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Demand-Side Management of Auto Traffic for Urban Parcel Delivery

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16. Abstract

Fueled by burgeoning e-commerce, urban parcel delivery (UPD) has emerged as a high growth market that is undergoing rapid technological change, particularly in the business-to-consumer segment. New classes of vehicles such as drones, droids, and autonomous ground vehicles, combined with new delivery models featuring crowdsourcing, parcel lockers, and mobile lockers, will enable a significant shift away from the conventional model of a dedicated delivery person operating a van. To reach the full potential of these changes to reduce costs and increase convenience, it is necessary to develop a complementary set of demand management strategies that will enable the next-generation parcel delivery system to mitigate current traffic congestion problems and avoid creating new ones. The project aims to (1) quantify the current and anticipated future contributions of UPD to urban congestion and related problems, such as traffic accidents and (2) identify opportunities for incentivizing consumers and delivery services to modify their behaviors to reduce the congestion impacts of UPD. To accomplish these objectives, the focus is on (1) demand models of e-commerce behaviors, (2) measuring the impact of delivery service operations on urban congestion using macroscopic fundamental diagrams, and (3) urban operations of drone deliveries to assess their potential for removing parcel delivery demand on roads. The modeling system will be used to assess the congestion reduction benefits of a range of policies geared toward encouraging consumers and service providers to adopt behaviors that reduce the congestion caused by urban delivery. In addition, an analytical framework for assessing the safety impacts, including non-recurring congestion reductions, of innovative UPD technologies is proposed. The method for identifying UPD crashes and statistical models for estimating UPD crash risks at TAZ levels by given demographic, roadway, and traffic conditions.

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Executive Summary

Fueled by burgeoning e-commerce, urban parcel delivery has emerged as a high growth market that is undergoing rapid technological change, particularly in the business-to-consumer segment. New classes of vehicles such as drones, droids, and autonomous ground vehicles, combined with new delivery models featuring crowdsourcing, parcel lockers, and mobile lockers will enable a significant shift away from the conventional model of a dedicated delivery person operating a van. In order to attain the full potential of these changes to reduce costs and increase convenience, it is necessary to develop a complementary set of demand management strategies that will enable the next-generation parcel delivery system to mitigate current traffic congestion problems and avoid creating new ones. The project aims to (1) quantify the current and anticipated future contributions of urban parcel delivery to urban congestion and related problems, such as traffic accidents; (2) identify opportunities for incentivizing consumers and delivery services to modify their behaviors in order to reduce the congestion impacts of urban parcel delivery. To accomplish these objectives, we have been focusing on (1) demand models of e-commerce behaviors, (2) measuring the impact of delivery service operations on urban congestion using macroscopic fundamental diagrams, and (3) urban operations of drone deliveries to assess their potential of removing parcel delivery demand on the roads. The modeling system will be used to assess the congestion reduction benefits of a range of policies geared toward encouraging consumers and service providers to adopt behaviors that reduce the congestion caused by urban delivery.

The COVID-19 pandemic brought about dramatic shifts in travel, including shopping trips. We investigated changes in e-shopping for food and non-food items by supplementing an April to May 2018 household travel survey (n=3,956 households) conducted by the Sacramento Area Council of Governments (SACOG) with a May 2020 follow-on panel survey (n=313 households) for one week early in the pandemic. Results demonstrate that impacts from added pickups and deliveries in the SACOG region during the first two months of the COVID-19 pandemic were limited and did not overwhelm curb management at retail, restaurant, and grocery establishments. Results also show that during the pandemic e-commerce tended to replace non-food shopping trips, but complemented restaurant and grocery trips. However, Forty percent of the sample households — predominantly lower income and/or older populations — still shopped only in-store for food while more affluent households appear to have isolated themselves from virus exposure through more extensive online shopping. We recommend extending the forms of accepted payment for online shopping and reducing fees and markups based upon payment method to reduce barrier to online shopping for those with limited resources. We identify possible consequences (e.g., more vehicle miles traveled and higher demand for curbside parking) if e-commerce food purchasing continues to grow post-pandemic or if in-person retail shopping returns to normal.

Delivery Service Providers (DSP) are affecting road delay and air pollution by parcel delivery traffic in different ways. Parked DSP vehicles reduce the amount of available parking for other road users, which induces cruising, which causes extra delay, pollution. The Macroscopic Fundamental Diagram is used to measure the impact of delivery service operations on urban congestion. A vehicle traffic simulation is set up to model delivery vehicle stops, where the vehicles double park and restrain the traffic flow during the stop. As a result, the network capacity declines by a certain amount. A theoretical model is developed to predict the reduced amount of network capacity because of these stops.

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The development in e-commerce presents the major driver for drone-based deliveries, which are traditionally made by truck and van, as an increasing number of urban residents rely on the Internet rather than going to brick-and-mortar stores for shopping. The increasing parcel delivery demand contributes to greater traffic congestion in road transportation system. UAV delivery utilizes the low-altitude airspace resource, and demand shifting from road traffic to air help mitigate the road traffic congestion situation. In addition, UAV delivery has shorter delivery times, lower maintenance costs, and environmental friendliness than traditional parcel delivery. We propose a framework of UAV system traffic management in the context of parcel delivery in low-altitude urban airspace, including clustering-based UAV path planning, systematic UAS traffic management with conflict resolution, and mechanism design for airspace resource allocation. Four traffic management models are proposed and especially the Batch Optimization (BO) model that strikes a balance between seeking a system optimum solution and maintaining computational tractability. Extensive numerical analysis is conducted with San Francisco as the case study area. Our results show the effectiveness of the proposed framework, particularly the scalability of the BO model compared to the other two models in UAS traffic management. We also find that payment by a UAV flight under the proposed mechanism depends critically on traffic density and the extent of interaction the UAV flight has with other flights.

The emerging UPD technologies will change the traffic pattern on surface roads. Not only the operations but also the safety performance of the roadway system will be impacted by the new technologies. The new UPD technologies may reduce the exposure of surface UPD trips that is positively associated with UPD crash risks; meanwhile, the replacement of human-driving UPD vehicles with autonomous ground vehicles may reduce the likelihood of UPD crashes by eliminating human errors that are the primary contributing factors in traffic crashes. In addition, the reduction of UPD crashes will mitigate non-recurring congestions caused by incidents. This study proposed an analytical framework to estimate the safety benefits, including non-recurring congestion reductions, by implementing innovative UPD technologies. As the first step, the research developed a procedure to identify UPD crashes (the most significant challenge in UPS safety studies). Based on the identified UPS crashes in Florida, the research team developed a statistical model to estimate UPD frequencies given demographic, traffic, and roadway information at Traffic Analysis Zone levels. The analysis framework, identification methods, and the preliminary model developed in this study can be the basis for assessing the comprehensive benefits of innovative UPD technologies and provide supporting decision making in developing and implementing the new technologies.

1. Introduction

This study aims to investigate how growth of urban parcel delivery demand may affect future traffic in urban areas, and how these impacts may be mitigated through, among other possibilities, increased use of non-road vehicles, such as UAVs.

We begin with an investigation of consumer demand for urban deliveries (Chapter 1). COVID-19 travel and business restrictions and closures present an opportunity to gain insights into how individuals with varying levels of technological capability, Internet-connectedness, personal mobility, and other key factors are managing their purchasing needs in a time of constrained travel. The transportation literature has long focused on the relationship between e-commerce and online shopping and personal shopping trips. Recently, the Sacramento Area Council of Governments (SACOG) addressed these questions in its 2018 household travel survey (HTS). Unfortunately, the unexpected pandemic rendered much of the information collected from this survey outdated or irrelevant. For example, changes in consumer shopping may be generating second-order effects (e.g., changes to curb use, changes in household car ownership) and even third-order effects (e.g., changes in land use). As such, it is important to develop a clear picture of these pandemic-influenced behaviors and how they could play out in the future. The first part of this research supplements recent 2018 HTS data with online surveys conducted during the early months of COVID-19 Stay at Home orders to develop a greater understanding of current and future online shopping patterns. Importantly, also examined are the demand for curbside pickup on public streets and in off-street lots for making deliveries.

Some pandemic effects may be present for years to come, and stakeholders at the local and regional levels will need to develop flexible strategies and infrastructure to deal with rapidly changing circumstances as counties and regions move forward with different stages of re-opening. Many cities, such as Los Angeles, Oakland, and San Francisco, greatly relaxed or eliminated parking meter enforcement at the beginning of the Stay-at-Home orders and/or are exploring expedited temporary loading zone applications (e.g., Sacramento, Oakland) and permits as part of pilot programs. Additionally, companies are responding to the pandemic in many ways, such as implementing waiting lists for online shopping services (teamocado, 2020; Petrova, 2020; Perez, 2020), constructing more urban delivery centers (Martineau, 2020), converting closed retail locations into online fulfillment centers (Kang, 2020), or instituting specific fees for e-commerce parcels (Ziobro, 2020). These shifting market realities are presenting consumers with different options from which to choose for their shopping needs compared to before the pandemic. This study examined changes in household travel behavior under such circumstances.

Recent work has focused on shopping motivations and consumer attitudes in explaining shopping behavior (Punel & Stathopolous, 2017; Le & Ukkusuri, 2019), and preliminary work since the onset of the pandemic has shown marked shifts in shopping behavior (Holguín-Veras & Encarnacion, 20202; Wunderman Thomson, 2020). Additionally, new open-sourced datasets from private companies (Contentsquare, 2020; Google, 2020) and publicly available data have revealed dramatic shifts in the retail purchasing habits of American consumers in response to Stay-at-Home orders and uncertain economic circumstances. No studies to date, however, have examined both changes in online consumer purchasing and e-commerce delivery service operations or their collective impact on public infrastructure. The first part of this study in chapter 2 fills in those gaps.

Delivery Service Providers (DSP) are affecting road delay and air pollution by parcel delivery traffic in different ways. These impacts are investigated in Chapter 3. The miles traveled increase overall travel demand, which affects other road users and increases delay and emissions. Parked DSP vehicles reduce the amount of available parking for other road users, which induces cruising and causes extra delay and pollution. Double-parking occurs when drivers are unable to locate a parking spot near their destination; DSP vehicles may park in street lanes, thereby creating a bottleneck, possibly the largest source of delay and pollution, and reduces street network capacity. This second part of this study measured the effect of DSPs on traffic outcomes including Vehicle Miles Traveled (VMT), arrival delay and air pollution. The Macroscopic Fundamental Diagram (MFD) was used to measure the impact of delivery service operations on urban congestion, which can be expressed as the relationship between number of vehicles in the system and the number of trips per unit of time and occupancy and VMT per unit of time, occupancy, and speed. A vehicle traffic simulation was set up to model delivery vehicle stops, where the vehicles double-parked and restrained traffic flow during the stop.

Chapter 4 examines the role UAV delivery in offloading deliveries from road vehicles. As a result of the large volume of parcel delivery, there has been an increasing number of delivery trucks and vans entering and driving around cities every day and contributing to greater traffic congestion, air pollution, noise, road deterioration, and safety concerns. Many delivery service providers, including Amazon, UPS, and DHL, have opened urban warehouses near or in city centers from which last-mile deliveries to customers are performed (Haag & Hu, 2019; Young, 2020a; Young, 2020b). The large number of online orders from restaurants, stores, and urban warehouses, especially during the pandemic, along with the expectation of delivery within an order of hours (SupplyChainBrain, 2020) have exacerbated the need for new delivery solutions to meet demand.

Although various innovations have been considered (Kafle et al., 2017; Ranieri et al., 2018; Le et al., 2019; van Duin et al., 2020; González-Varona et al., 2020), delivery by Unmanned Aircraft Vehicles (UAVs) (drones) is increasingly perceived as an integral part of the future solution for urban freight movement to provide fast, point-to-point deliveries, and industrial and commercial applications of drones have been proliferating over the last few years. As part of the parcel delivery demand shifting to the air, UAV delivery helps mitigate the traffic congestion in the road transportation system. Established logistics companies and startups have already begun using drones for package delivery; FedEx Express and Wing Aviation recently completed their first scheduled commercial-to-residential drone deliveries in the US (Norman, 2019). In 2019, UPS received the first broad Federal Aviation Administration (FAA) approval for drone delivery (Josephs, 2019), and Amazon also received approval for its Prime Air drone delivery fleet (Palmer, 2020); the cost of delivery per package is estimated to be only two thirds or less of traditional ground vehicle-based delivery (Sudbury & Hutchinson, 2016).

