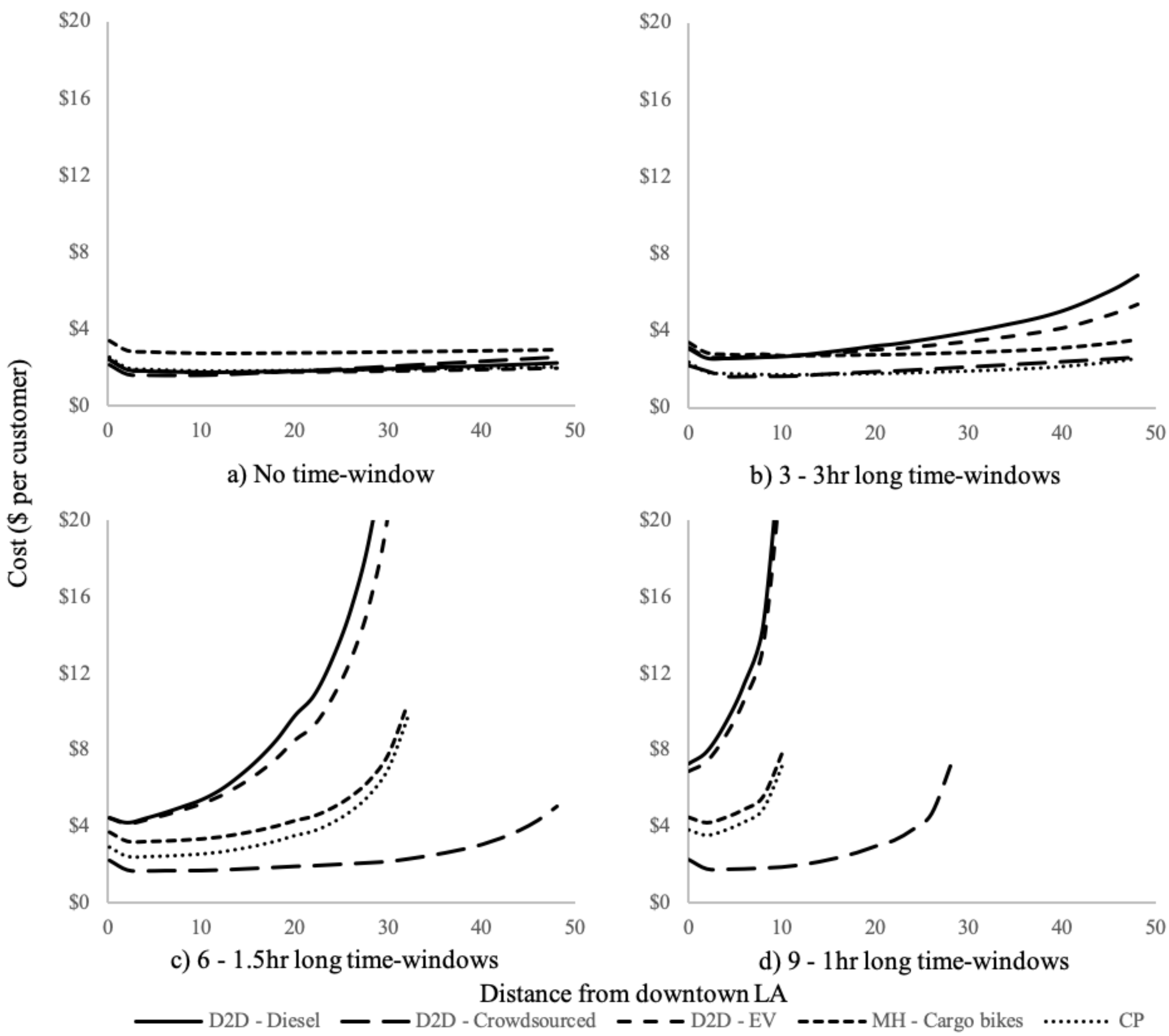

Figure 6. E-retailer last-mile structure comparisons – Total cost per customer

Service comparisons

One of the main objectives of this paper is to understand the efficacy of different last-mile strategies, namely, door-to-door delivery with diesel (D2D - Diesel), electric (D2D - electric) and crowd-sourced fleet (D2D - Crowdsourced), micro-hub based delivery in combination with cargo-bikes (MH - Cargo bikes), and collection point based pickup (CP). For the latter two scenarios, the study assumes 15 such facilities to be located within the service region, and that all of the market is served through these facilities ($N_{MH} = 15,\ p_{MH} = 1$ and $N_{CP} = 15,\ p_{CP} = 1$ respectively). Of particular interest are the impacts on total and emission costs. From Figure 6, one can notice that as time-windows get stricter, micro-hubs based delivery and collection point based pick-up outperform conventional truck based delivery, be it diesel or electric fleet. Amongst the two, while electric fleet has a high procurement cost, the lower operating costs over the period of 10 years of operation renders operational as well as external benefits. Back to collection points, as the responsibility of deliveries is transferred from e-retailer to the customer traveling to pick-up at the collection point, the operational cost reduces at the expense of higher emission cost (Figure 7).

