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Multimodal Strategies for Mitigating Congestion from Urban Parcel Delivery

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National Institute for Congestion Reduction
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16. Abstract

The explosive growth in e-commerce, the increasing urgency of de-carbonization, the rapid advances in UAV technology, and the continuous disruptive development of the gig economy create needs and opportunities for dramatic improvements in urban package delivery. E-commerce may greatly increase the demand for such deliveries, traditionally made by truck and van, as urban residents substitute purchases made over the Internet for those acquired in brick-and-mortar stores. To mitigate the congestion impact of truck and van traffic, as well as reduce costs and travel times, last-mile delivery should in many cases be shifted toward non-motorized modes (e.g., walkers and bicyclists) and UAVs. While there is literature on how to optimally configure urban delivery systems composed of these modes, most of the research in this area does not consider these problems in the context of urban congestion. In addition to the familiar issues of urban street congestion, in the future, we may also see congestion above the city from UAV traffic, as the use of these vehicles for urban package delivery and other purposes intensifies.

In this project, we develop a suite of multimodal, congestion-sensitive strategies for urban delivery, by integrating traditional motorized vehicles, non-motorized modes, and UAVs. Building on prior research for modelling and managing urban road congestion as well as logistics studies for UAV route optimization and scheduling, we develop new models that combine UAVs with other modes for integrated and coordinated urban package delivery. The impacts of the new multimodal strategies on roadway operations and safety are evaluated.

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Table of Contents

Figures

Tables

Executive Summary

With burgeoning e-commerce and rapid technological change in the parcel delivery system, conventional truck delivery is shifting to new classes of vehicles such as drones, autonomous ground vehicles, cargo bikes, and non-motorized vehicles, and combined with new delivery models featuring crowdsourcing, parcel lockers, and mobile lockers. Multiple modes can be operated synergistically to improve the efficiency of urban parcel delivery networks. For example, replacing the last-mile truck delivery with nonmotorized vehicles helps mitigate traffic congestion results from truck traffic and double-parking activities. In order to attain the full potential of multimodal delivery to reduce costs and increase convenience, it is necessary to develop a complementary set of management strategies. The goal of this work is to summarize and compare multimodal delivery strategies with different combinations of delivery modes. This work mainly considers combining trucks, electric cargo bikes, and drones for last-mile delivery. We develop delivery models with various delivery strategy scenarios including truck only, truck or drones, trucks with drones onboard, two-echelon truck and drone delivery, two-echelon truck, and drone/ cargo bikes delivery. The performance of these delivery models is compared. Then, congestion models are developed to learn the relationship between the congestion impact on road networks caused by delivery traffic and different multimodal delivery strategies. Macroscopic Fundamental Diagrams (MFD) are used to conduct simulations. The fitted analytical congestion model has a high goodness of fit. The congestion model will be integrated into the delivery models in the future.

The key intellectual merit of this project is the fusion of knowledge of various research areas for congestion reduction, multimodal delivery strategies with congestion effect, evaluation of double-parking effect from traditional truck traffic, and safety benefits of new delivery vehicles. The new knowledge and insights about multimodal delivery strategies and congestion reduction will benefit researchers, planners, transportation administrators, private sectors, and the public.

Chapter 1. Introduction

In the high-growth parcel delivery market, dramatically increased traditional truck deliveries are contributing to traffic congestion, air pollution, noise, road deterioration, and safety concerns. The benefit of integrating multiple types of delivery vehicles has been explored recently, especially new types of vehicles including electric bikes, drones, auto-robots, crowdsourcing, etc. Delivery by these non-motorized vehicles and Unmanned Aircraft Vehicles (UAVs) is increasingly perceived as an integral part of the future solution for urban freight movement to provide fast, point-to-point deliveries. As part of the parcel delivery demand shifting to non-motorized vehicles and drones in the air, delivery by new vehicle types helps mitigate the traffic congestion in the road transportation system.

Multiple modes can be used synergistically to manage urban road congestion from parcel delivery. Trucks with drone onboard Vehicle Routing Problem (VRP) have been very popular and well-studied in the context of urban parcel delivery networks [1, 2, 3, 4, 5]. [1] design the truck with drone onboard delivery models under different settings, estimate costs using Continuous Approximation (CA) methods, and compare the performance with truck-only delivery. It concludes that trucks with drones on board can be economically beneficial, especially with multiple drones onboard. Cargo bikes are also very popular in last-mile delivery networks [6, 7, 8]. The delivery route cost trade-offs between trucks and electric cargo bicycles are explored under multiple scenarios with different route characteristics [6]. The potential benefit of integrating autonomous robots is explored in [9] by developing scheduling procedures to determine the truck route along robot depots and drop-off points, such that late customer deliveries are minimized. Though different multimodal delivery models have been proposed, limited existing research comprehensively summarizes and compares different combinations of multimodal delivery strategies.

A multi-echelon network with local transshipment centers is required in order to integrate cargo bikes, auto-robots, and other types of vehicles in last-mile delivery. Many existing papers worked on location routing problems for multi-echelon delivery networks and explored the benefit of inventory management [10, 11, 12, 13, 14, 15]. A two-echelon location-routing model is proposed in [13], and it suggests that transshipment platforms can significantly improve delivery process efficiency with proper fleet type and capacity. [15] design a strategic last-mile three-tiered multimodal delivery network, estimate route costs, and formulate facility location and routing models using a real-world case study. It considers all aspects of the multimodal delivery problem jointly and simultaneously in an integrated approach, including network design, location routing problem, cost approximation, model applications, etc. This work compares network design efficiency with different combinations of multiple delivery modes.

Cost estimation is required when comparing the performance of different multimodal delivery networks. Travel distance approximation is the main component of delivery cost estimation. [16, 17] approximated the single warehouse VRP tour distance by constructing a snaking swath route of near constant width, and analytically estimated the total travel distance in both L1 and L2 metrics using Continuous Approximation (CA). The developed analytical distance formula is implemented in many delivery models [1, 15, 18, 19]. CA method is commonly used in urban freight distribution management to generate analytical forms [20, 21, 22]. In our work, we integrate the CA method of distance estimation into our optimization problems for on-demand distribution and mode decisions.

Chapter 2. Multimodal Delivery Strategies

The integrated delivery strategy is conceptualized by combining trucks, cargo bikes, and UAVs with congestion effects in this section. We start with multimodal delivery models without congestion effects in section 2.1, then the congestion model is developed and added to delivery models in section 2.2. We focus on strategic same-day parcel delivery instead of instant food or grocery delivery. Thus, the delivery time window is not introduced to the models. We designed the delivery models in both ring-dial networks and grid-based networks. Different mode combinations are considered and compared.