UAV delivery has several advantages over traditional parcel delivery, such as shorter delivery times, lower maintenance costs, and environmental friendliness (Lee et al., 2016; Lim & Jung, 2017). When deployed at a sufficiently large scale, UAV delivery may also help reduce road safety risks and mitigate traffic congestion on the ground. Moreover, as a result of the pandemic, the trend of shifting from physical stores to online shopping has been accelerated by roughly five years (Perez, 2020), thereby imposing even greater pressure on logistics service providers, which are struggling to solicit sufficient workers to meet delivery requests, particularly ensuring that orders arrive to customers within promised time windows. In the midst of the pandemic, delivery workers are exposed to a high risk of virus infection due to frequent contact with store staff and customers during order pickup and delivery. Once they are infected, the virus can quickly spread to more people as well as

locations. UAV delivery, which is contact-free, can help mitigate the spread of the virus and solve the imbalance between order demand and delivery capacity—if not for the current pandemic, then perhaps for a future one.

With potentially large demand for UAV delivery in the foreseeable future, the need for and importance of efficiently managing UAV traffic in urban airspace is increasing. Many countries have already started developing traffic management methods for UAV operations (Kopardekar et al., 2016; Unmanned Airspace, 2019), and the subject has attracted much interest in the research community (Labib et al., 2019; Ho et al., 2019). Although there is a body of literature on how to optimally configure urban delivery systems with UAVs from the perspective of formulating and solving vehicle routing problems, most existing research does not consider the UAV delivery problem in the context of path conflicts and airspace congestion. The ability to safely and efficiently resolve conflicts will become increasingly urgent as the use of UAVs for urban package delivery and other purposes intensifies. There has been little research on integrating UAS traffic management with UAV delivery. The study of strategic traffic management in the context of an UAV delivery system, in particular the systematic efficient allocation of congestible airspace resources to UAVs, is particularly lacking. Prior work on planning UAV delivery systems has focused on problems such as the UAV vertiport facility location problem (Vascik & Hansman, 2019; Fadhil, 2018; Rath & Chow, 2019), maximizing the number of delivered packages by UAV while satisfying battery consumption constraints (Kim et al., 2020), and evaluation of collision risk in small UAV systems (Weinert et al., 2018). None of these studies are concerned with identifying and efficiently resolving path conflicts in in a UAV system that features the high traffic intensities that may be required to meaningfully relieve road congestion or reduce pandemic spread. The third part of this research in chapter 4 attempts to fill this gap.

Emerging urban parcel delivery (UPD) technologies will fully change the traffic pattern on surface roads; consequently, the technologies will influence not only operations but also the safety performance of the roadway system. The is the focus of Chapter 5. The new UPD technologies may reduce the exposure of surface UPD trips that is proportional to UPD crashes; meanwhile, the replacement of human driven UPD vehicles with autonomous ground vehicles may reduce the likelihood of UPD crashes by eliminating human errors that are the primary contributing factors in traffic crashes. In addition, the reduction of UPD crashes will mitigate non-recurring congestion caused by incidents (25 percent of congestion) (FHWA, 2021).
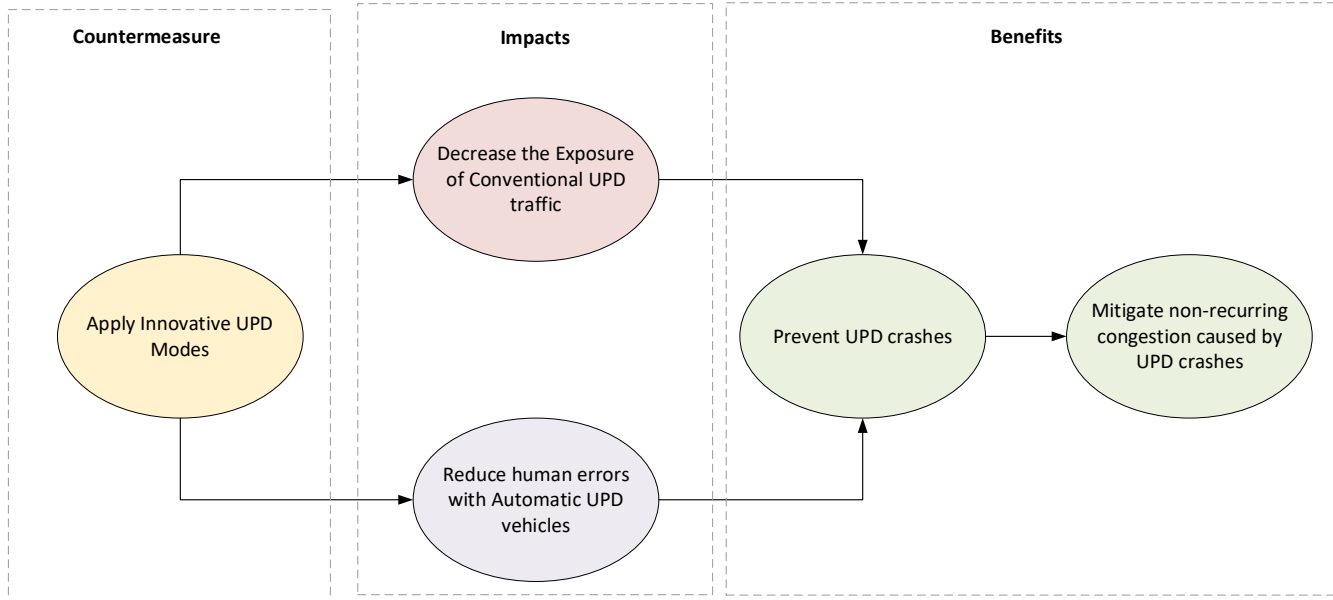
Figure 1-1. Impacts of emerging UPD technologies on safety and non-recurring congestion

A few previous studies were found that examined parcel delivery-related crashes and associated contributing factors. A previous study (Byun et al., 2017) examined the contributions of motorcyclist-related and accident-related characteristics to food delivery motorcycle crashes in South Korea and reported that the factors of rider age, gender, work experience, company scale, and time of day impact food delivery motorcycle crash risk. Another study (Ibrahim et al., 2018) used cameras to monitor 15 courier riders' hazards and crash scenarios during their delivery trips in Malaysia and found that "a courier rider encounters 30 hazardous riding events and 5 near misses on average for each hour of delivery trip." The identified contributing factors include obstruction of view and lane changing and overtaking maneuvers and involved riding/driving behaviors. Chung et al. (2014) investigated the injury severity of crashes involving delivery-purpose motorcycle and vehicle in metropolitan areas in Korea. The modeling results showed that violation behavior involving improperly weaving through traffic and crossing the center line are more likely to cause severe injuries in delivery-motorcycle crashes. Xie et al. (2015) explored the safety impacts of shifting delivery truck trips from daytime regular hours to nighttime off-hours. A safety performance model developed was developed based on truck crashes, traffic volume, and geometric design features collected on 256 road segments in Manhattan, New York. A multivariate Poisson-lognormal model with integrated with measurement errors was used to address the inherent correlation of specific truck crash types. Results revealed that off-hour delivery does not significantly increase the overall risk of truck crashes compared to daytime delivery.

There are some limitations in the previous studies—three studies (Byun et al., 2017; Chung et al., 2014; Ibrahim et al., 2018) conducted analysis at the crash level and did not develop models to predict delivery crash frequencies based on regional characteristics (demographic, geometry, and traffic), and one study (Xie et al., 2015) modeled truck crashes at the segment level; however, it did not distinguish parcel delivery crashes and trips from general truck crashes and traffic. No studies or methods were found to address the safety impacts of UPD delivery modes.

2. Demand Models of E-Commerce Behaviors

Due to the COVID-19 pandemic, beginning in March 2020, many regions in the US experienced rapid changes in travel patterns, with much of the populace staying at home for work and school and reducing out-of-home trips for shopping, entertainment, socializing, and personal business. This led to an increase in the use of retail purchase pick-up and delivery services, exacerbating concerns around traffic congestion and curb management problems in large cities such as New York and San Francisco. Questions arise in addition to these about whether concerns also apply in mid-sized cities and whether an increase in shopping from home leads to a proliferation of issues with pickups and deliveries. To gather more information about mid-sized California cities, participants were re-sampled from the 2018 Sacramento Area Council of Governments (SACOG) household travel survey (2018 HTS) of 8,191 individuals, representing 3,956 households, over a rolling six-week period from April to May 2018. This was the first region in the state to collect detailed information on e-commerce use and use behavioral modeling to compare pre-pandemic shopping to pandemic-related shifts in consumer purchasing and receipt for nine types of essential and non-essential commodities (including groceries, meals, clothing, paper products and cleaning supplies). Responses were collected from 327 individual respondents, representing 313 households, in May 2020. Descriptive statistics were developed to examine changes in weekly shopping trips and online ordering during the pandemic to assess likely traffic and curb use impacts. Respondents were also asked about their prospective behavior once the pandemic ends, and considered were if and how current changes might persist in the future based on their responses.

In comparison to the 2018 HTS data, 2020 respondents reported all household behavior for an entire week via one online survey, showing purchases at a much higher level of commodity detail than in 2018; the interaction between the 2020 and 2018 commodity types is shown in Table 2-1.

Table 2-1. Comparison of Commodity Categories between 2018 HTS and 2020 Supplement

Survey	Parcel (non-food)	Food	
2018 HTS	Other routine shopping—FedEx, UPS, USPS packages	Groceries	Take-out, meals
2020 Supplement	Clothing, paper products and cleaning supplies; * home office items; medication; * childcare items; * other non-food items	Groceries	Prepared meal or beverages (i.e., from restaurant or café)
		Other food items (e.g., specialty foods, farmer's markets, farm boxes, meal preparation kits)	

*Indicates an essential non-food commodity; all food commodities are considered essential.

Using the subsample responses from both 2018 and 2020, a multinomial logit (MNL) model was estimated with four possible household outcomes during the observation week-1) no shopping, 2) only in-person shopping, 3) only online shopping, and 4) both in-person and online shopping. As these four outcomes were mutually exclusive for any given week, an MNL model was selected to provide a view of what variables influence the likelihood of each outcome. MNL models can be used, for example, to answer how much more likely a female-identifying individual is to shop online for food than a male-identifying-individual, both pre- and post-pandemic. This type of framework is useful for analyzing population level demographic differences in behavior and can be used to produce estimates for behavior in light of different policy interventions. Importantly, MNL models do not assign any causal relationship between variables; they only provide an explanation of differences. Modeled separately were food and non-food weekly shopping patterns because it was hypothesized that the motivations for food and non-food purchases are quite different, as evidenced by the

rates shown in Table 2-2. Table 2-3 shows the food MNL model results with selected significant variables; the same also applied to non-food shopping.

Table 2-2. Rates of Shopping Patterns, 2018

Weekly Pattern	Percent of rMoves Sample (n=2,838)		Percent of 2020 COVID-19 Subsample (2018) (n=313)	
	Non-food	*Food*	*Non-food*	*Food*
Only in-person shopping	27.4	88.4	26.3	87.5
Both in-person and online shopping	44.2	7.7	51.7	9.8
Only online shopping	14.5	0.2	12.5	0.0
No shopping	13.9	3.7	9.4	2.8
	100	100	100	100

Table 2-3. Food MNL Model Results with Selected Variables

	2018 & 2020 Parameters		2020 COVID-19 Subsample Parameters	
	Parameter	Std. Error	Parameter	Std. Error
ASC No shopping	**-6.05*****	**1.35**	**3.58***	**1.99**
ASC Online only			**-3.62*****	**1.35**
ASC Both in-person and online	**-2.69*****	**0.67**	**2.38*****	**0.83**
Single Person HH - No shopping	**1.86****	**0.85**	-2.65	1.88
Single Person HH - Both in-person and online	**-2.05*****	**0.79**	**1.69***	**0.91**
HH Income 100k+ - No shopping	0.97	1.08	**-3.04***	**1.72**
HH Income 100k+ - Both in-person and online	**1.05***	**0.60**	-0.70	0.71
Female-identifying - Online only			**1.75****	0.85
Female-identifying - Both in-person and online	**0.76***	0.43	-0.83	0.51
Respondent had travel disability - No shopping	**2.00****	**1.00**	-1.85	1.47
Respondent had travel disability - Both in-person and online	**1.21***	0.73	-1.22	0.87
Unknown disability status - No shopping			**-2.24****	1.09
Amazon Prime: member since at least 2018, both in-person and online	-0.64	0.42	**1.57*****	0.50
Grocery delivery: COVID signup - No shopping			**3.06***	1.63
Grocery delivery: COVID signup - Online only			**2.66****	1.08
Shared burden for all shopping needs - No shopping			**2.11***	1.15
Shared burden for all shopping needs - Online only			**-2.02***	1.10

Results demonstrate that impacts to curb management in the SACOG region during the first two months of the pandemic and response were limited and did not overwhelm existing infrastructure at retail, restaurant, and grocery establishments. Pandemic-induced changes to retail shopping varied widely by commodity. Although overall trip making fell 54 percent during the 2020 observation week compared with 2018, e-commerce ordering replaced a large percentage of non-food trips, with such deliveries down only 2 percent. On the other hand, e-commerce food deliveries rose 375 percent, with purchases and pickups complementing restaurant and grocery trips (and potentially inducing some additional grocery trips). Even with that level of increase in deliveries, it was found that e-commerce food purchases did not result in comparable reductions in in-person trips for food items (e.g., restaurant food, groceries, etc.), as 85 percent of food purchases among the sample population involved taking a trip.