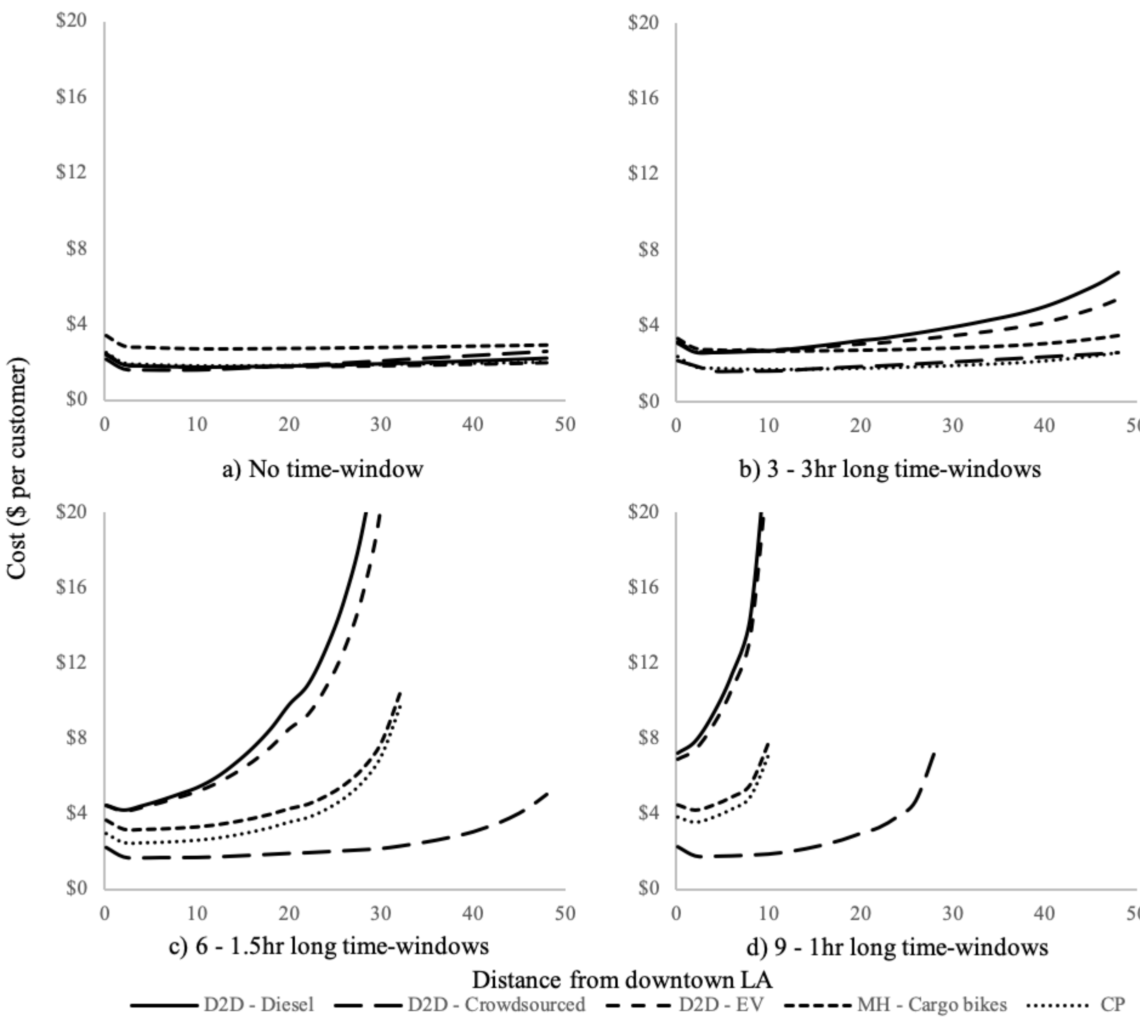

Figure 7. E-retailer last-mile structure comparisons – Emission cost per customer

On the other hand, the crowd-sourced delivery, due to its lower cost services (lower time-based fee, and no or lower upfront cost), renders significant reductions in shipping costs to the retailer, while at the same time since deliveries are consolidated, emissions could reduce. And with stricter temporal constraints, the difference in operating with one's own fleet and crowd-sourcing the delivery grows even further. For instance, at the optimal facility locations, the shipping costs by outsourcing the deliveries reduce by 30%, 50%, 65% and 71% as time-windows get smaller. As discussed above, time-windows lead to poor load utilization, therefore requiring a larger fleet size. However, when the deliveries are outsourced, the retailer does not have to purchase more vehicles, but has to hire more crowd-sourced drivers. These benefits remain, though slightly reduced, even when the company assumes an upfront cost (which is smaller than the vehicle purchase cost). However, the business may increase its operational risk if it relies solely on crowd-sourced drivers; thus, it may need to incentivize driver supply at an increased cost (similar to how ride-hailing services do).

Sensitivity Analyses

To explore beyond the results from the case study, the authors performed sensitivity analyses. In particular, this study looks at the market size effects and the impacts from improved/reduced service efficiency on the delivery operations (D2D - Diesel). The market size effects pertain to impacts from altering the size of the service region and/or number of customers served, while service efficiency pertains to vehicle speed (in the last-mile) and service time per customer. The following figures demonstrate these effects on total cost (Figure 8), emission cost (Figure 9), fleet size (Figure 10), at the optimal, and the optimal facility location (Figure 11) under 3-hr time-window.

As one would expect, a larger customer base helps consolidating operations thus resulting in lower costs per customer as also evident from Figure 8. But because the market is already well consolidated an increase of 33% in customer base from 60k to 80k results only in a minor reduction of ~3% in per customer costs. Given a fixed customer base, changes in the size of the service region affects the inter-stop distance. Thus, when the service region is too large for a facility to serve, opening up another facility and in turn dividing the responsibilities of service can be useful for the operator. Overall, the market size effects here demonstrate that a sparsely populated service region results in higher costs compared to a densely populated service region. However, it is important to note that the iso-cost contour curves do not overlap with the iso-density contour curves (straight lines emanating from 0,0 but not mapped in the figure). Some iso-density curves are steeper while others are flatter compared to the iso-cost curves. This observation thus bolsters the idea of opening up additional facilities and dividing the service region into smaller regions to reduce costs, specifically when the iso-cost curves are steeper than iso-density curves.