2.1 Multimodal Delivery Models without Congestion Effects

We conceptualize an integrated delivery strategy without congestion effects in this section. Delivery models in different road network structures are proposed including both circular and grid-based networks. In the circular network, we are able to express delivery cost by different modes in closed analytical form using continuous approximation. However, it is not applicable to regions other than circular road networks. The grid-based network is easier to generalize to different network shapes but is difficult to analytically capture the congestion effects, which will be addressed in section 2.2.

2.1.1 Circular Network Model

We designed a two-echelon last-mile delivery network. The delivery trips are from a few warehouses to local transshipment centers, and then to many sparse customer locations. The first echelon of delivery trips is completed by truck tours, and the second echelon by electric cargo bikes or drones. Our two-echelon multimodal delivery strategy determines the vehicle types and corresponding serving locations and optimizes delivery system efficiency.

a) Two-Echelon Network Design

The last-mile parcel delivery system is developed as a two-echelon network. Three types of facilities are considered including hub warehouses (H), local points (L), and customers (C). The hub warehouses are regarded as the origin of last-mile traffic flow. The hub warehouses are mostly large facilities owned by delivery service companies that hold inventory and prepare parcels. They are usually located far from the city center. The local points (L) are also micro-distribution warehouses that receive shipments from hub warehouses. Temporary staging is allowed in local points but not permanent storage. Local small warehouses and transshipment points are usually categorized as local points to transfer and handle goods. Customers (C) are the end point of last-mile delivery. It includes both customer home and self-service points.

Our work focuses on an idealized circular city, where we assume N hub warehouses are located on the boundary of the city. Local points are distributed on the evenly spaced circular rings within the city. The density of local points along their ring is related to their distance to the city center. We assume n rings within the entire circular region with $\frac{R}{n}$ distance between adjacent rings. Customers are randomly distributed in the entire region with a certain demand density function.

In our two-echelon network, we define the first echelon as parcel delivery trips from hub warehouses to local points, and the second echelon as trips from local points to customers. We consider three vehicle types: trucks, small vans, and drones. Trucks are assigned to only the first echelon and are only responsible for delivery tours visiting local points. Small vans and drones are used in the second echelon to deliver goods from local points to customers.

We assume N warehouses are evenly located on the boundary of an idealized circular city with the same distance to each other. The entire circular region is divided into N pizza slices, each of which is served by a warehouse. Our customer demand density $\alpha(r)$ depends on the distance between the customer location and the city center. We only focus on one pizza slice in later modeling as they are exactly the same.

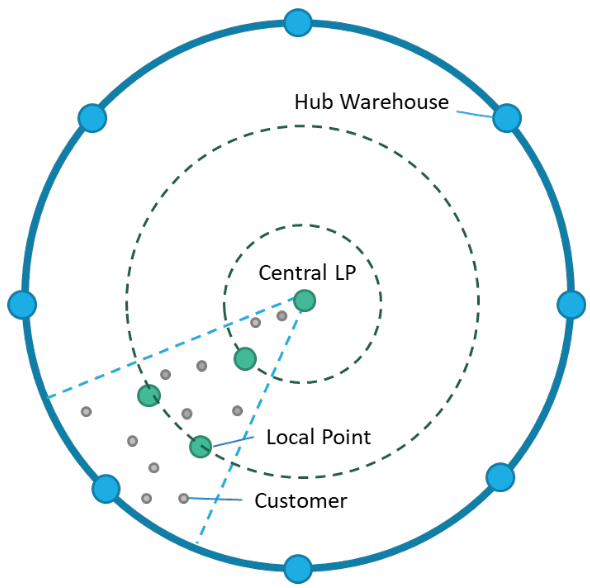

Figure 1. Two echelon delivery network design

Table 1. Parameters and Variables

Parameters	Definition	Unit
N	Number of hub warehouses	#
n	Number of evenly spaced rings within circular region	#
$\beta(r)$	Density of local points per unit area	# Local points/km^2
R	Radius of idealized circular city	km
$\alpha(r)$	Customer demand density per unit area	# Customer parcels/km^2
C_t	Parcel load capacity of a truck	#/truck
C_v	Parcel load capacity of a small van	#/van
e_0	Unit travel time cost by truck	$\$/min$
e_1	Unit travel time cost by small van	$\$/min$
e_2	Unit travel time cost by drone	$\$/min$
v_{van}	Van speed	km/min
v_{drone}	Drone speed	km/min
Variables	**Definition**	**Unit**
r_{local}	Distance between wedge to local point center	km
w'	Wedge width	km
L'	Wedge length	km
Auxiliary variables	**Definition**	**Unit**
C_{van_i}	Delivery cost by van in wedge i	$\$$
C_{drone_i}	Delivery cost by drone in wedge i	$\$$
D_{van}	Delivery distance of a van tour in wedge i	km
D_{tour}	Delivery distance of a truck tour in a pizza slice	km
D_{truck}	Total truck delivery distance in a pizza slice considering truck rate	km

b) First Echelon Delivery Strategy

In our first-echelon delivery network, trucks are responsible for delivering parcels from warehouses to local points within the same pizza slice. We look at only one pizza slice at the current point because other pizza slices are the same. We assume the truck will depart from the hub warehouse on the city boundary and visit local points on its way to the city center, then go back to the same hub warehouse. (See figure 2 red line for truck tour trip). We approximate the truck tour in a ring-radial sector to a rectangular region with the same area size so that the total customer parcel demand stays consistent. According to Daganzo, 1983, the path in a rectangular swath that visits all the points by moving along the strip without backtracking and turning back when reaching one end is validated as only less than 5% difference in path length with several other experiments in a rectangular shape.