Even facing a global pandemic, it is observed that 40 percent of the sample population shopped only in-store for food during the observation week. Model results indicate that these shoppers were more likely to be older and from households earning below the median. Those households that did not change their shopping behavior during the pandemic may represent e-commerce laggards in the future. Conversely, more affluent populations demonstrate a strong shift toward e-commerce, shopping online for non-food items and complementing in-person food shopping with e-commerce during the pandemic. Taken together, these results signal a higher exposure risk in populations (e.g., older adults) that may be more vulnerable to serious complications from contracting COVID-19 and/or higher exposure to the virus due to performing essential work.

Demographic variables shown to be highly significant in explaining weekly shopping decisions prior to the pandemic (e.g., gender, household income, household size) do not explain changes to trip-making and e-commerce ordering frequency in May 2020. This suggests that the major factors affecting pandemic shopping behavior may not be captured by demographic information collected by standard transportation data collection efforts. Lifestyle variables, such as household Amazon Prime memberships, positively and significantly affect the likelihood of households shopping online for food and non-food items. This points to the influence of non-food shopping services on food shopping, and a need to collect more household information (e.g., physical and digital subscriptions, credit card-based e-commerce incentives) to help explain these new shopping patterns. Additionally, there was a large proportion of new e-commerce food shoppers, with a 25 percent signup rate for groceries and 22 percent for prepared food. Among these new users, observed were a strong shift toward shopping only online for food and a limit on the frequency of-in person shopping. This safety-minded behavior may be tempered by high demand for and difficulty finding delivery slots, particularly for groceries.

Also examined were changes in weekly household shopping between 2018 and 2020 with descriptive statistics. Table 2-4 and Figure 2-1 show a shift away from in-person shopping only toward complementing in-person food shopping with e-commerce. About two-thirds of those who did in 2018 continued to do so, but almost one quarter shopped in person only in 2020. Figure 2-2 shows the weekly parcel shopping changes from 2018 to 2020.

Table 2-4. Changes in Food Shopping, 2018–2020

2018 Weekly Behavior	2020 weekly behavior (n=313)				2018 Total
	In-person Shopping Only	*Both In-person and Online*	*Online Shopping Only*	*No Shopping*	
In-person only	41%	51%	5%	2%	286 (87%)
Both	22%	69%	3%	6%	32 (10%)
Online only	0%	0%	0%	0%	0 (0%)
No shopping	56%	11%	22%	11%	9 (3%)
2020 Total	130 (40%)	169 (52%)	18 (6%)	10 (3%)	327
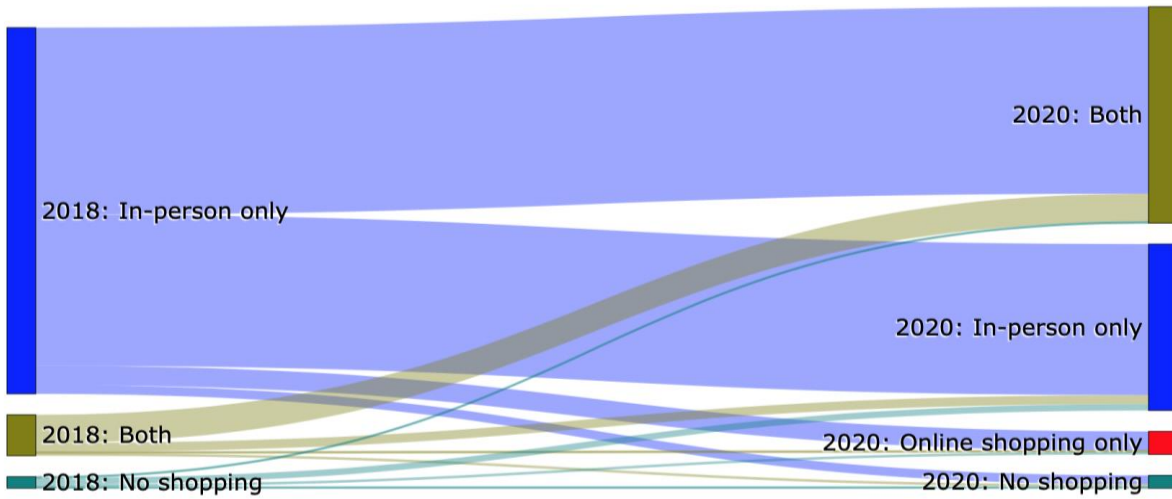
Figure 2-1. Addition of e-commerce food purchasing to in-person behaviors, 2020
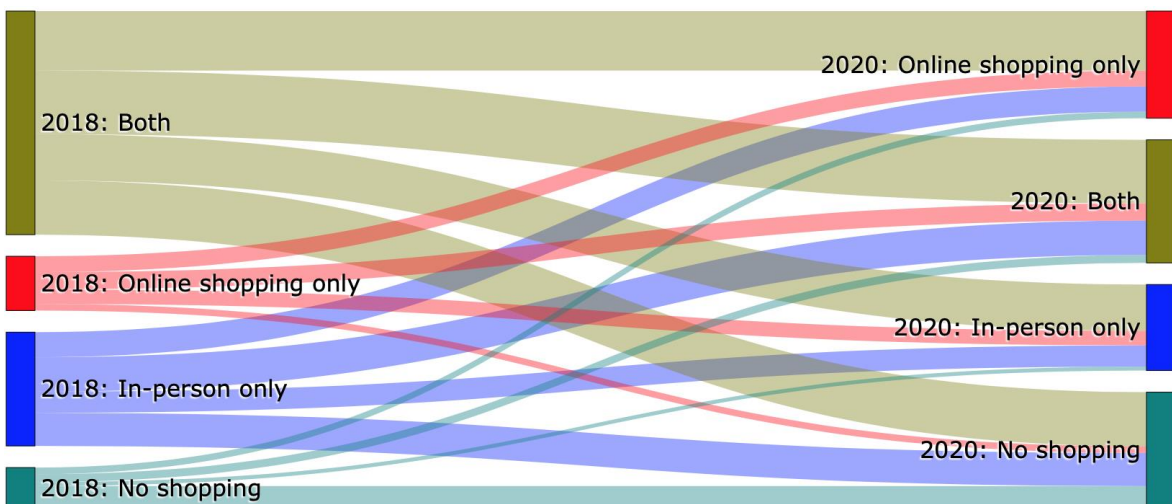
Figure 2-2. Weekly parcel shopping, 2018–2020

In light of these results, it is suggested to improve future analyses by using consistent definitions of e-commerce and collect more precise information about shopping, particularly online shopping. Also suggested are strategies to expand e-commerce access—particularly for food—to a broader range of people by:

- Expanding the forms of payment accepted
- Limiting item markups and/or fees based upon payment type
- Offering call-in order options

The curbside and parking implications of these demand shifts for different types of commodities were addressed. Given the stated 5-10-year growth acceleration of retail e-commerce predicted by some experts (e.g., Mahmassani et al., 2020), the likelihood and implications that certain behaviors will persist after the pandemic was addressed. If food e-commerce continues to complement and/or begins to induce additional trips the sustainability benefits (i.e., lower VMT) from food e-commerce delivery, economies of scale could

diminish and the demand for short-term parking and loading at restaurants could eclipse that of longer-term metered parking.

Respondents indicated that once the pandemic is over, they plan in-person non-food retail shopping. If so, in-person shopping trips may rise even more if the pandemic substitution effect of e-commerce on trip-making shrinks. As concerns about virus transmission decrease with more widespread vaccination and immunity, many of those currently using grocery ordering platforms may return to in-person shopping, undercutting the growth of e-commerce.

As states and the nation progress toward post-pandemic life, emerging and pandemic-induced long-term changes in business (e.g., more outdoor sidewalk dining, increased curbside pickup) could compete for curb space with traditional curb uses, including long-term metered parking. Thus, policymakers will need to balance the needs of all types of curb users and make safety—both health and traffic-related—a priority.

Conclusions

In this study, we observed a concentration of exposure among populations at higher risk for serious complications from the COVID-19 virus and populations with fewer means. Households should not have to weigh making a trip to the store to put food on the table with exposing themselves to a deadly virus; however, this behavior evident in the news and in the study sample; this was a key takeaway from this study. Households continuing to shop only in-person were overrepresented by those earning under $50,000 per year, male-identifying survey respondents, and older survey respondents, particularly those over age 65. Conversely, households earning $100,000 per year are underrepresented in this subgroup, as are younger survey respondents (below age 35). This points to a concentration of risk and potential exposure among older and less affluent households, who may be most vulnerable to serious complications from contracting COVID-19.

Also addressed are curbside and parking implications of these demand shifts for different types of commodities. Given the stated 5–10-year growth acceleration of retail e-commerce predicted by some experts (e.g., Mahmassani et al., 2020), the likelihood and implications that certain shopping behaviors will persist after the pandemic are addressed. If food e-commerce continues to complement and/or begins to induce additional trips the sustainability benefits (lower VMT) from food e-commerce delivery, economies of scale could diminish, and the demand for short-term parking and loading at restaurants could eclipse that of longer-term metered parking.

As states and the US progress toward post-pandemic life, emerging and pandemic-induced long-term changes in business (e.g., more outdoor sidewalk dining, increased curbside pickup) could compete for curb space with traditional curb uses, including long-term metered parking. Thus, policymakers will need to balance the needs of all types of curb users and make safety—both health and traffic-related—a priority.

3. Impact Measurement of Delivery Service Operations on Urban Congestion

## Variables Impacted by Urban Congestion

The impact of Delivery Service Operations (DSO) on traffic outcomes was measured, including delay and air pollution. Traffic delay is the difference between the actual arrival time of road users and their desired arrival time. Air pollution is the total emission of CO_2, NO_2, $PM - 2.5$. and other polluting substances.

There are several ways in which DSO can impact delay and air pollution. The first is via VMT—DSO adds traffic demand to the road and burns fuel, which increases total traffic volume, decreases average speed, and increases delay and air pollution. The second is via parking spaces—DSO vehicles that park take up parking places that would otherwise be used by other users, which increases cruising, congestion, delay, and air pollution. Third, DSO vehicles often double-park, thereby blocking lanes of traffic. Such blockages introduce additional bottlenecks into the street network and reduce the flow of traffic. This study focused on the impact of double-parking of DSO vehicles on network traffic flow, as it is the factor that impacts delay and air pollution the most by indirectly slowing down other road users.

MFD Function

The impact of DSO on urban traffic was measured within the so-called Macroscopic Fundamental Diagram (MFD) framework (Figure 3-1). MFD is a function that relates varies network-level traffic variables to each other. For example, it expresses traffic flow as a function of the number of vehicles in the network and average network speed as a function of the number of vehicles. MFD is a useful tool for analyzing DSO effects, as it is demand-independent and can be used to analyze DSO impact under any scenario.

The goal of this study was to analytically approximate the impact of DSO on network capacity and compare the theoretical prediction to the network flow observed in simulation of street traffic.
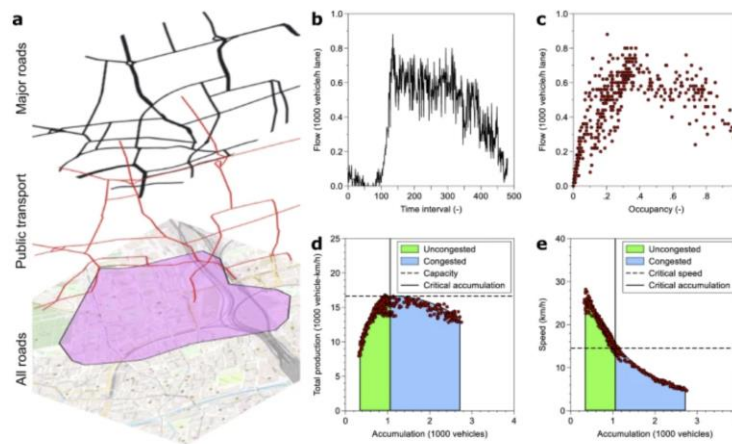
**Figure 3-1. Macroscopic Fundamental Diagram for city neighborhood**
Source: Loder, A., Ambühl, L., Menendez, M., et al. Understanding traffic capacity of urban networks.
Sci Rep 9, 16283 (2019)

Effect of Double-Parking on MFD

This study notes that double-parking delivery vehicles change the shape of the MFD function, which can have dramatically varying effects on the road network. In many cities, these effects may not be observable by the existing observations of delivery operations due to the relatively low volume of operations. As DSO volume increases in the future, the effects will become more apparent.