The service efficiency on the other hand has more dramatic effect on costs, particularly for service time. An increment in service time per customer by 3 times from 1 min to 3 mins results in about 2-3 times increase in costs per customer. While vehicle speeds do not have as significant affect when the service time is small, the contour lines tend to flatten as the service time increases, signifying the effects of congestion. Particularly when the service time is 3 mins, a 3x reduction in vehicle speed results in ~1.6 times higher costs per customer. This thus reinforces the arguments made earlier that temporal restrictions have significant impacts on last-mile delivery efficacy. In addition to that, these results bode well for low-volume low-cost vehicles such as cargo bikes or vehicles deployed for crowd-sourced delivery. Last-mile deliveries into dense areas such as downtown can be susceptible to congestion and access unavailability (resulting in increased service time). Such vehicles can flourish under such delivery conditions, due to its ease of access given that there is appropriate infrastructure in place. This is true especially when time-windows are also imposed as any disadvantage due to a lower capacity is mitigated by lower consolidation levels forced by temporal restrictions in the first place. Similar conclusions can be drawn for emission costs as well.

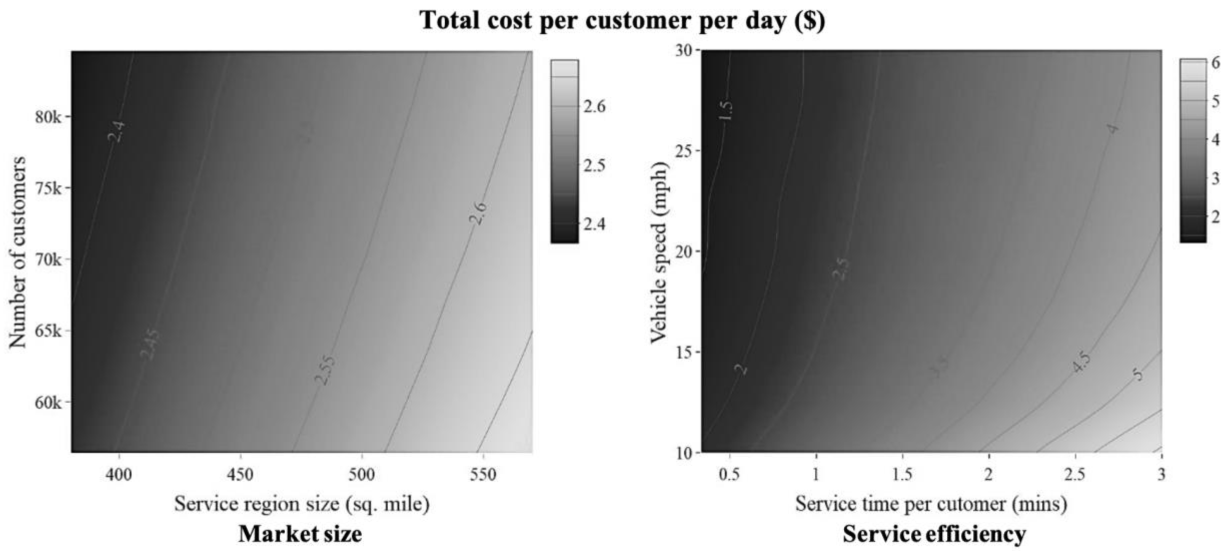

Figure 8. Impact of market size and last-mile efficiency on total cost per customer

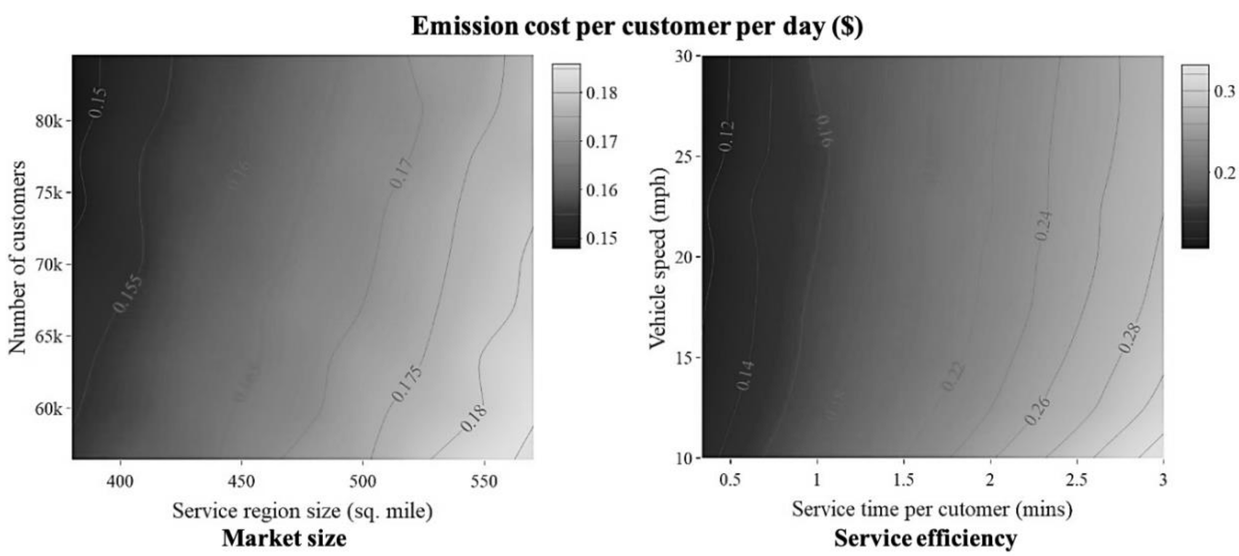

Figure 9. Impact of market size and last-mile efficiency on emission cost per customer

For any last-mile distribution, the number of vehicles that need to be deployed would depend upon the efficiency of the vehicle; its volume capacity, ease of access and parking (which affects customer service time), vehicle speed, and the size of the market. The relatively flat contour curves in the first of the two graphs in Figure 10 demonstrates the significant impact of market size, in particular the impact of customer base of the e-retailer on the size of the fleet. While the relatively steep contour curves in the latter of the two graphs show the impact of service time on the same. The fact that vehicle speed is insignificant when making vehicle procurement decision strengthens the case for cargo-bikes but under the delivery conditions expressed above. Yet again temporal effects are more dramatic than market size effects.