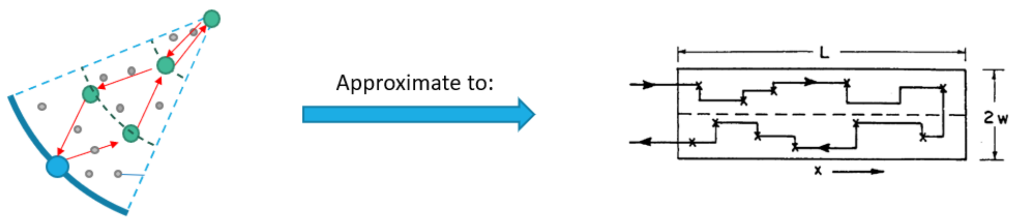

Figure 2. First echelon truck delivery tour estimation

In the current pizza slice, the number of local points is calculated by the local points density:

$$n_{local} = \frac{2\pi}{N}\int_0^R \beta(r) r dr \qquad (1)$$

The pizza slice is approximated to a rectangular region with the same area size:

$$2wL = \frac{\pi R^2}{N} \qquad (2)$$

Then, we can estimate the average travel distance per truck trip as:

$$D_{tour} = 2L + \frac{w}{3} n_{local} \qquad (3)$$

Where $2L$ stands for the horizontal truck travel distance, and $\frac{w}{3}$ stands for the average vertical displacement between any two adjacent local points.

After manipulation with equation (2) and (3), the average travel distance per truck trip is written as:

$$D_{tour} = \frac{\pi R^2}{Nw} + \frac{w}{3} n_{local} \qquad (4)$$

By the intrinsic property of equation (4) with respect to w, we can calculate the optimal width and length of the approximated rectangular region.

$$w^* = \sqrt{\frac{3\pi R^2}{N n_{local}}} \qquad (5)$$

$$L^* = \frac{1}{2}\sqrt{\frac{n_{local}\pi R^2}{3N}} \qquad (6)$$

The total truck travel cost in one pizza slice is calculated considering the truck rate and cost coefficient:

$$rate_{truck} = \frac{2\pi\int_0^R \alpha(r) r dr}{NC_t} \qquad (7)$$

$$TC_{truck} = \frac{e_0}{v_{truck}} \cdot D_{truck} = \frac{e_0}{v_{truck}} \cdot D_{tour} \cdot rate_{truck} = \frac{e_0}{v_{truck}} \cdot \frac{4\pi^2 R}{N}\sqrt{\frac{2\int_0^R \beta(r) r dr}{3}} \cdot \frac{\int_0^R \alpha(r) r dr}{NC_t} \qquad (8)$$

c) Second Echelon Delivery Strategy

In our second echelon delivery network, each parcel is delivered from the assigned local point to customer either by small vans operated with other road traffic or drones flying in the low-altitude urban airspace. We assume a circular serving region of each local point. Each local point is responsible for all customers located within its serving region. The radius of the local point serving region should be large enough so that all local points can cover the entire pizza slice.

Within the serving region of each local point, the customer parcel demand density is assumed to be constant $\alpha(d)$, where d is the distance between the local point and city center. Parcels delivered by drones are dedicated trips with only one parcel delivered at a time. While parcels delivered by small vans are shared trips with multiple parcels delivered in a tour. Vehicle routing problems are involved in the van tour. We chose the delivery zones to be wedge-shaped sectors in concentric rings similar to Newell, 1986, but with a small circle in the innermost ring. (See Figure 3). In each wedge-shaped sector, we compare the delivery cost of van tours with that of many dedicated drone trips. The parcels in each wedge will be delivered by the vehicle type with the smaller total cost. The total delivery cost of a local point is the sum of delivery cost in each wedge. Considering the loading capacity of small vans, the delivery cost is higher for wedges farther from local point since the linehaul distance traveled from local point to the wedge is longer. Time limitation for a single van delivery tour is not considered at current stage because our study focuses on same-day parcel delivery and the local point serving region is not as large as more than one day tour is needed.

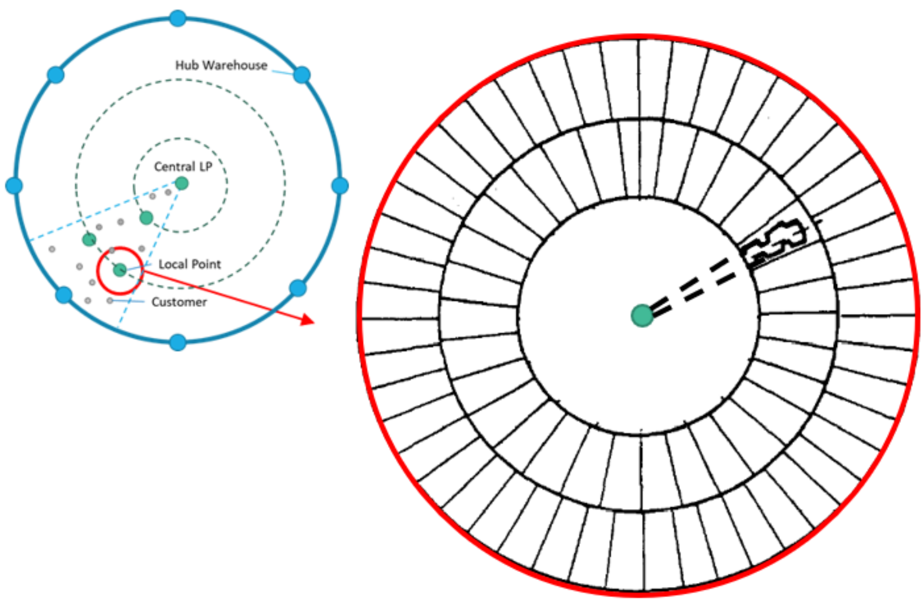

Figure 3. Second echelon delivery trips estimation

The total delivery cost of a local point is determined by the sum of wedge costs:

$$\sum_{wedge\_i} Min(C_{van\_i}, C_{drone\_i}) \qquad (9)$$

Where C_{van_i} is the delivery cost by vans in wedge i, and C_{drone_i} is the delivery cost by drones.

We first calculate trip length and delivery cost of wedge-shaped sectors outside the inner ring. Approximate each wedge-shaped sector to a rectangular similar to Figure 2. The optimal width and length of the wedge can be estimated by equation (10)-(12), and the delivery cost of a van tour in a single wedge can be calculated by equation (13).

$$2w'L'\alpha(d) = C_v \quad (10)$$

$$w'^* = \sqrt{\frac{3}{\alpha(d)}} \quad (11)$$

$$L'^* = \frac{C_v}{2}\sqrt{\frac{1}{3\alpha(d)}} \quad (12)$$

$$C_{van\_i} = \frac{e_1}{v_{van}} \cdot D_{van} = \frac{e_1}{v_{van}} \cdot (2r_{local} + 2L' + \frac{w'}{3}C_v) = \frac{2e_1}{v_{van}} \cdot (r_{local} + \frac{C_v}{\sqrt{3\alpha(d)}}) \quad (13)$$

The drone trip cost is simply the sum of many dedicated trips.