This point is illustrated in Figure 3-2, which shows two MFDs for a notional city street network. Higher MFD corresponds to the scenario with no DSO operations and, therefore, unconstrained flow; this is the "initial" MFD, before DSO effects. The lower MFD corresponds to the scenario with lower flow that results from DSO-induced network blockages that we discussed above; this is the "final" MFD.
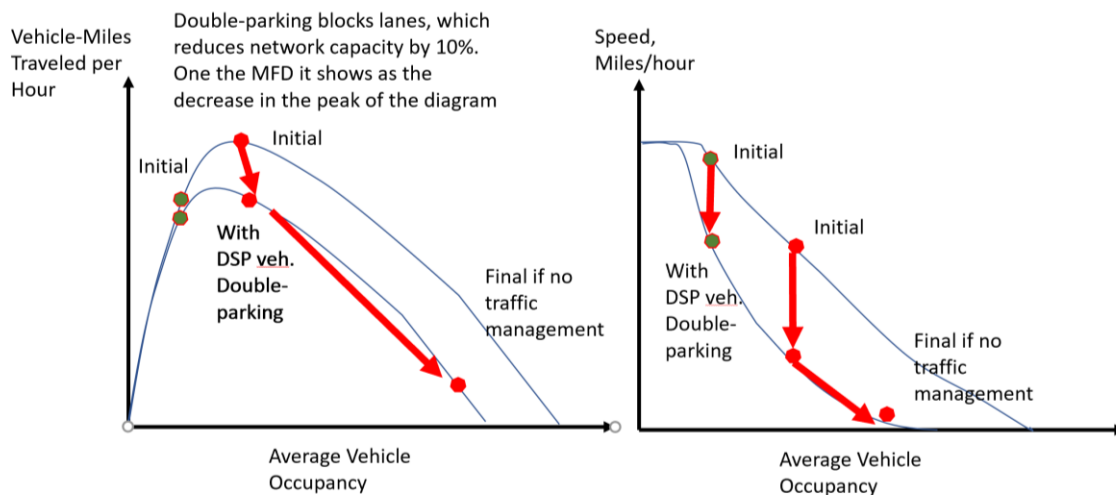
Figure 3-2. Effect of double parking on MFD—accumulation-flow MFD (*left*), accumulation-speed MFD (*right*)

There are two general scenarios. The first scenario (green dots) is relatively benign. The initial state on the initial MFD is in the unconstrained region of the MFD. In this region, increased demand on the network is satisfied, as there is not gridlock present. Adding more vehicles on the road leads to increasing traffic flow. If DS operations are introduced into the network, the MFD is lowered, but the final traffic state of the network remains in the unconstrained region. The result is that traffic flow is reduced slightly.

The second scenario is more extreme. In it, the initial traffic state is at the peak of the MFD. This means that the network is operating at capacity; therefore, adding more vehicles to the network will uncontrollably reduce traffic flow until the entire network is paralyzed with gridlock. Once the DS operations are present, the MFD switches to the final MFD function. As a result, the initial traffic state now moves from the capacity state to the constrained portion of the MFD. If input controls are absent (no traffic management), the number of vehicles in the network increases with time. As the new traffic state is now in the constrained portion of the MFD, an increase in the number of vehicles leads to a decrease in traffic flow. The network now is in the feedback loop, where traffic flow keeps decreasing indefinitely until the network is paralyzed with gridlock. In this case, the impact of DSO is very large; traffic flow decreased from the maximum level allowed by the network to zero.

The flexibility of the MFD framework is such that these extreme scenarios, as well as any other scenarios, can be easily modeled without the need for much observational data. If the mathematical expression is obtained for the MFD as a function of DSO operational variables, changes in speed, delay, and air pollution in the entire network can be predicted. This study focuses on the simulated impacts of DSO on network capacity. In principle, this can be extended to model the impact of DSO on the whole shape of the MFD, not just the capacity—the maximum of the MFD.

Simulation and Results

A microscopic network traffic simulation was set up using Aimsun simulation software and run for a 10x10 square grid street network with 400 links and 100 intersections. All intersections were identical and have the same green and red times and no offsets. It was assumed that streets have two lanes in each direction, and the double-parked vehicle stops in the right lane. To simulate the impact of DSO, delivery vehicle double-parked stops were simulated, such that the average stop time was equal, on average, to 5 minutes, and the number of stops per hour per link ranged between 0.25 and 12. The theoretical model predicts that traffic network capacity $Q_{network}$ is given by the follow constraint:

$$Q_{network} \leq q_m \frac{G}{C} \Delta$$

where q_m is the maximum unconstrained traffic flow through the intersection during the green phase of the traffic light, G/C I the proportion of time the traffic light is green, and Δ is the control parameter—the average proportion of time a double-parked vehicle is present at a given link. This parameter is equal to the product of average double-parked stop time and the average number of stops per unit of time. More DSO means that Δ is higher. The parameter varied between 0 and 1.

Figure 2-3 shows the simulation results and the theoretical prediction for capacity as a function of the number of DSO double-parked stops. The x-axis corresponds to parameter Δ, and the y-axis is the measured network capacity. Black dots are average traffic capacity traffic states as measured over 12-minute periods, and the red line is the theoretical prediction. As shown, the prediction from the model is in good agreement with the results of the simulation—maximum traffic flow in the network is typically less than or equal to the constraint described above.

In the future, this work can be extended in several ways. First, the shape of the entire MFD as the result of DSO operations can be modeled. Second, a large number of possible DSO scenarios and their impacts for various network configurations can be modeled. Third, the MFD model can be used to compute arrival delay and air pollution values that result from delivery service operations.
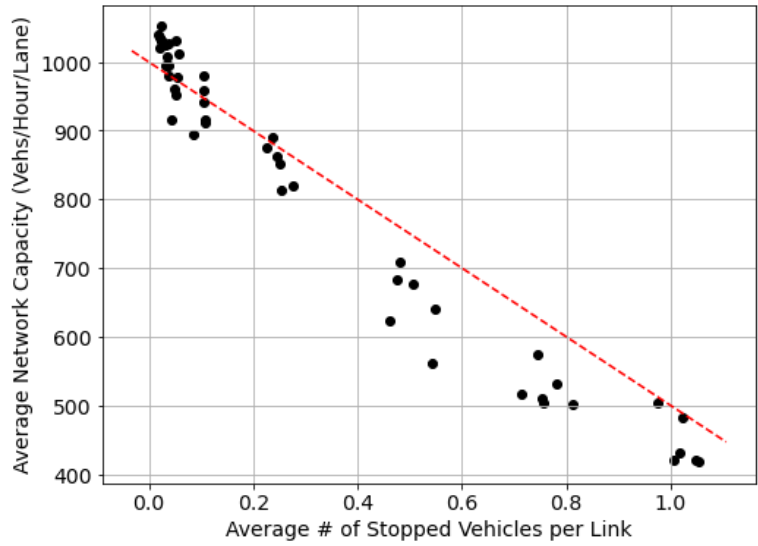
Figure 3-3. Observed traffic flow as function of stop duration
Red line is theoretical expectation; black dots are observations from simulation.

4. Traffic Management and Resource Allocation for UAV-based Parcel Delivery in Low-altitude Urban Space

The explosive growth in e-commerce, increasing urgency of de-carbonization, and rapid advances in technologies and the gig economy are demanding and providing abundant opportunities for considerable efficiency improvements in UPD. In particular, the development in e-commerce is the major driver for drone-based deliveries, which are traditionally made by truck and van, as an increasing number of urban residents rely on the Internet rather than going to brick-and-mortar stores for shopping. In New York city, for example, more than 1.5 million packages were delivered every day in 2019 (Haag and Hu, 2019). As a result of the large volume, we are seeing an increasing number of delivery trucks and vans entering and driving around cities every day, contributing to greater traffic congestion, air pollution, noise, road deterioration, and safety concerns. Shifting part of urban parcel delivery demand from road traffic to air mitigate the congestion situation in ground transportation system. In order to alleviate the demand pressure of road traffic, we focus on UAV system traffic management for the first year to allow demand shifting to air by UAV delivery.

This research proposes a framework of UAV system traffic management in the context of parcel delivery in low-altitude urban airspace, including clustering-based UAV path planning, systematic UAS traffic management with conflict resolution, and mechanism design for airspace resource allocation. The methodology herein includes four components required to simulate and evaluate the proposed strategic UAS traffic management—UAV path planning, conflict detection, and strategic conflict resolution. Also, as efficient conflict resolution requires truthful information about flight operator preferences, the fourth component is the design of a mechanism that induces truthful information reporting by UAS operators through a payment scheme.

Deterministic Clustering-based UAV Path Planning

The routing approach is simplified by assuming a set of discrete altitudes and finding the shortest 2D path at each altitude. The optimal travel altitude is determined by minimizing a linear cost function associated with both horizontal and vertical flying. To generate the most representative altitude candidates based on the topography of terrain and the elevation of building obstacles, a clustering approach is employed to characterize the height and proximity of the numerous static obstacles in a dense urban core area. Based on the generated altitude candidate set, horizontal shortest paths that avoid obstacles are then generated for each altitude candidate. The vertical and horizontal costs are compared to determine the optimal travel altitude and 2D cruise path at that optimal altitude. Also identified is an optimal 2D path at a different altitude, which may be used to resolve conflicts.

Figure 4-1 shows the elevation map of all static obstacles in part of the San Francisco downtown area. The K-means clustering algorithm is applied to perform clustering over all virtual buildings. Through clustering, a very large number of elemental static obstacles will be represented as a much smaller number of clusters that are similar with respect to height and location (Figure 4-2). As noted, the horizontal shortest paths for each UAV mission are generated by the Saturated FM2 algorithm at each candidate altitude. Figure 4-3 shows the horizontal shortest obstacle-free path results of an OD pair. The optimal flight path is then determined by the one with least total travel cost, which is 108 meters in this specific case.
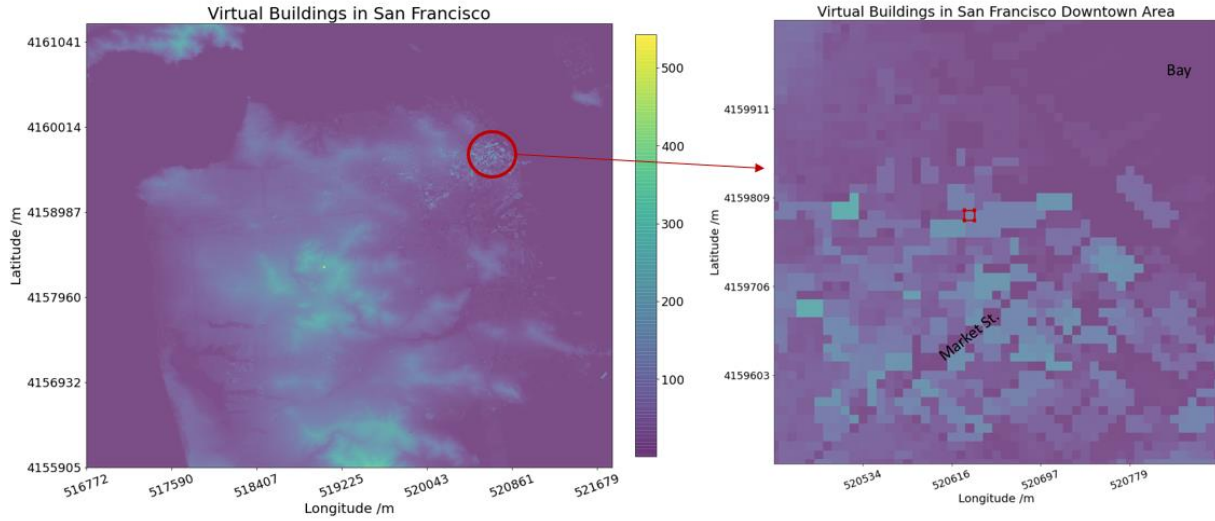
Figure 4-1. Virtual buildings of both geographic and above-ground obstacles in San Francisco
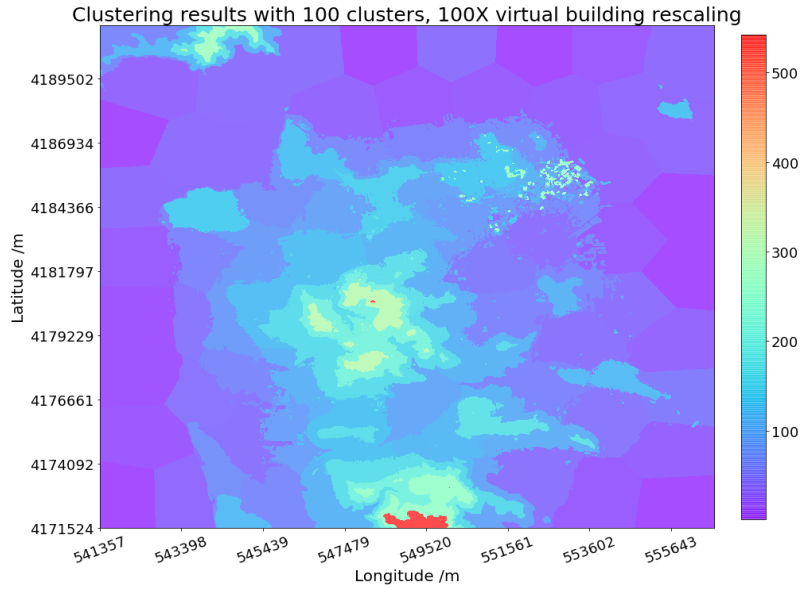