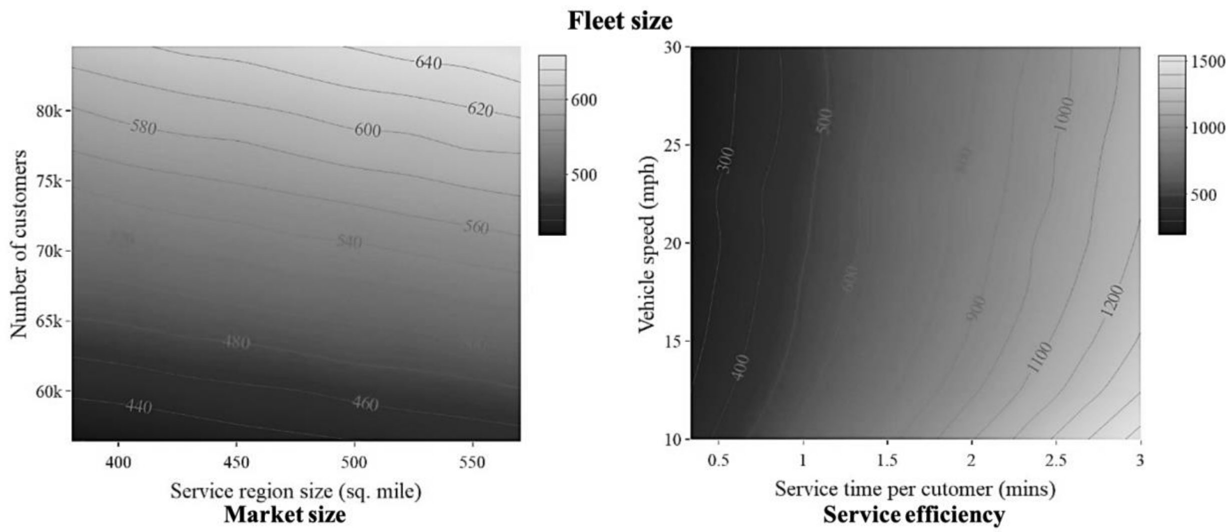

Figure 10. Impact of market size and last-mile efficiency on fleet size

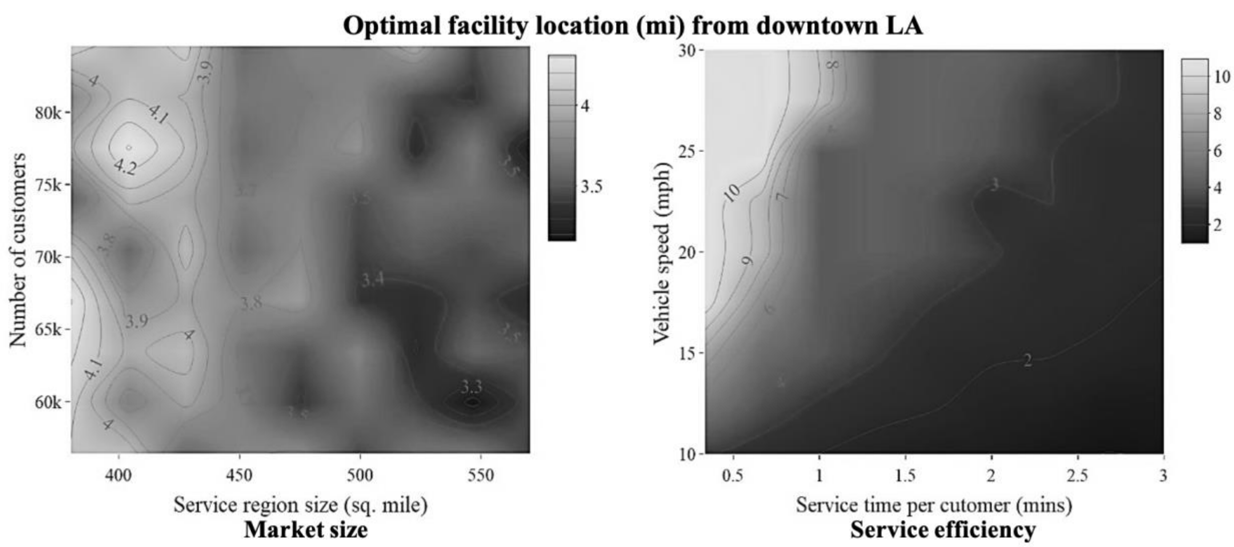

Figure 11. Impact of market size and last-mile efficiency on optimal facility location

Next, the study looks at the market size effects and service efficiency impacts on the optimal location of the facility (Figure 12). In the former of the graphs, one can observe a hill under densely populated conditions and a trench under sparsely populated conditions. Although the difference between the apex and the nadir is barely a mile. More dramatic impacts can be observed the second graph that reveals a plateau which abruptly falls into a valley as service efficiency reduces. The plateau region is of particular interest as it shows that beyond a certain threshold of service efficiency any additional improvements cannot push the facility further away from the service region as other factors possibly transportation cost come into play. In addition, throughout the spectrum of speed and service time values, the optimal facility location remains inside the service region. This will significantly change and so will all the sensitivity analysis done prior as time-windows is relaxed or further restricted. Again, under specific conditions (short time-windows and appropriate infrastructure) deploying cargo bikes or crowd-sourcing deliveries can help locating further away from the service region, and in turn reducing fixed, operational as well as emission cost. In the text above, the study assesses the service efficiency effects for 3-hr time-window. The results in the Appendix (Figure 15 and Figure 16) extend that analysis for delivery under no time-window and 1-hr time-window, the two extremes. While the results here are not too different from the ones presented in the text, the results are of particular interest as one can observe a continuous and gradual variation in cost and location from one extreme of no time-window, to the other extreme of 1-hr time window.