$$C_{drone\_i} = \frac{e_2}{v_{drone}} \cdot (2r_{local} + L')C_v = \frac{e_2}{v_{drone}} \cdot (2r_{local}C_v + \frac{{C_v}^2}{2\sqrt{3\alpha(d)}}) \quad (14)$$

For delivery cost in the inner ring, F. Robuste et al, 2014 compared the performance of several classic heuristic vehicle routing algorithms in a circular region and suggested Clarke & Wright, or Fisher & Jaikumar algorithms under different demand density scenarios. There has been a lot of existing research showing that the total trip distance is proportional to $\sqrt{AN}$ in a single depot Traveling Salesman Problem (TSP). The small van tour cost can be estimated in equation (15). The drone trips cost is in equation (16).

$$C_{van\_0} = \frac{e_1}{v_{van}} \cdot 0.68\sqrt{AN} = \frac{e_1}{v_{van}} \cdot \frac{0.0567\pi {C_v}^2}{\sqrt{\alpha(d)}} \quad (15)$$

$$C_{drone\_0} = \frac{e_2}{v_{drone}} \cdot \frac{4\pi\alpha(d)L'^3}{3} \quad (16)$$

d) Experiments

Numerical analysis has been conducted using the above models with idealized scenarios. In December 2019, around 100,000 packages are delivered in San Francisco daily (Lim, 2019). Assuming 8-hour delivery time per day, the average demand density is around 2 $packages/min \cdot km^2$. We use the maximum speed of the current top drone model, 70mph, in our research. And 20mph for small vans. The operation cost coefficient of drones and vans include unit cost for labor, maintenance, electricity or fuel, and equipment. The drone cost per package kilometer is estimated to be one-third or less of the UPS delivery cost (Sudbury, 2016). The loading capacity of the small van is set to 20 parcels. Given the area of SF is 121 km^2, the radius of idealized circular region with the same area is about 6 km. The maximum radius of possible serving region of a local point is 3 km when assuming only one local point in a pizza slice. In this case, we plot the relationship between the delivery cost of a single wedge by vans and drones in Figure 4. Considering the inner circle delivery cost as well, our delivery strategy suggests using vans in the most inner circle and drones in wedges outside. We also applied different cost coefficients of vans and drones. When the unit delivery cost ratio of van to drone is less than 5, our model suggests vans for the entire region; when ratio is between 5 and 9, our model suggests vans for the most inner region, then drones for middle rings and followed by vans for outer rings; when ratio is between 9 and 11.3, our model suggests van inside with serving radius related to specific cost ratio and drone outside; When ratio is beyond 11.3, using drones for the entire region.

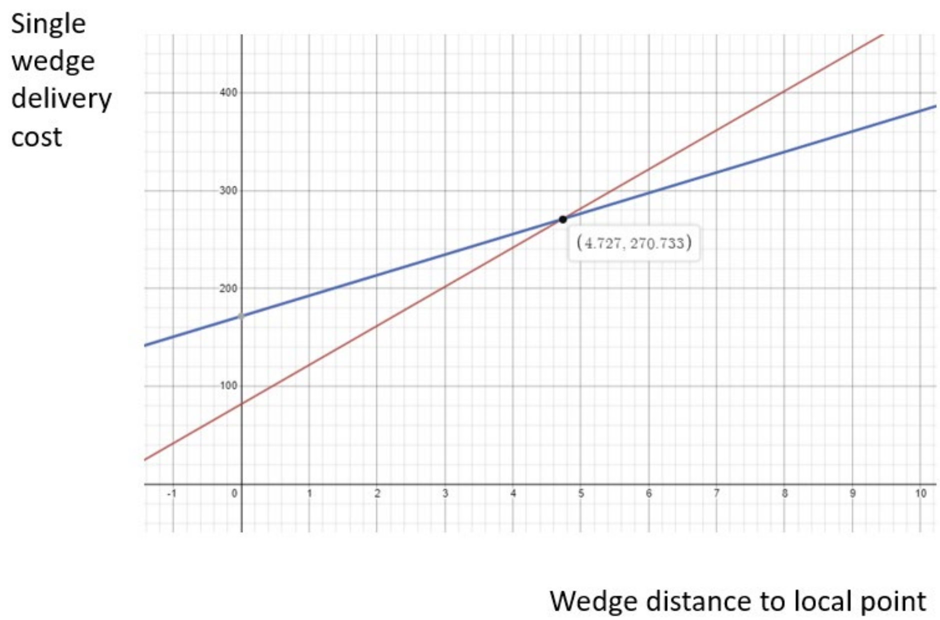

Figure 4. Numerical experiments results

e) Conclusions and Impacts

We conceptualized the integrated delivery strategy combining trucks, small vans, and UAV without congestion effects in circular network. Our delivery strategy is able to make decisions on vehicle mode selection and delivery location and range, so that the system delivery efficiency is optimized. The proposed multimodal last-mile delivery strategies leverage untapped potential of non-traditional modes to balance demand and capacity on urban road networks. UAVs have the potential to significantly reduce the cost and time of making last-mile deliveries. The integration of different vehicle modes will yield coordinated strategies for multimodal urban delivery that leverage the synergistic strengths of motorized surface vehicles, non-motorized modes, and UAV while accounting for both road and airborne congestion.

The current work also lays a solid foundation for congestion effect evaluation in next step research. The later research will further reveal how alternative delivery strategies can alleviate traffic congestion in urban areas can reduce congestion impacts on the activities themselves as well as other urban vehicles.

2.1.2 Grid Network Model

In this section, five zone-based delivery strategies with different mode combinations are conceptualized. These strategies include all-truck model, truck/drone model, truck-with-drones-on-board model, truck/cargo bike model, and truck and cargo bike/drone model. The first three models involve a single echelon delivery network while the last two involve a two-echelon network.

a) Single Echelon Delivery Scenarios

In the single echelon delivery network, delivery zones are identified and served independently. We work in a city- or county- level metropolitan region with a single hub warehouse. Delivery vehicles are assumed to depart directly from the hub warehouse to the delivery zones, and finish deliveries to customers within the zone, then go back to the hub warehouse. Thus, we need an efficient zone size to make good use of vehicle capacity. For same-day parcel delivery, parcel demand and destination are known at the beginning of the day. An efficient zone size is one for which one fully loaded vehicle can serve one day of delivery demand. Since trucks are involved in all three scenarios in the single echelon delivery network, the zone size will be determined by truck capacity and parcel demand density. We assume there are enough trucks at the warehouses. Three scenarios are considered in the single echelon delivery network, including all-truck scenario, truck or drone scenario, truck-with-drones-on-board scenario. The models determine the delivery vehicle mode, by estimating and comparing the total delivery costs.