Figure 4-2. Clustering results of San Francisco virtual buildings
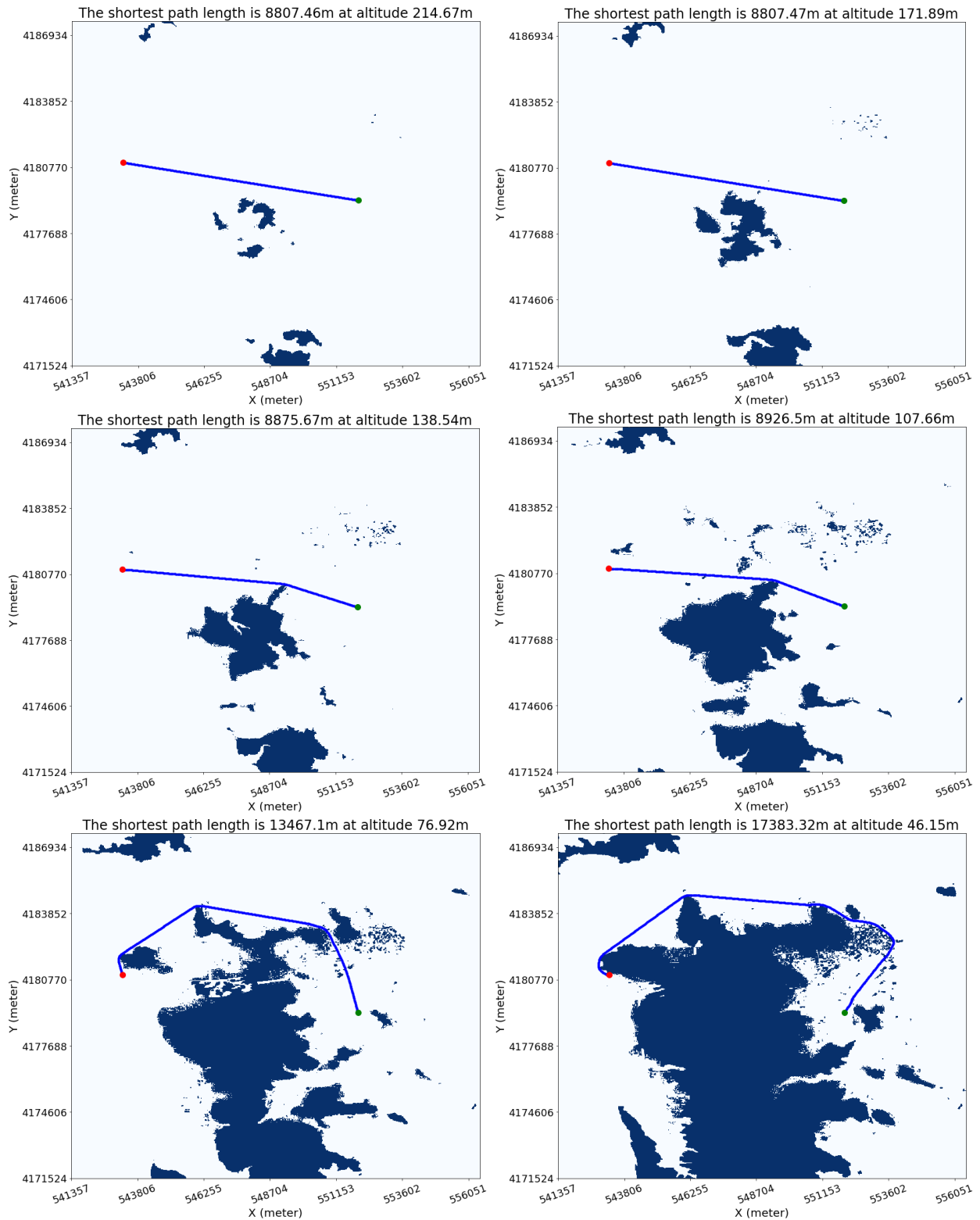
Figure 4-3. Shortest horizontal obstacle-free path results by Saturated FM2 of one OD example

Traffic Management Models

A range of traffic management models of varying sophistication is proposed, each of which aims to efficiently schedule and route each UAV flight while resolving UAV path conflicts. First, flight pairs whose candidate paths create a spatial conflict are detected. A spatial conflict is also as a temporal conflict if, based on the desired departure times of the two conflicted flights, there would be simultaneous occupancy of the conflict region. The temporal conflicts must be resolved by means of either departure delay or an alternative path. Traffic management models will decide how to assign delay or to reroute flights to resolve each temporal conflict.

The alternative models, in order of simplicity, are the Sequential Delay (SD) model, the Sequential Delay/Reroute (SDR) model, and optimization models. The SD model assigns flights a priority order and resolves a conflict between two flights by delaying the flight with the lower priority. A desirable feature of this model is that it requires no inputs other than the desired routes and the flight sequence, which might be established, for example, by the order in which UAV flight requests are received by the traffic manager. The SDR model is also based on flight priority but may resolve a conflict either by delaying a flight or assigning the flight a different path (or possibly both). This model requires UAV operators to submit cost information so the operator can choose the conflict resolution strategy with the least cost.

In contrast to the sequential models, the optimization model assigns delays and paths to minimize the total cost of eliminating all conflicts. For this model, the operator requires additional cost information for each UAV mission. Further, to assure that operators provide truthful information, this model must be paired with a mechanism design that is incentive compatible. Furthermore, the full optimization model is computationally intensive when traffic density is high. This motivates a variant of the model that assigns flights in batches that are constructed so that most conflicts are between flights in the same batch. The full and batch optimization models are named FO and BO, respectively. Flight conflicts between batches are resolved sequentially based on batch priority.

Table 4-1 shows the results of four traffic management model with 1000 UAV missions scheduled to depart in 30 minutes time interval. As expected, the FO model yields the smallest system cost and the SD model yields the largest. The system cost from the BO model is in between, which is expected, as it performs optimization based on decomposed flight clusters. The system cost increases as the length of the time period decreases. Note that the system cost difference among the four models is very small relative to the absolute values of the total costs. This does not indicate these traffic management models are not efficient, as the system cost if all UAV flights taking their optimal paths without departure delay is also very large, at $227.

Congestion cost, which is the system cost minus the ideal system cost ($227) is presented in Table 4-1 as well. Also reported are the amount of system delay, the number of delayed flights, and the number of flights taking alternative paths. Delays are much higher in the SD model, which does not allow altitude reassignment. The other model results do not exhibit clear trends with respect to delay and altitude reassignment. This is because these models are based on the cost of delaying or assigning new altitudes to flights, which is flight specific. In the 30-minute case, for example, the SDR model has fewer delayed flights and flights taking alternative paths than the BO model. Furthermore, the FO model is able to assign on average shorter delays to flights with smaller unit delay cost and, consequently, lower total cost.

The percentages of congestion cost saving of the three models are also presented, which are calculated as the difference of the congestion cost with respect to the SD model divided by the congestion cost of SD model. The percentages clearly indicate that all three models perform much better than the SD model. The FO model and the BO model consistently have congestion cost savings of above 90 percent in all four lengths of the simulation period. In contrast, the percentage of congestion cost savings for the SDR model diminishes as the simulation period becomes shorter, because it is not able to account for inter flight differences in delay cost when adjusting flight trajectories. Overall, the comparison results suggest that while the BO model yields a slightly suboptimal solution, the cost penalty is modest.

Table 4-1: Comparison Results of Four Traffic Management Models

		Length of Simulation Period (min)			
		60	*30*	*15*	*5*
Total cost ($)	FO	227.2	227.6	228.0	228.5
	BO	227.3	228.1	228.7	229.5
	SDR	227.5	228.5	231.8	233.8
	SD	234.0	242.8	249.2	256.9
Congestion cost ($)	FO	0.2	0.6	1.0	1.5
	BO	0.3	1.1	1.7	2.5
	SDR	0.5	1.5	4.8	6.8
	SD	7.0	15.8	22.2	29.9
Delay (seconds)	FO	29	120	629	478
	BO	49	308	447	676
	SDR	69	340	1,328	1,569
	SD	2,133	4,475	6,243	8,254
Number of delayed flights	FO	5	16	20	29
	BO	5	20	25	28
	SDR	5	12	28	33
	SD	16	30	42	66
Number of flights taking alternative (non-optimal) path	FO	9	17	26	36
	BO	12	21	32	43
	SDR	11	12	27	40
Percentage of congestion cost saving relative to baseline	FO	96.8%	96.2%	95.5%	95.0%
	BO	95.2%	92.8%	92.4%	91.7%
	SDR	93.4%	90.4%	78.6%	77.2%

Mechanism Design

In the mechanism of traffic management, UAV flight schedules and paths are assigned to reduce the total cost of resolving all conflicts, based on the information from central controller. The central controller has the information on unit delay cost and path cost of all UAV flights. Such information is likely to be obtained by asking individual UAV operators. For example, the unit delay cost of an UAV flight may depend on the urgency of the package to be delivered. This gives rise to the issue of whether the information reported from each UAV operator is truthful, as a UAV flight may deliberately misreport the information to get a more favorable route or lower delay than from reporting truthfully (Zou et al., 2015; Ball et al., 2020). The section addresses this issue by adapting the Vickrey-Clarke-Groves (VCG) mechanism to the UAS traffic management context.

Under the assumption that a VCG mechanism is in place, the resulting payment for each of the 1,000 UAV flights is calculated for a 30-minute period. Figure 4-4 uses different colors to denote the payment of 1,000 flights along with their paths assigned by BO model at an altitude of 77 meters. Conceptually, a flight with more conflicts tend to impose more "externalities" on other flights, thereby incurring more payment. It is observed that most UAV flights have relatively low payments. At the altitude of 77 meters, three flight paths on the left part of the graph do not conflict with any other flight at this altitude and have very low payment; however, the payment is non-zero, as some other flights may be assigned their second least-cost paths to avoid conflict with these paths.
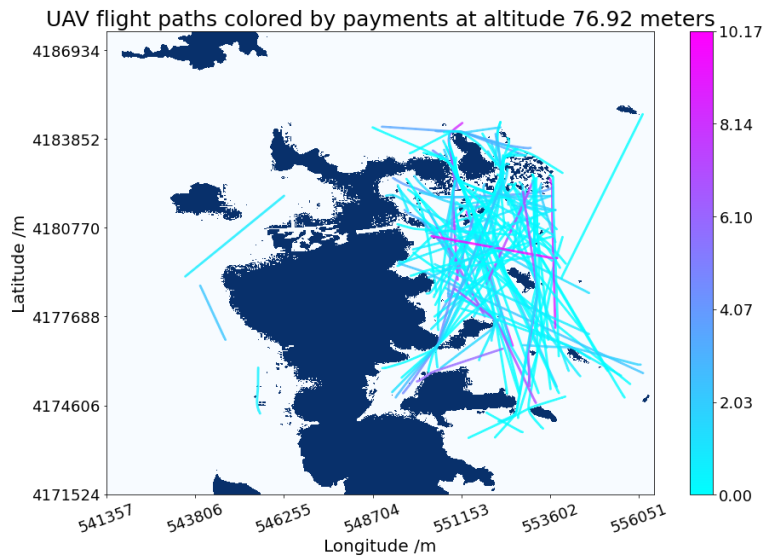
Figure 4-4. Visualization of paths colored by payments at altitude 77 meters

This research proposes a framework of UAS traffic management including clustering-based UAV path planning, systematic UAS traffic management with conflict resolution, and mechanism design for airspace resource allocation. The UAV path planning algorithm takes advantage of clustering obstacles to generate representative altitude candidates, which is more efficient than the evenly spaced altitudes assumed in most research of UAV system planning and analysis. In determining the optimal travel path, the tradeoff between horizontal shortest path length and vertical travel distance at different altitudes is recognized.