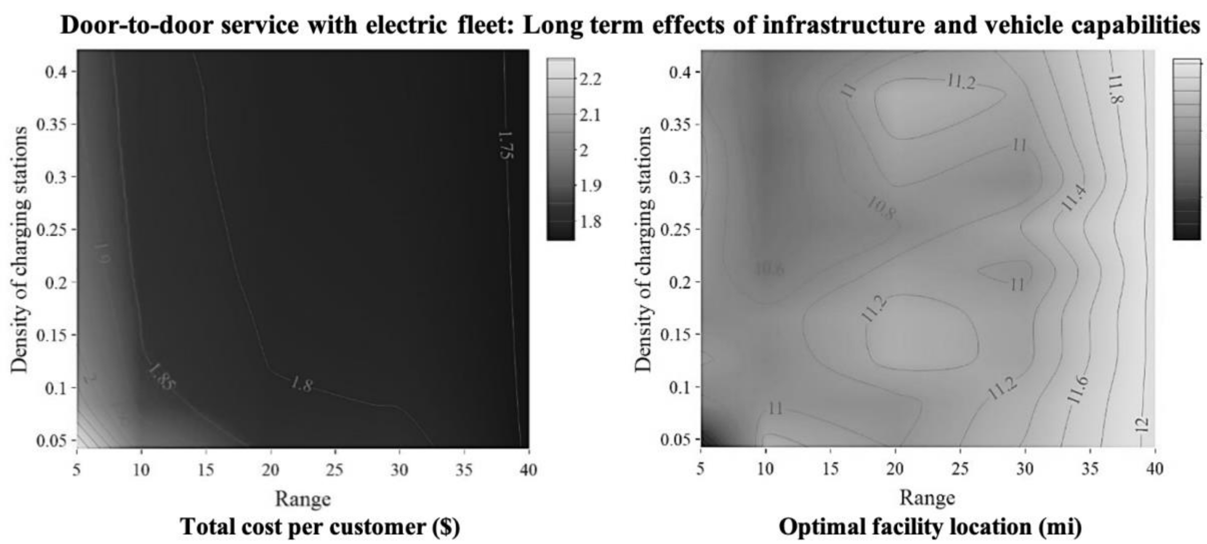

Figure 12. Long term effects on door-to-door service with electric fleet

For electric vehicle based last-mile delivery, the study analyses the short-term and long-term effects, i.e., in the short-term the facility location is fixed at 48 miles from downtown LA, while in the long-term e-retailer is allowed to re-optimize to locate at the optimal location that results in least total cost. These effects pertain to the impacts from availability (density) of charging infrastructure and vehicle capability (range). The results are particularly interesting as one can draw two key inferences from here. Firstly, it is evident that density of chargers does not have a significant impact on last-mile operations if the facility can re-locate closer to the customers, wherein the vehicle range would suffice for a delivery tour (Figure 12). However, if the facility cannot relocate at all or sufficiently close to the customers, vehicle range (or rather insufficient vehicle range) can cause disruption in last-mile operations, as delivery vehicles need to de-tour and re-charge at a charging station (Figure 13).