Scenario 1: All Truck

In this scenario, only trucks are assumed to deliver parcels to all delivery zones. This scenario is used as the base case for later comparison of different combinations of multiple modes. The delivery network is divided into grid-based delivery zones in advance. Each truck trip is only responsible for one delivery zone and returns to the hub warehouse directly right after delivery.

The total delivery cost includes parcel handling cost and operational cost. The parcel handling cost involves parcel preparation, sorting, loading and unloading. Let n_z be the number of deliveries stops in zone z and ρ_z be the average number of dropped parcels per delivery stop in zone z. There are $n_z \cdot \rho_z$ total number of parcels to be delivered in zone z. For each delivery zone z, the total parcel handling cost H_z equals unit handling cost by truck per parcel c_T^H multiplying total number of parcels in the zone.

$$H_z = c_T^H \cdot n_z \cdot \rho_z \qquad (17)$$

The operational cost can be calculated as the product of unit time-based truck operational cost c_T^O and travel time. For each truck delivery trip, the total travel distance includes two-way linehaul distance d_z between hub warehouse and the zone, and VRP tour distance D_z in the zone. According to [17], with many randomly scattered demand points, a near optimal VRP tour can be constructed by lapping the region containing the points with nearly parallel laps. The entire zone can be covered by a snaking swath of near constant width, and points are visited along the swath. The optimal swath width that minimizes the expected total tour length can be calculated in both L1 and L2 metrics. Since we assume Manhattan distance as the truck travel distance metric, the VRP tour distance can be estimated as Equation 18.

$$D_z = 1.15 \cdot \sqrt{A_z \cdot n_z \cdot \rho_z} \qquad (18)$$

where A_z is the area of zone z. Let v_l be the linehaul truck travel speed, and v_s be the inter-stop truck travel speed in VRP tour. The total travel distance per truck trip is $\frac{2d_z}{v_l} + \frac{D_z}{v_s}$. Let Ω_T be truck loading capacity. The number of truck trips in zone z can be calculated as $\frac{n_z \cdot \rho_z}{\Omega_T}$. The truck time-based operational cost O_z is expressed in Equation 19:

$$O_z = \frac{n_z \cdot \rho_z}{\Omega_T} \left(\frac{2d_z}{v_l} + \frac{D_z}{v_s}\right) c_T^O \qquad (19)$$

Thus, total delivery cost for this scenario can be calculated:

$$Total\ cost = \sum_z c_T^H \cdot n_z \cdot \rho_z + \sum_z \frac{n_z \cdot \rho_z}{\Omega_T} \left(\frac{2d_z}{v_l} + \frac{D_z}{v_s}\right) c_T^O \qquad (20)$$

Scenario 2: Truck/Drone

The second scenario has the same delivery network setup as the first scenario but with drone deliveries involved. Drones are operated independently from trucks. We assume drones depart from the hub warehouse, deliver a single parcel per trip, and go back to the warehouse. A mode decision is introduced in this scenario to determine whether each zone is served by either trucks or drones. If a zone is assigned to be served by drones, all parcels in the zone will be delivered by individual drone trips. The second scenario delivery model is formulated as an Integer Linear Programming. The decision variables and parameters are described in Table 2.

Table 2. Decision Variables and Parameters

Set	Description
Z	Delivery zones in the network
Decision Variable	Description
I_z	Binary variable. Equals 1 if zone z is served by trucks, otherwise drones.
Auxiliary Variables	Description
H_z	Parcel handling cost in zone z
O_z	Time-based operational cost in zone z
L_z	Drone launch and recovery cost in zone z
Parameters	Description
n_z	Number of deliveries stops in zone z
ρ_z	Average number of dropped packages in zone z
d_z	Average distance from warehouse to demand points in zone z. Linehaul travel distance.
D_z	VRP tour distance in zone z per truck trip
Ω_T	Truck loading capacity
v_l	Truck line haul travel speed
v_s	Truck inter-stop travel speed in VRP tour
v_D	Drone speed
c_T^H	Truck handling cost per parcel
c_D^H	Drone handling cost per parcel
c_T^O	Unit time-based truck operational cost
c_D^O	Unit time-based drone operational cost
c_D^S	Launch and recovery costs per drone trip
U_D	Maximum drone travel distance within battery limit
ε	Delivery zone width

The delivery model is formulated as follows:

$$Min \ \sum_z (H_z + O_z + L_z) \tag{21}$$

s.t.

$$H_z = c_T^H \cdot n_z \cdot \rho_z \cdot I_z + c_D^H \cdot n_z \cdot \rho_z \ \cdot (1 - I_z) \tag{22}$$

$$O_z = c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \left(\frac{d_z}{v_l} + \frac{D_z}{v_s}\right) \cdot I_z + c_D^O \cdot n_z \cdot \rho_z \cdot \frac{2d_z}{v_D} \cdot (1 - I_z) \tag{23}$$

$$L_z = c_D^S \cdot n_z \cdot \rho_z \cdot (1 - I_z) \tag{24}$$

$(2d_z + \varepsilon) \cdot (1 - I_z) \leq U_D$ (25)

$I_z \in \{0,1\} \qquad \forall\, z \in Z$ (26)

The objective function minimizes the total delivery cost. The total delivery cost is composed of parcel handling cost, operational cost, and drone launch and recovery cost. Constraint (22) defines the parcel handling cost. The first term calculates the handling cost if the zone is served by truck, while the second term is for drone. Different handling cost coefficients are used as the parcel sorting, loading and unloading times are different for truck and drone. Constraint (23) defines the operational cost with the first term if the zone is delivered by truck and the second term if by drone. The first term is similar to that from scenario 1, the multiplication of cost coefficient, number of truck trips and trip travel time. For drones in the second term, the travel time is calculated as the two-way Euclidean distance between origin and destination divided by drone speed, and multiplying the number of drone trips. Constraint (24) defines the extra launch and recovery cost for drone delivery, which is calculated as the cost coefficient multiplies by the number of parcels in the zone. The unit launch and recovery costs are composed of drone launching, reaching cruising altitude, and landing. Constraint (25) limits that only delivery zones located within drone flying range from the warehouse will be considered for mode choice.