In addition, four traffic management models are proposed to systematically assigns schedules to UAV flights with conflict resolution. These traffic management models allocate spatial and temporal airspace resource to each UAV mission, while determining the departure time and which path to take for each UAV flight. The BO model, which can solve large-scale systems in short time while making a slight compromise on solution optimality, is more attractive than the FO and SDR models to solve large-size problems. Finally, as traffic management requires private information from UAV operators, it is important that the private information received is truthful. To this end, a VCG-style mechanism is adapted, in which the payment made by an UAV flight is the "externalities" caused by the flight to the rest of the system. Payment made by a UAV flight increases with traffic intensity and the extent of interactions a flight has with other flights.

This study presents the beginning of integrating UAS traffic management with UAV delivery that deals with allocating spatial-temporal airspace resources to UAV missions. Multiple directions can be further explored in

future research. First, the BO model is proposed as an approximation of the FO model; further research could be directed to investigating other heuristic approaches to solve the FO model and comparing solution quality and computation efficiency. Second, stochastic factors could be introduced, for example, by accounting for uncertainties in weather and UAV performance (obstacle detection, flying stability, etc.) while determining the optimal and second-optimal paths of each UAV mission. Third, the performance of the different models could be tested in more areas with varying population density, tall building concentration, and terrain types, especially given the particular landscape and topology of San Francisco. Doing so will help glean more generic insights about UAS traffic management. Finally, as last-mile urban delivery is shifting toward nonmotorized vehicles and drones, it would be interesting to look into traffic management in a multimodal context involving UAVs and ground modes to enhance the overall efficiency of the delivery system while meeting demand.

5. Urban Parcel Delivery Safety Impacts

As the first step to investigating the impacts of innovative UPD technologies on safety and non-recurring congestions, this study aimed to develop an analysis framework for assessing the safety impacts and non-recurring congestions of UPD modes, identify UPD crashes from historical crash database, and develop preliminary models to predict the UPD crash likelihood based on demographic, roadway, and traffic factors.

Analysis Framework

Based on the relationship among UPD modes, UPD crashes, and non-recurring congestions described in Figure 1-1, the research team proposed an analysis framework as shown in 5-1. The framework includes three elements:

- **UPD Travel Demand Model** to estimate the change of conventional UPD traffic in a spatial unit (i.e., TAZ, road segments, or others) due to the implementation of innovative UPD modes. The model could be statistical prediction models considering various explanatory variables or a simple estimation of reduction factors by different UPD modes.
- **UPD Crash Model** to estimate the change of UPD crashes due to the change of surface UPD traffic.
- **Non-Recurring Congestions Model** to estimate the non-recurring congestion caused by UPD crashes. The model could be a statistical prediction model or a calculation table (i.e., Exhibit 10-17, *2010 Highway Capacity Manual*) by different facility types.

This study focused on the UPD crash model; two other models will be explored in future studies.

Identification of UPD Crashes

A UPD crash is defined as a traffic collision event in which at least one UPD vehicle is involved. In existing crash databases at national or state levels, there is no data field to indicate if UPD vehicles are involved or not. The absence of UPD crash data is a major challenge in modeling delivery-related crashes. To address the challenge, this study developed a procedure to identify UPD crashes from Florida crash databases, as shown in Figure .

Crash reports for commercial vehicle crashes are available in the Signal Four Analytics (University of Florida, 2021) system. Based on the interested area and year, commercial vehicle crash reports were downloaded for four years (2016–2019) in Florida Department of Transportation (FDOT) Districts 1, 2, 4, 5, 6, and 7. The crash reports includes data fields that indicate if a delivery vehicle was involved in a commercial vehicle crash, including:

- Make and model of vehicle in a crash
- Motor carrier name and address of vehicle in a crash
- Commercial usage code
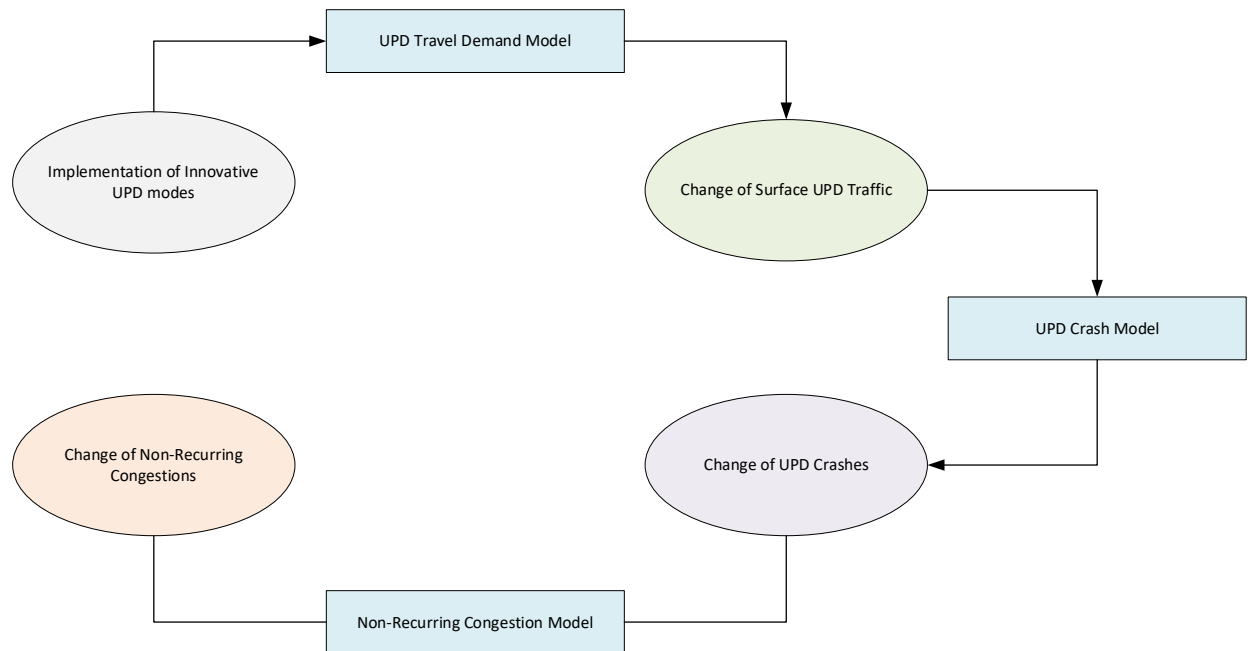
Figure 5-1 Analysis framework for assessing impacts of innovative UPD modes on safety and non-recurring congestion

Examples of critical data fields are shown in Figure 5-2. As the total number of crash reports is more than 100,000, manual review each report is very time consuming. Thus, a UPD crash identification tool based on optical character recognition (OCR) and key word matching was developed based on Python.

Vehicle 3	Motor Vehicle Type 1 Vehicle in Transport	Hit and Run 1 No	Veh License Number 2216689	State FL	Reg. Expires	Permanent Reg.	VIN 1GBCS10A5P2904774		
Year 2010	Make USPS	Model USPS	Style 2D	Color WHI	Extent of Damage Disabling	Est. Damage 1000	Towed Due To Damage Yes	Vehicle Removed By PRIVATE	Rotation Owner Request

Motor Carrier Name FED-EX GROUND		US DOT Number 265752		
Motor Carrier Address 1000 FEDEX DRIVE		City and State CORAOPOLIS, PA	Zip Code 15108	Phone Number
Comm/Non-Commercial 1	Vehicle Body Type 20 Medium/Heavy Trucks (more than 10,000 lbs (4,536 kg))	Vehicle Defects (one) 1 None	Vehicle Defects (two)	Emergency Vehicle Use 1 No	Special Function of MV 1 No Special Function

Figure 2-2 Examples of critical data fields in Florida crash reports

Critical steps in identifying UPD crashes are as follows:

- **OCR Text Extraction** – crash reports downloads from Signal Four Analytics in PDF format; this component converts the PDF files into images, then uses OCR technology to detect the text from images.

- **Text Filter** – Key words in specific boxes are crucial to identifying UPD crashes. A quick way to select UPD crashes from more than 100,000 crashes report is to monitor these specific boxes and the crash narrative. In this component, a key word library and two key word matching mechanisms were designed to support UPD crash identification:

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- Keyword generation – A keyword library is generated for keyword matching. Based on observation of UPD crashes reports, key words always include commercial delivery company name and address and specific words such as "Amazon," "UPS," "delivery truck," "parcel delivery," etc.; thus, a library contains major commercial delivery company information and UPD-related words are designed. Keyword matching based on this library is applied on each crash report.

- Exact matching – This mechanism checks if there is a word in a crash report that exactly matches any word in the keyword library. If there is a word in the data fields or crash narrative that exactly matches the keyword library, it is identified as a UPD crash.

- Fuzzy matching – Crash reports can be handwritten or printed; handwriting varies due to different writing habits, so text recognition accuracy can be jeopardized, e.g., "ups" can look like "aps" and detected as "aps." Hence, a fuzzy keyword matching is essential. Fuzzy keyword matching uses a similarity indexing score (0–100; 0 is totally unmatched, 100 is exactly matched) to compare words between crash reports and the keyword library. A threshold is defined to consider whether two words are the same. A similarity indexing score over the threshold (80) is consider as matched. A similarity indexing score of 50–80 is considered plausible for further review. Fuzzy keyword matching is developed based on the *FuzzyWuzzy* Python library (*Fuzzywuzzy*, 2021).

• **Manual Review** – A text filter outputs the labeled UPD crashes that may contain false positive cases because of fuzzy keyword matching. The number of labeled UPD crash reports is limited; therefore, false positives should be removed by manual review. In addition, plausible UPD crashes are reviewed to confirm they are truly UPD crashes.

Identified UPD crashes are summarized in 5-1.