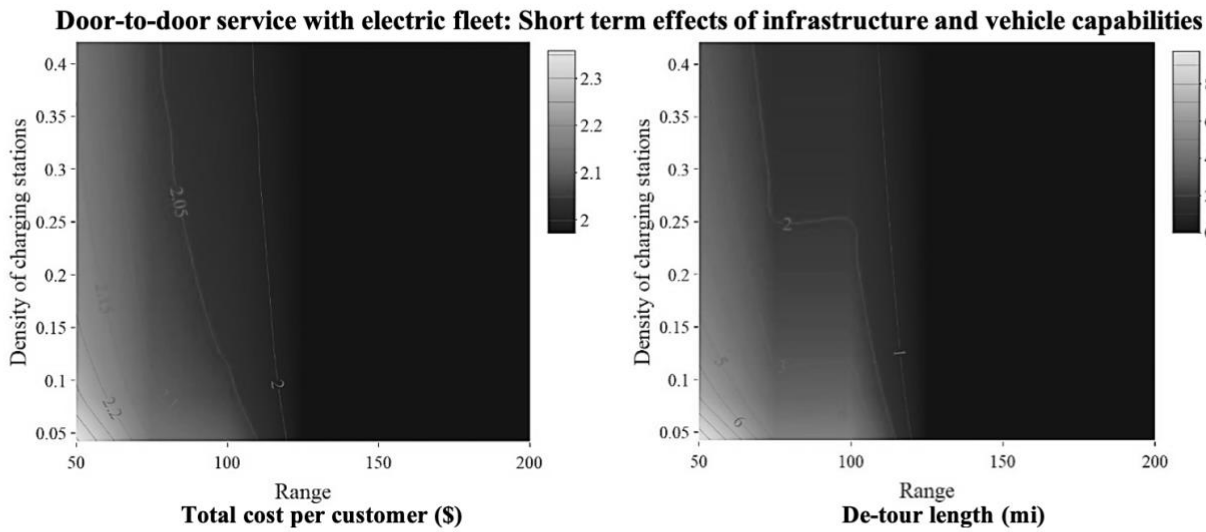

Figure 13. Short term effects on door-to-door service with electric fleet

Lastly, the study looks at the sensitivity impacts for micro-hubs and collection point based last-mile delivery (Figure 14). The sensitivity effects pertain to the impacts from share of cargo that is processed through micro-hubs or collection points and the number of such facilities. The results for these two different delivery structures show an opposite trend. While on one hand, total costs from an additional echelon of consolidation are unaffected by the share of packages processed through micro-hubs but by the number of such facilities, total costs for collection point-based pick-up are sensitive to the share and not so much to the number of facilities. For the former, the trend observed can be ascribed to the reduction in transportation costs as more facilities are opened leading to shorter delivery tour lengths, while for the latter, as the responsibility for delivery in outsourced to the customer itself, the transportation costs reduce, and hence number of facilities has no role to play here. An exact opposite trend is observed for emission costs, however. Since the micro-hubs work in combination with cargo-bikes, a larger share of packages delivered through cargo-bikes results in reduced emissions, thus number of facilities does not have a role to play here. On the other hand, as more collection points open up, customers travel less, thus pollute less, while the share of customers has relatively muted effect. As far as the optimal location of the facility, the e-commerce fulfillment center is concerned, the higher the number of customers serviced through the collection point or micro-hubs, the further away the facility can relocate as the trucks departing from this facility have lesser and lesser customers to serve.

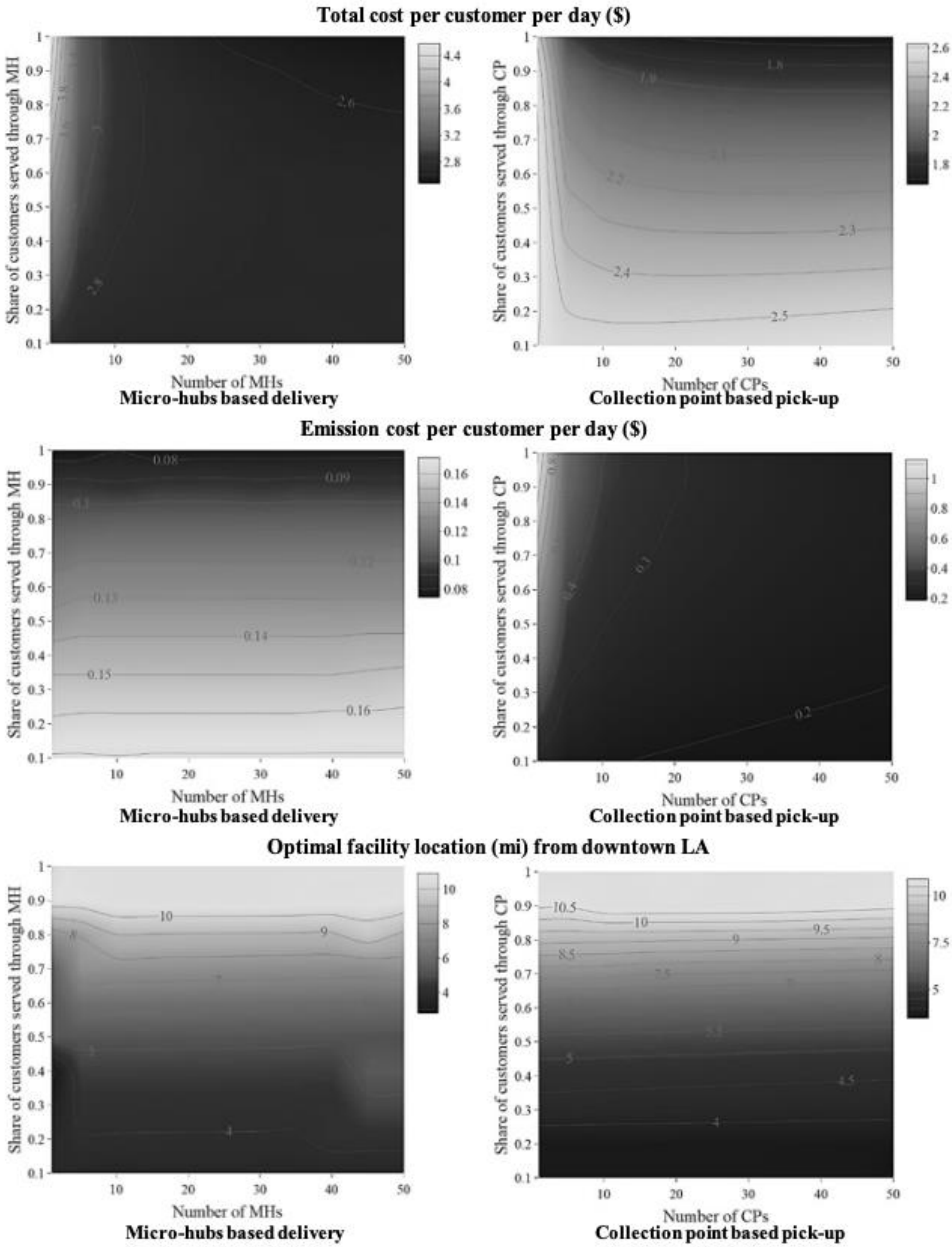

Figure 14. Impact of micro-hubs and collection points

V. Discussion and Conclusions

The rise of e-commerce and the consequent need to redirect freight towards sustainability has renewed academic interest in last-mile operations. Moreover, the e-commerce market has become ever more demanding, forcing e-retailers to make attractive offers to customers, such as free shipping, free returns, reliability, and traceability, among others. Retailers are offering shorter delivery time-windows (e.g., same day, two-hour, one-hour), and in so doing, increasing customer expectations.

It could be argued that e-commerce delivery services are logistically efficient and could further be made environmentally sustainable with the ability to consolidate and replace inefficient shopping trips. However, the results of this study show that externality costs increase exponentially as shorter delivery time-windows are introduced. While companies could mitigate increased operational costs by locating closer to their customers (consistent with other facility location studies) (Jahangiriesmaili et al., 2017), delivery time-windows still increase the overall rate of emissions generated to serve the market. Technically, the shorter the time-windows, the lower the possible consolidation level, resulting in more activity (miles traveled), more resources used to deliver a fixed number of shipments, and more externalities produced. There are strategies, such as using cleaner vehicles, alternative delivery modes, or demand consolidation at delivery points, which could mitigate some of these impacts.