Scenario 3: Truck with Drones on Board

In this scenario, trucks are operated with drones on board in the same delivery trip. Each truck trip with drones on board is assigned to one delivery zone. Similar to previous scenarios, each delivery zone is assumed to be covered by a snaking swath of near constant width. We consider multiple drones on each truck. There are various operational possibilities with multiple drone deliveries [4, 23, 24, 25, 26]. Since we are exploring and comparing the benefit of different mode combinations for parcel delivery, we take the same setting of trucks with multiple drones in [4]. We consider the situation where each truck is equipped with n drones. The truck will visit the first of a sequence of n+1 stops in the swath. Then n drones launch from the truck at each truck stop, and each of the drones visit one of the following n stops and return to the truck which has moved to (n+2)th stop. Figure 5 illustrates the example of a truck trip with three drones on board. Three drones launch from the truck at each truck stop and finish the following three deliveries, then return to the truck at the fifth stop. Trucks are assumed to travel along road networks, which is approximated by Manhattan distance, while drones travel in Euclidean distance in the air.

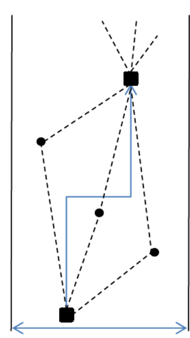

Figure 5. Truck with drones on board [4]

The total delivery costs include parcel handling cost, operational cost and drone launch and recovery cost. Similar to previous scenarios, the parcel handling cost can be calculated as Equation 1. Since package preparation and sorting, loading and unloading have been completed at the truck delivery stage, only truck parcel handling cost is considered. The drone launch and recovery cost is expressed in Equation 27:

$$L_z = c_D^S \cdot n_z \cdot \rho_z \cdot \frac{n}{n+1} \qquad (27)$$

where $n_z \cdot \rho_z \cdot \frac{n}{n+1}$ is the number of parcels delivered by drones in zone z. The time-based operational cost is calculated as:

$$O_z = c_T^O \cdot (\frac{n_z \cdot \rho_z \cdot D_Z^T}{v_s} + \frac{d_z}{v_l}) + c_D^O \cdot n_z \cdot \rho_z \cdot \frac{D_Z^D}{v_D} \qquad (28)$$

where D_Z^T and D_Z^D are the expected truck and drone travel time per delivery respectively. The two expected travel times were estimated using continuous approximation methods in [4]. Let δ be the parcel demand density per unit area, w be the swath width, and n be the number of onboard drones. The expected horizontal travel distance between adjacent deliveries is $w/3$, and the expected vertical travel distance is $1/\delta w$. The expected truck travel distance per delivery can be calculated as:

$$D_Z^T = \frac{w}{3} \frac{1}{n+1} + \frac{1}{\delta w} \qquad (29)$$

The expected drone travel distance per delivery is as follows:

$$D_Z^D = \frac{2n}{n+1} \sqrt{(\frac{w}{3})^2 + (\frac{n+1}{2\delta w})^2} \qquad (30)$$

where $2\sqrt{(\frac{w}{3})^2 + (\frac{n+1}{2\delta w})^2}$ is the expected travel distance of each drone delivery trip, and there are n out of $n + 1$ drone delivery trips in each truck stop cycle. In the square root term, the expected horizontal and vertical drone travel distances are $w/3$ and $\frac{n+1}{2\delta w}$ respectively. According to [37], the weighted average of the optimal swath widths for truck delivery (w_T^* that minimizes Equation 13) and drone delivery (w_D^* that minimizes Equation 14) is:

$$w^* = \sqrt{n+1} \sqrt{\frac{3}{\delta}} (\frac{c_T^O + \sqrt{2} n c_D^O}{c_T^O + 2n c_D^O}) \qquad (31)$$

The total delivery cost is $\sum_z (H_z + O_z + L_z)$.

b) Two Echelon Delivery Scenarios

In the two-echelon delivery network, a second-level facility, local transshipment center, is introduced (see Figure 6 for network definition). Figure 7 presents the delivery procedure in the multi-echelon network. First-level delivery vehicles are assumed to depart from hub warehouse to local transshipment center, transfer parcels to the second-level delivery vehicles, and return to hub warehouse. The second-level vehicles are responsible for parcel delivery from the local transshipment center to customers in each delivery zone. All the parcels are assumed to be delivered through local transshipment centers. Two delivery scenarios are considered in our two-echelon network. Trucks are used as first-level delivery vehicles in both scenarios. Scenario 4 considers only cargo bikes for the second-echelon delivery as the base case, while in scenario 5 each delivery zone is served either by drones or cargo bikes.