Table 5-1 Summary of Identified UPD Crashes

Year	Crash Type	District 1	District 2	District 4	District 5	District 6	District 7
2016	Commercial crashes	5214	4829	8238	7318	8546	4728
	UPD crashes	77	98	86	112	141	73
2017	Commercial crashes	5579	5163	8670	8056	9182	4970
	UPD crashes	80	116	131	131	142	96
2018	Commercial crashes	5703	5005	9219	8482	8662	5449
	UPD crashes	96	117	143	69	158	98
2019	Commercial crashes	5825	5023	8234	8571	8832	5382
	UPD crashes	104	123	138	163	165	101

```
                                   ┌─────────────────┐
                                   │   Commercial    │
                                   │ Vehicle Crash   │
                                   │ Reports in PDF  │
                                   │     format      │
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┌────────────────────────────────┐  ┌─────────────────┐
│ • Covert PDF to images         │  │                 │
│ • Process images with OCR      │- -│   OCR Text      │
│   technologies                 │  │   Extraction    │
│ • Extract plain text contents  │  │                 │
│ • Output searchable crash      │  └─────────────────┘
│   reports in plain texts       │           │
└────────────────────────────────┘           ▼
┌────────────────────────────────┐  ┌─────────────────┐
│ • Major delivery vendor names  │  │                 │
│   and their variants           │- -│   Keyword       │
│ • UPS, USPS, FEDEX, DHL,       │  │   Generation    │
│   Amazon, …                    │  │                 │
│ • Can be expanded in future    │  └─────────────────┘
│   studies                      │           │
└────────────────────────────────┘           ▼
┌────────────────────────────────┐  ┌─────────────────┐
│ • Scan all crash reports       │  │                 │
│ • Check critical data fields   │- -│  Exact Matching │
│   and narrative                │  │                 │
│ • If there is any word exactly │  └─────────────────┘
│   match the keyword, label it  │           │
│   as UPD crash reports         │           ▼
└────────────────────────────────┘        ╱ If  ╲     Yes
                                          ╲matched╱ ──────┐
                                           ╲    ╱         │
                                            │ No          │
                                            ▼             │
┌────────────────────────────────┐  ┌─────────────────┐  │
│ • Scan the unmatched crash     │  │                 │  │
│   reports                      │  │                 │  │
│ • Compare words similarity in  │- -│ Fuzzy Matching │  │
│   critical data fields and     │  │                 │  │
│   narrative                    │  └─────────────────┘  │
│ • If similarity indexing score │           │           │
│   > 80, label it as UPD crash  │           ▼           │
│   reports：If similarity       │                       │
│   indexing score between 50 to │                       │
│   80, label it as plausible    │                       │
│   report                       │                       │
└────────────────────────────────┘                       │
┌────────────────────────────────┐  ┌─────────────────┐  │
│ • Manually review plausible    │  │                 │  │
│   crash reports                │- -│ Manual Review   │  │
│ • Check the entire crash report│  │                 │  │
│   to verify if it is a UPD     │  └─────────────────┘  │
│   crash                        │           │           │
└────────────────────────────────┘           ▼           │
                                   ┌─────────────────┐    │
                                   │  Identified UPD │◄───┘
                                   │     Crashes     │
                                   └─────────────────┘
```
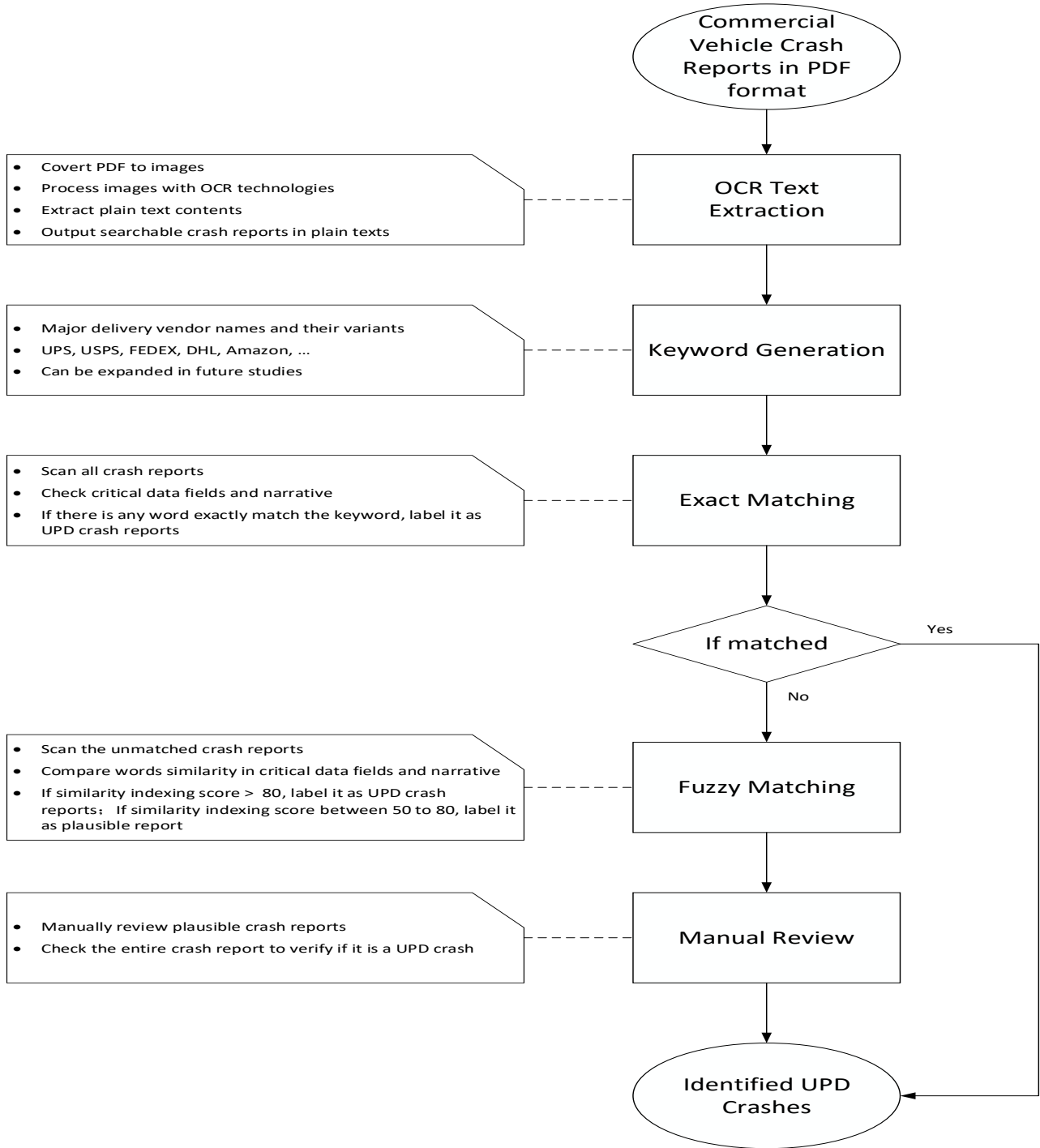
Figure 5-3 Procedure for UPD crash identification

Development of Preliminary UPD Crash Models

The risk of UPD crash occurrence is a function of UPD vehicle exposure (trips), traffic patterns, and roadway characteristics, and others. Given the reduction of UPD vehicle exposure due to new UPD technologies, it could

estimate the change of the UPD crash risk using the function. This study developed a statistical model to describe the relationship between UPD crash frequencies and contributing factors. The statistical model was developed at the traffic analysis zone (TAZ) level considering two factors:

- UPD crashes are extremely rare and random events. A small spatial unit (roadway segment) may result in the zero-inflation issue that predominate units have zero observations of UPD crashes. To avoid the biased and inconsistent estimation caused by the zero-inflated issue, this study adopted a bigger spatial unit (TAZ) as the analysis unit.

- Many UPD crashes occur on minor roads (local streets, private roads, etc.), and existing roadway databases do not include these minor roads. It is difficult to obtain roadway characteristics for these facilities (i.e., AADT, geometry, etc.) from the databases. The research team analyzed UPD crashes in a relatively large unit (TAZ) to avoid missing UPD crashes on minor roads.

Although this study identified UPS crashes for four FDOT Districts, it was impossible to build models across all Districts due to the work in matching demographic, geometry, and traffic data to each zone. Thus, model development was based on data collected in Hillsborough County, which is the fourth most populous county in Florida (in FDOT District 7). The modeling procedure is shown in Figure 5-4.
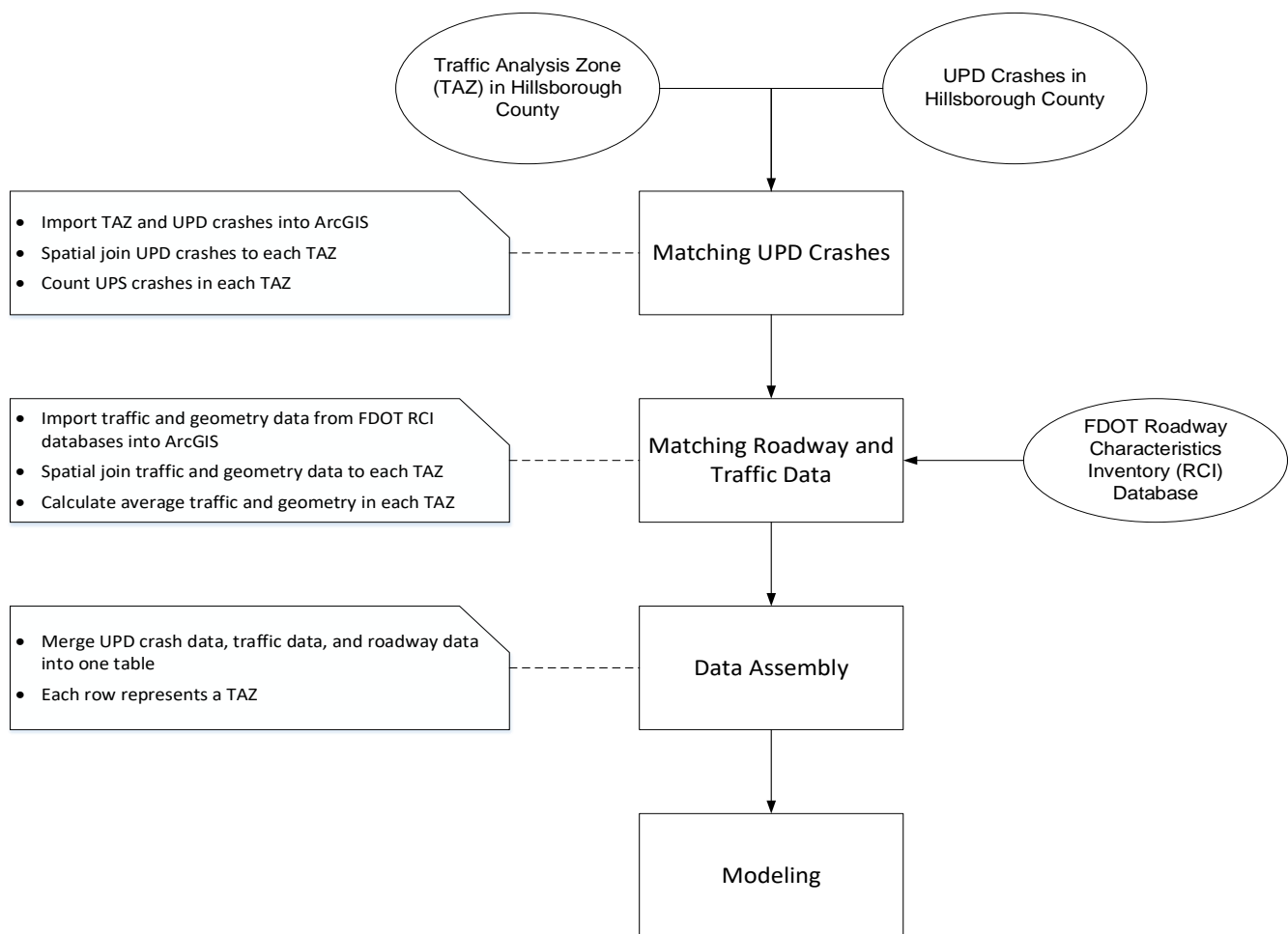
**Figure 5-4. Procedure for data merging and modeling**

Data Preparation

The identified UPS crashes were spatially joined (point to polygon) into each TAZ in ArcGIS Pro. The number of UPS crashes falling in a TAZ was counted as the UPS crash frequency for four years in the TAZ. Figure 5-5 shows the spatial join between UPD crashes and TAZs in Hillsborough County.
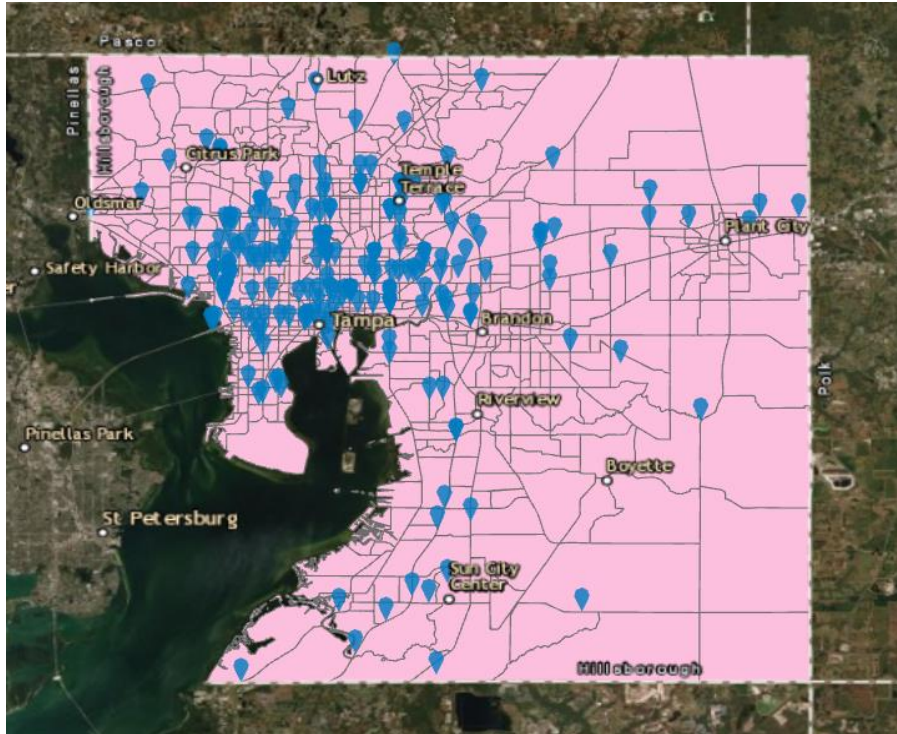
Figure 5-5 Spatial join between UPD crashes and TAZs in Hillsborough County