In fact, the study found significant benefits from out-sourcing delivery, either in the form of customers picking up their packages at the collection points or by crowd-sourcing deliveries. In particular, the results show the benefits (reduced operating costs) of out-sourcing delivery, though these benefits may be realized at the expense of social costs in the form of additional externalities. However, under specific settings out-sourcing deliveries can operate sustainably, as also discussed by Odongo (2018) for the case of crowd-sourced deliveries. In particular, the study found that crowd-sourcing deliveries can produce significant gains for the e-retailer and at the same time reduce externalities when temporal constraints are binding, and capacity constraints are not. Although strict working conditions as is the case with short time-windows may dissuade crowd-shippers in taking up delivery responsibilities, thus reducing driver supply (Ermagun et al., 2019). While this study did not evaluate secondary and further impacts of using crowd-sourcing services, the results indicate the potential for their increased use. Future research should study the potential sustainability impacts of increased use of crowd-sourcing delivery services. The passenger counterpart of such services are now a few years into the market with positive and negative effects being seen in transportation, and in such areas as labor, safety, and economic development. In addition, this study, argues for the use of cargo bikes. The results show that delivery to dense localities under short time-windows can benefit from deploying cargo-bikes especially with a bike infrastructure in place. This is consistent with results from other studies, such as Tipagornwong and Figliozzi (2014), who analyzed the competitiveness of cargo bikes with traditional diesel trucks. All the above discussed strategies in a sense try to remediate the consequences of what is the fundamental current challenge in distribution, a trend towards almost instant deliveries. Thus, it is imperative to identify the type of intervention–supply- or demand-driven, or regulatory policy—that will internalize the full costs resulting from these services to the company, the consumer, or both.

The results also highlight the importance of considering these freight trends in planning efforts, especially those related to land use. For instance, providing land uses for the location of these facilities near customers will reduce emissions and costs; albeit the increased freight activity may generate negative impacts locally. These could bring along unintended consequences considering that the ability to locate closer to the customer may foster even faster deliveries, which are clearly not sustainable. An important consideration here is the fact that the traditional system and planning processes have been observing an opposite trend in the form of logistics sprawl, where larger facilities have moved to the outskirts of cities. These facilities, as part of regular retail distribution networks (through retail stores) traditionally sent consolidated shipments to the stores and served other markets, thus having the ability to be located further away, and benefiting from lower facility costs. Today, the retail landscape is changing and delivering goods through multiple channels, many with the consumer as the final destination. All of these changes require fundamental reconsiderations of traditional logistics problems (for researchers) and decisions (for carriers and other logistics agents). The companies are still adapting, whereas the planning process is lagging; this is even more critical at the local level.

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VII. Data Management

Products of Research

2016 American Time Use Survey – This survey is conducted by the United States Department of Labor, Bureau of Labor Statistics. The ATUS measures the amount of time people spend doing various activities, such as paid work, childcare, volunteering, and socializing. The team used the data to estimate a number of shopping behavior econometric models.

Socio-demographic data – The team used the publicly available data from the U.S. Census Bureau. The team used the data to generate synthetic populations for the empirical analyses, and during model development.

Co-Star – Co-Star is a real estate manager. The team modeled spatial variations for warehouse sales price using the warehouse purchase data from Co-Star. The team only used the data to generate the case study information.

Analytical tool – This file contains essential information to use the Last-Mile Analytical Tool. This tool models last-mile delivery and different city logistics measures in the context of e-commerce delivery.

Based on the structure of last-mile distribution (described above) we have four types of tours:

Tour Type I: Inbound movement between Fulfillment center to E-commerce Fulfillment Facility
Tour Type II: Vehicle movement between E-commerce Fulfillment Center and service region
Tour Type III: Vehicle movement between micro-hubs and customers
Tour Type IV: Vehicle movement between customers and collection point

Data Format and Content

The project uses the following public datasets:

The 2016 **American Time Use Survey (ATUS)**. The team uploaded to the Dryad system the files used saved in Comma-delimited (csv) format. Some variables have been removed to comply with legal and ethical guidelines. However, the entire ATUS data can be accessed from https://www.atusdata.org/atus/about_atus.shtml.

Socio-demographic data. The files uploaded Census data for Los Angeles in Comma-delimited (csv) format. Census data for LA. This data was employed to expand on the individual shopping behaviors to develop local/regional (in this case for LA) e-commerce demand. Note this data does not contain individual information but aggregated demographics for LA City.

The project used the following proprietary datasets:

Co-Star. Industrial and commercial real estate information for the Los Angeles, Orange, Empire, Riverside, and San Bernardino. The team is not able to share the raw-data due to the proprietary information.

Analytical Tool. The Analytical Tool is a .xlsm file named "Last-mile Analysis.xlsm". This excel sheet contains the following sheets:

1. Input

   This is the main/starting page of the tool. The Input sheet comprises of all the required inputs for last-mile analysis that pertain to

   - Service region characteristics: size of the service region, total e-commerce demand and more.
   - Demographics: Demographics in conjunction with the shopping behavior model (presented in "Demand Gen" sheet) are used to estimate the e-commerce demand of the service region.
   - Operator characteristics: type of distribution structure, type and number of facilities, planning horizon and more.
   - Vehicle characteristics: vehicle specifications.
   - Tour-vehicle combination: Vehicle used corresponding to tour type.
   - Charging levels: EV charging levels power and price.