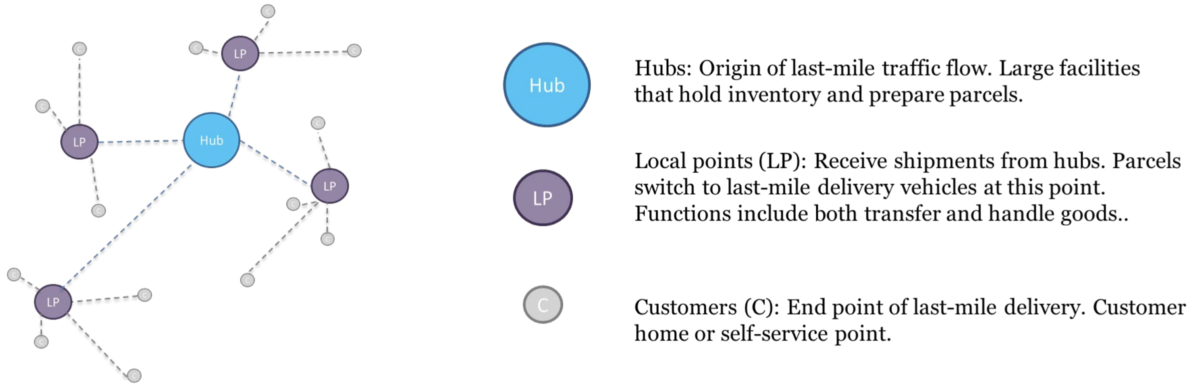

Figure 6. Multi-echelon network definition

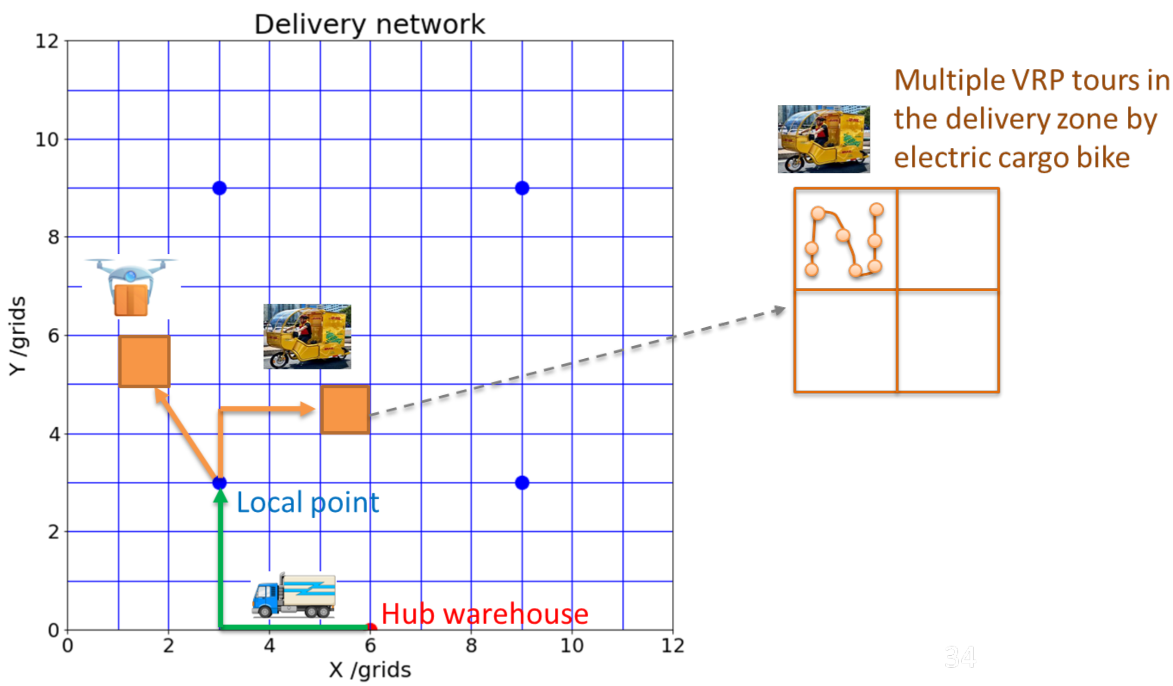

Figure 7. Multi-echelon network delivery procedure example

Scenario 4: Truck and Cargo Bikes

In scenario 4, truck and cargo bikes are operated cooperatively, where trucks bring packages from the hub warehouse to the local transshipment centers and cargo bikes move packages from local transshipment centers to individual customers in each zone. Parcels are resorted and transferred from the first level to the second-level vehicles at the local transshipment centers. A candidate list of local transshipment centers is predetermined. The delivery model determines which local transshipment centers will be in use and assigns delivery tasks from corresponding delivery zones to each local transshipment center.

In the first echelon, similar to previous scenarios, the delivery zone size is determined by demand density and truck capacity, so that one full-loaded truck can exactly deliver one-day demand of the zone in a single VRP tour. However, in the second echelon, the cargo bike VRP tour can deliver far fewer parcels per trip because of its smaller loading capacity. Each delivery zone will be served by multiple cargo bike trips. It is more efficient in terms of total travel distance to further divide the delivery zone to many smaller cargo bike zones and have multiple VRP tours. The cargo bike zone size can be determined such that one fully loaded cargo bike can deliver one-day demand of the smaller zone.

The delivery model is formulated as an Integer Linear Programming. The new decision variable I_{zl} determines the corresponding delivery zones that will be served by each local transshipment center, as well as if each center will be in use or not. The additional variables and parameters are present in Table 3.

Table 3. Additional Decision Variables and Parameters Description for Scenario 4

Set	**Description**
L	Local transshipment center candidates
Decision Variable	**Description**
I_{zl}	Binary variable. Equals 1 if zone z is served by local transshipment center l.
Auxiliary Variables	**Description**
R_l	Parcel transfer cost at local transshipment center l
Parameters	**Description**
d_l	Distance from the hub warehouse local transshipment center l
d_{lz}	Distance from local transshipment center l to zone z
b_z	Number of cargo bike zones in delivery zone z
D_Z^C	Cargo bike VRP tour distance per trip
Ω_B	Cargo bike loading capacity
v_{Bl}	Cargo bike linehaul travel speed
v_{Bs}	Cargo bike inter-stop travel speed in VRP tour
c_C^H	Cargo bike handling cost per parcel
c_B^O	Unit time-based cargo bike operational cost
c_l	Unit parcel transfer cost at local transshipment center l
U_l	Maximum number of parcels can be proceeded by local transshipment center l.
T	Maximum daily working time for human

The delivery model is formulated as follows:

$$Min\ \sum_z(H_z + O_z) + \sum_l R_l \quad (32)$$

s.t.

$$H_z = (c_T^H + c_C^H) \cdot n_z \cdot \rho_z \quad (33)$$

$$O_z = \sum_l \left(c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \frac{d_l}{v_l} \cdot I_{zl} + c_B^O \cdot b_z \cdot \left(\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}\right) \cdot I_{zl}\right) \quad (34)$$

$$D_Z^C = 1.15 \cdot \sqrt{\frac{A_z}{b_z} \cdot \frac{n_z \cdot \rho_z}{b_z}} \quad (35)$$

$$R_l = \sum_z c_l \cdot I_{zl} \cdot n_z \cdot \rho_z \quad (36)$$

$$\sum_z I_{zl} \cdot n_z \cdot \rho_z \le U_l \quad (37)$$

$$\left(\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}\right) \cdot I_{zl} \le T \quad (38)$$

$$\sum_l I_{zl} = 1 \quad (39)$$

$$I_{zl} \in \{0,1\} \qquad \forall\, z \in Z \quad (40)$$

The objective function minimizes the total delivery cost. The total delivery cost is composed of parcel handling cost, operational cost, and parcel transfer cost. Constraint (33) defines the parcel handling cost, which includes handling cost for truck and cargo bike, since each parcel will be loaded on and unloaded from both truck and cargo bike. The cargo bike parcel handling cost will be much smaller because parcel preparation and sorting have been completed in the first echelon for truck. Constraint (34) defines the operational cost with the first term for trucks and the second term for cargo bikes. In the second term, $\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}$ calculate total cargo bike travel time for zone z with the first term for two-way linehaul travel time from local transshipment center to delivery zone and the second term for VRP tour time in smaller cargo bike zones. Similar to Equation (3-2), each cargo bike VRP tour distance can be estimated as Constraint (35). Constraint (36) defines the parcel transfer cost in the local transshipment center l, which includes cost for moving parcels from trucks to second-echelon vehicles. Constraint (37) limits the number of parcels processed at each local transshipment center so as not to exceed its capacity. Constraint (38) requires that each cargo bike VRP tour trip cannot be longer than daily working hour. Each delivery zone can only be assigned to one local transshipment center in constraint (39).