In addition to UPS crashes, traffic data (AADT, truck percentage) and geometry data (speed limit, number of through lanes) were also spatially matched to each TAZ. As one TAZ may contains one or more traffic/geometry features, the average of traffic/geometry data was calculated for each TAZ. An example of calculating average AADT is given in Figure 5-6. Calculation of average speed limit, number of lanes, and truck percentage are similar.
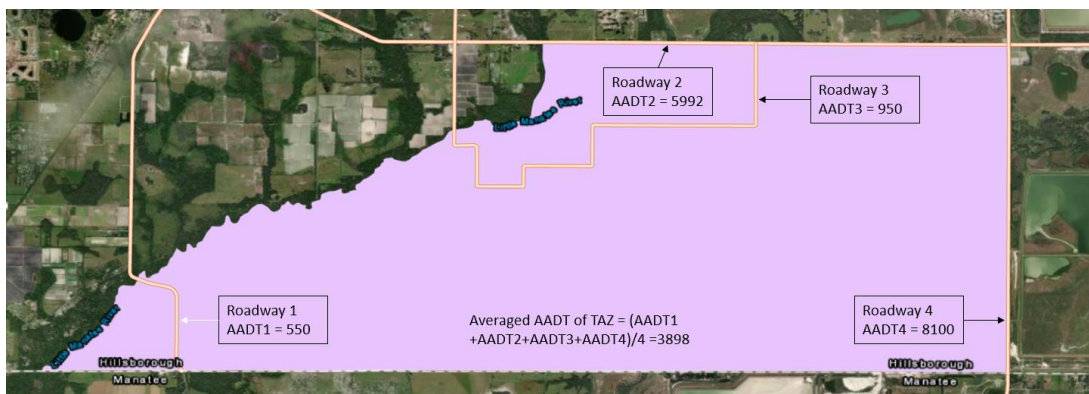
Figure 5-6 Example of calculating average AADT for TAZ

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Except for crash, traffic, and geometry data, demographic data (projected in 2015) were also matched from the US Census 2010. The matched data are shown in Table 5-2.

Table 5-2 Descriptive Statistics of Matched Data

Variable (N=779)	Mean	SD
UPD crash frequency for four years (2016–2019)	0.489	0.848
Population density (per 10,000 sf)	1.091	1.030
Natural logarithm of dwelling units less than 2 indicator (1 if value less than 2; 0 otherwise)	0.047	0.212
Natural logarithm of dwelling units between 2–6 indicator (1 if value between 2–6; 0 otherwise)	0.343	0.475
Natural logarithm value of dwelling units greater than 6 indicator (1 if value greater than 6; 0 otherwise)	0.610	0.488
Averaged AADT of TAZ at 10,000 multiplies	2.192	1.110
Averaged speed limit of TAZ (mph)	41.582	6.864
Percentage of truck traffic during peak hours greater than 13% indicator (1 if value than 13%; 0 otherwise)	0.035	0.185
Average number of lanes of TAZ	1.900	0.323

Model Development

As the dependent variable (UPD crash frequency) is count data with overdispersion (variance greater than mean), the negative binominal (NB) model is a natural selection for modeling UPD crashes. A stepwise procedure was used to select explanatory variables at a significance level of 90 percent or more. The fitted NB model is shown in Table 5-3.

Table 5-3 Fitted Negative Binomial Mode for UPD Crashes

Variable	Coefficient	z	p-value	95% CI
Constant	-0.407	-0.800	0.424	[-1.406, 0.591]
Population density	-0.232	-2.41	0.016	[-0.420, -0.043]
Categorized natural logarithm value of dwelling less than 2 indicator	0.707	2.66	0.008	[0.187, 1.228]
Categorized natural logarithm value of dwelling between 2–6 indicator	Baseline			
Categorized natural logarithm value of dwelling greater than 6 indicator	0.344	2.31	0.021	[0.052, 0.637]
Average AADT of TAZ	0.317	4.81	0.000	[0.187, 0.446]
Percentage of truck traffic during peak hours greater than 13% indicator	0.640	2.31	0.021	[0.098, 1.182]
Average speed limit of TAZ	-0.026	-2.12	0.034	[-0.050. -0.001]
Dispersion parameter (α)	0.841			[0.545, 1.299]
Model Statistics				
Number of observations	779			
Log-likelihood	-714.332			
Pseudo R^2	0.027			

The formula for predicting expected UPD crash frequency is given below:

$$Y = e^{-0.407-0.232 \cdot PD+0.707 \cdot DU1+0.344 \cdot DU2+0.317 \cdot AADT+0.64 \cdot TF-0.026 \cdot SPLMT}$$

where Y is the expected UPD crash frequency for four years; PD is the population density (per squared feet); $DU1$ is the indicator of the natural logarithm of dwelling units < 2; $DU2$ is the indicator of the natural logarithm of dwelling units > 6; $AADT$ represents the average Annual Average Daily Traffic at 10,000 multiples; TF is the indicator of truck percentage > 13; and $SPLMT$ is the average speed limit.

The fitted model (Table 5-3) indicates that demographic characteristics (population density and dwelling units) significantly influence the likelihood of UPD crash occurrence. However, the impacts of these factors are counterintuitive—UPD crash frequency is more likely to decrease with an increase in population density, and the middle dwell unit range (2 < the logarithm of dwell units < 6) experiences the lowest UPD crash frequency than the smallest dwell unit and the largest dwell unit ranges. This finding indicates that population density and dwell units are not indictors of UPD demand. Theoretically, more population and more dwell units imply more frequent UPD travel and, consequently, high UPD crash frequencies. Some unobserved factors that associate with population density and dwell units may cause this counterintuitive result. For example, high population density areas may have more roads with high safety standards; thus, UPD crashes may be reduced. More detailed data are needed to address the impacts of demographic factors on UPD crash frequencies.

AADT and truck percentage, which can be used as rough indicators of UPD exposures (assuming that UPD traffic is proportional to the two factors), present significant impacts on UPD crash frequencies. With an increase in AADT, UPD crash frequencies tend to increase. If truck percentage is higher than 13 percent, the likelihood of UPD crash frequencies is more likely to increase.

Average speed limit indicates the distribution of roadway classifications in a TAZ—the higher the average speed limit, the more high-class roads exist in the TAZ. The model implies that a TAZ with more high-class roads, which usually have high safety standards and UPD vehicles with relatively fewer stops, tend to experience a low UPD crash frequency.

Conclusions

This study preliminarily explored UPD crashes and identified contributing factors to UPD crash occurrence. The developed analysis framework and prediction model can be used as the basis for assessing the safety impacts of innovative UPD technologies. There are still some limitations that need to be addressed in future research:

- No UPD travel data or model was found to estimate UPD traffic. The fitted model had to use alternatives to roughly indicate UPD travels. In the Phase II study, the research team will search for or develop UPD traffic data or models to improve the performance of the model and connect to the change of conventional UPD exposures due to implementing innovative UPD technologies.
- This study did not assess the impacts of UPD crashes on non-recurring congestion. The Phase II study will explore a method to estimate non-recurring congestion caused by UPD crashes.
- Identification of UPD crashes included major delivery vendors (DHL, FedEx, UPS, USPS, Amazon). However, small delivery vendors such as food delivery might be missed. The Phase II study will expand the keywork library to include more types of delivery crashes.

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6. Contributions and Impacts

The models for urban congestion developed from this research project are sensitive to urban delivery activities. They can assess how current delivery activities contribute to urban congestion and how the alternative delivery activities alleviate traffic congestion in urban areas in terms of congestion reduction percentage or reduction of vehicle hours. The zone-based incident/accident models can be used to estimate incidents/crashes under current delivery activities and reduction of incidents/crashes under alternative delivery scenarios.

This research starts with modeling the demand of e-commerce behaviors by analyzing how different characteristics are impacting food or non-food travel behaviors before and after pandemic. With increasing demand of online shopping results from burgeoning e-commerce and pandemic, the research follows by measuring the impact of delivery service operations on urban congestion using macroscopic fundamental diagrams. Then, we work on urban operations strategies of drone deliveries to assess their potential of removing parcel delivery demand on the roads. More specifically, we propose a framework of UAV system traffic management in the context of parcel delivery in low-altitude urban airspace, including clustering-based UAV path planning, systematic UAS traffic management with conflict resolution, and mechanism design for airspace resource allocation. Lastly, we focus on assessing safety impacts, including non-recurring congestion reductions, of innovative UPD technologies.

Contributions

For each of the four parts summarized above, we present the main findings and contributions. In the first part of demand models of e-commerce behaviors, our results show the solution to 1) how demographic characteristics affect pandemic shopping behavior, 2) how near-term shopping behaviors might play out in the longer term, and 3) new opportunities for partnering between public and private stakeholders around the curb. For example, model results indicate that prior to the pandemic, higher income households were less likely to shop only online for non-food items, whereas after the pandemic these same households began substituting in-person trips for online purchases.

The second part of the study analytically approximates the impact of DSO on network capacity and compare the theoretical prediction to the network flow observed in simulation of street traffic. The impact of DSO on urban traffic was measured within the Macroscopic Fundamental Diagram (MFD) framework. The study shows the simulation results and the theoretical prediction for capacity with different numbers of DSO double-parked stops. The prediction from the model is in good agreement with the results of the simulation. In the future, the shape of the entire MFD as the result of DSO operations can be modeled. Second, a large number of possible DSO scenarios and their impacts for various network configurations can be modeled. Third, the MFD model can be used to compute arrival delay and air pollution values that result from delivery service operations.

In the third part of urban operations strategies using drone delivery, we efficiently utilize the low-altitude airspace resources, and propose a framework of UAS traffic management including clustering-based UAV path planning, systematic UAS traffic management with conflict resolution, and mechanism design for airspace resource allocation. This work enables efficient traffic management of UAV systems when traffic demand partially shifted to the low-altitude urban airspace. It mitigates the congestion impact from truck and van traffic, as well as reduce costs and travel times. In addition, the familiar issues of urban street congestion, in the

future we may also see congestion above the city from UAV traffic, as use of these vehicles for urban package delivery and other purposes intensifies.

In the last part of study, we propose a framework for assessing safety impacts, including non-recurring congestion reductions, of innovative UPD technologies. The framework can be used to comprehensively evaluate the benefits of new UPD modes and provide decision making support to develop and implement the new technologies. This study also developed a procedure based on Fuzzy language processing technologies to identify UPD crashes from historical crash databases. The identification procedure addresses the most significant challenge in UPD safety management and analysis and provides reliable UPD crash data. A statistical model was developed based on the identified UPD crashes that estimates UPD crash frequencies for a TAZ given demographic, roadway, and traffic characteristics of the TAZ.

Impacts

The models of urban congestion developed from this research project can benefit practitioners from several perspectives. 1) By modeling the demand of e-commerce behaviors, the results can aid planners and policymakers in understanding both short- and long-term effects of pandemic-induced changes to shopping behavior in mid-sized cities/regions. The information can also give recommendations to practitioners when making decisions. For example, the results recommend that it will be important to track growth of the e-commerce industry in the longer term, to better understand if e-commerce will replace existing trips, complement them, or induce more new trips and to identify whether delivery drivers or individual customers will be making greater use of the curb space in front of commercial businesses. It will be key to balance the needs of all types of curb users and keep safety — both viral and traffic-related — a priority. At present, many COVID-19 testing facilities are currently using re-purposed surface parking lots, providing examples from which retail businesses and planners can learn. In the longer term, the re-purposing of parking lots to higher and better uses, such as housing, is warranted. 2) Measuring the impact of DSO on network capacity gives practitioners a quantitative sense of the arising problems including double parking, longer VMT, causing traffic bottlenecks etc. Understanding the causes of congestion problems help make policy decisions. 3) The proposed framework of using drone delivery to remove road delivery traffic provides practitioners a solution to reduce urban congestion from parcel delivery. The traffic management framework of efficiently assigning schedules and resolving conflicts can serve as a preliminary study to develop operational tools to be applied in practice. 4) The study of the comprehensive assessment of innovative UPD modes including the developed framework, identification method, and statistical model can be the basis of future studies.

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