Data Access and Sharing

The project uses publicly available information. Any dataset compiled during the project using the various data sources follows the same access and sharing policies as the original data. The research team did not use any data with private or confidential information with the exception of the Co-Star data. Due to the nature of that data, the team is not able to provide access to the dataset. The team made available the datasets used for the different modeling estimation processes, as well as the data used in the scenarios when implementing the framework through Dryad. Any other user should reference the research team and this project as directed by the National Center for Sustainable Transportation.

Data can be found at: https://doi.org/10.25338/B82K67

Reuse and Redistribution

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

Pahwa, Anmol; Jaller, Miguel (2020), Analytical Modeling Framework to Assess the Economic and Environmental Impacts of Residential Deliveries, and Evaluate Sustainable City Logistics Strategies, v2, UC Davis, Dataset, https://doi.org/10.25338/B82K67.

VIII. Appendix: Service efficiency impacts under varying time-windows

In the text above, the study assesses the service efficiency effects for 3-hr time-window. The results below extend that analysis for delivery under no time-window and 1-hr time-window, the two extremes. While the results here are not too different from the ones presented in the text, the results are of particular interest as one can observe a continuous and gradual variation in cost and location from one extreme of no time-window, to the other extreme of 1-hr time window.

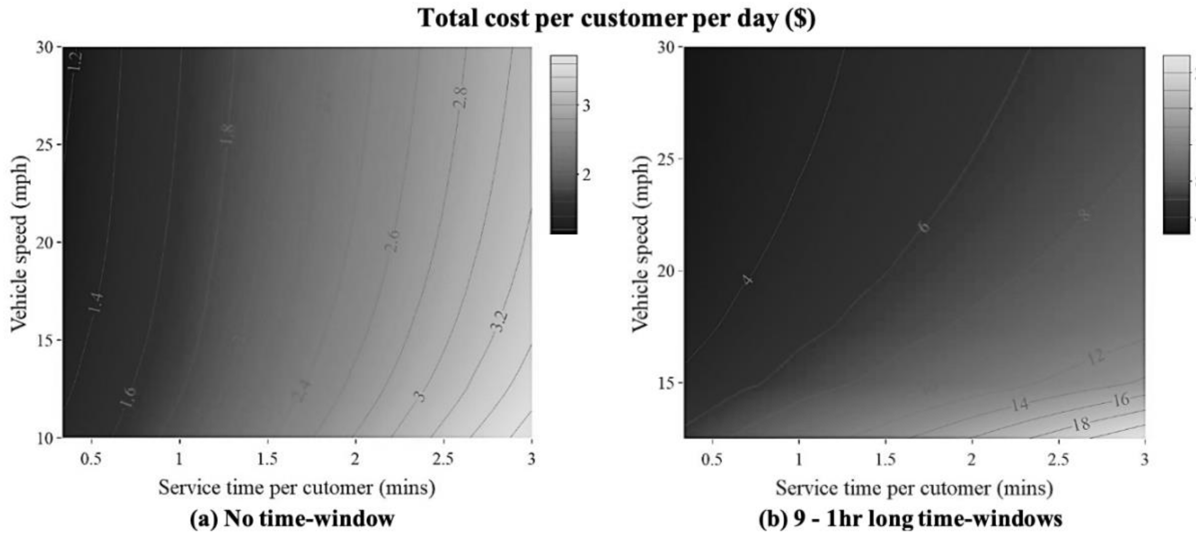

Figure 15. Last-mile efficiency effects on total cost per customer under varying time-windows

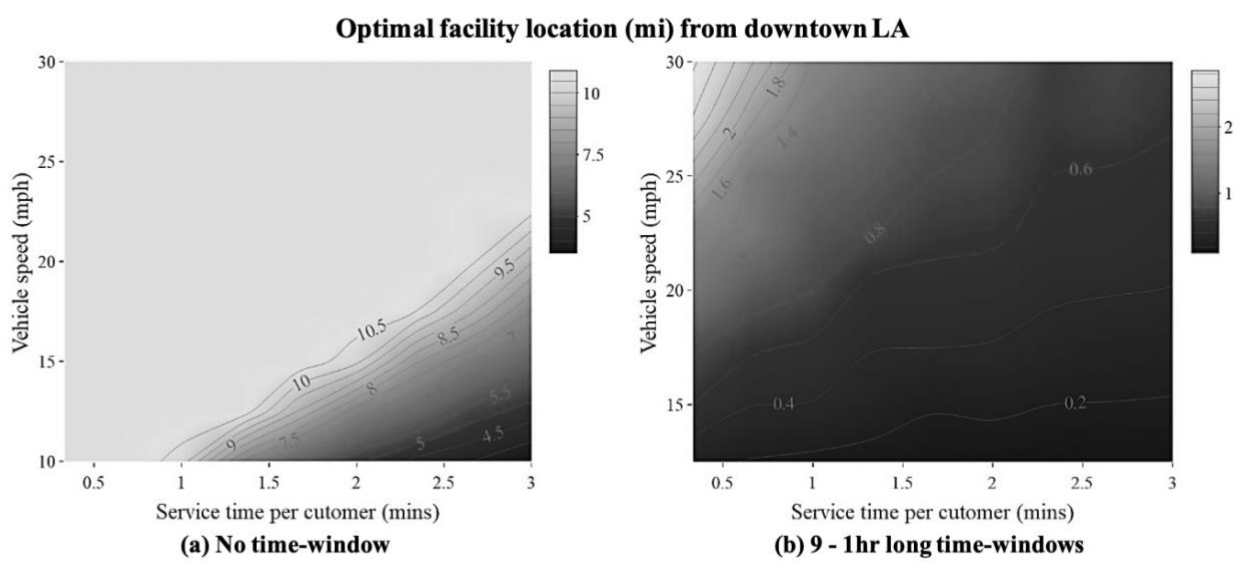

Figure 16*. *Last-mile efficiency effects on optimal location under varying time-window