Scenario 5: Truck and Cargo Bikes/Drones

Multiple delivery modes are considered for the second echelon in scenario 5. Either cargo bikes or drones are used to finish the delivery from local transshipment centers to delivery zones. The delivery model is formulated in a generalized way that is able to consider more than two delivery modes in the second echelon, which may involve auto robots, crowdsourcing, etc. in the future. Similar to scenario 4, the delivery zone will be divided into many smaller cargo bike zones if cargo bikes are used. All parcels in the delivery zone will be delivered individually from the local transshipment center if drones are used. This delivery model determines both the delivery tasks assignment for local transshipment center, and the second echelon vehicle mode for each delivery zone. The model is formulated as an ILP, see variables and parameters in Table 4 and formulation as follows.

Table 4. Additional Decision Variables and Parameters Description for Scenario 5

Set	**Description**
M	Second echelon deliver mode choices set
Decision Variable	**Description**
I_{zlm}	Binary variable. Equals 1 if zone z is served by local transshipment center l, and taking mode m in the second echelon.
Auxiliary Variables	**Description**
T_{zlm}	Second echelon total delivery travel time to serve zone z from local transshipment center l by mode m
Parameters	**Description**
c_m^H	Handling cost per parcel by mode

$$Min \ \sum_z (H_z + O_z) + \sum_l R_l \quad (41)$$

s.t.

$$H_z = \sum_{l,m} (c_T^H + c_m^H \cdot I_{zlm}) \cdot n_z \cdot \rho_z \quad (42)$$

$$O_z = \sum_{l,m} (c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \frac{2d_l}{v_l} \cdot I_{zlm} + c_m^O \cdot T_{zlm} \cdot I_{zlm}) \quad (43)$$

$$T_{zl0} = b_z \cdot (\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}) \quad (44)$$

$$D_Z^C = 1.15 \cdot \sqrt{\frac{A_z}{b_z} \cdot \frac{n_z \cdot \rho_z}{b_z}} \quad (45)$$

$$T_{zl1} = \frac{2d_{lz}}{v_D} \cdot n_z \cdot \rho_z \quad (46)$$
$$R_l = \sum_{z,m} c_l \cdot I_{zlm} \cdot n_z \cdot \rho_z \quad (47)$$
$$\sum_{z,m} I_{zlm} \cdot n_z \cdot \rho_z \leq U_l \quad (48)$$
$$\left(\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}\right) \cdot I_{zlm} \leq T \quad (49)$$
$$(2d_{lz} + \varepsilon) \cdot (1 - I_{zlm}) \leq U_D \quad (50)$$
$$\sum_{l,m} I_{zlm} = 1 \quad (51)$$
$$I_{zlm} \in \{0,1\} \qquad \forall\, z \in Z, l \in L, m \in M \quad (52)$$

The total delivery cost in the objective function (41) is the same as scenario 4. Constraint (42) defines the parcel handling costs for both first and second echelon vehicles. Constraint (43) defines the operational cost with the first term for trucks and the second term for second echelon delivery vehicles. In the second term, travel time by either cargo bikes or drones T_{zlm} are specified in constraint (44) and (45) respectively. In constraint (46), the cargo bike VRP tour distance D_Z^C in smaller zones is calculated by constraint (47). Constraint (48) defines the parcel transfer cost, and constraint (49) limits the local transshipment center capacity. Constraint (50) requires that each cargo bike VRP tour trip cannot be longer than daily working hours. Constraint (51) specifies drone delivery range based on battery energy capacity.

c) Experiments

In this section, five multimodal delivery models are compared in an idealized zone-based network. We work on a square network region divided into many grids, where each grid is treated as a delivery zone in the model. We assume the hub warehouse is located on the boundary of the region edge. Constant parcel demand density is assigned to the region using San Francisco data. In December 2019, around 100,000 packages are delivered in San Francisco daily (Lim, 2019). Daily demand density is about 800 pkg/km2, given San Francisco area is 121 km2. The grid size of the idealized network is determined as the grid area contains daily parcel demand that can be delivered by exactly one full-loaded truck. Given truck loading capacity is 400 parcels (Assmann et al, 2020), the grid width is set to be 0.7km. We work on a $14 \times 14\ km$ network with 20×20 delivery grid zones.

Comparisons of different multimodal delivery models require reasonable parameter settings. The parcel handling costs by different modes are calculated as the multiplication of hourly labor cost and average handling time per parcel by the mode (Gevaers, et al, 2014). The parcel handling cost includes parcel preparation and sorting, loading, and unloading, etc. Hourly California blue collar wage $22.77 () is used as the labor cost. The average handling time per parcel can be calculated as the average delivery stop time by each mode divided by the average number of dropped parcels per stop. We use 2, 1, 0.5 minutes as expected per parcel stop time for trucks, cargo bikes and drones (Assmann et al, 2020; Campbell, et al, 2017). The parcel handling cost coefficients are $0.88, $0.38, $0.19 for truck, cargo bike and drones correspondingly. In the two-echelon network, since most parcel handling tasks are completed at truck level, we assign a small value $0.06 (10s handling time) to second-echelon cargo bike per parcel handling cost, and ignore that for drones.

Truck time-based operational cost coefficient includes two components, driver costs $30/hr and vehicle costs $37/hr (Leslie, 2021), with total $67/hr. Driver costs include driver wages and benefits, and vehicle costs include fuel, truck lease or purchase payments, repair and maintenance, truck insurance premiums, permits and licenses, tires, tolls. The operational cost coefficient for electric cargo bike includes $30/hr driver cost and $9/hr vehicle costs (Sheth et al, 2019). For drone operational costs, we take into account $0.34/hr initial investment (Welch, 2015), $20/hr labor costs (Jung, Kim, 2022), and $0.94/hr vehicle costs (French, 2017), with total $21.28/hr. The initial investment per drone including software is $4000, and has a lifespan of 5 years with 9 hour daily operation time and 5 days per week (Welch, 2015). The drone vehicle costs include insurance, maintenance, and electricity for battery recharging. The loading capacity of each truck is 400 parcels, and 40 parcels for electric cargo bikes (Assmann et al, 2020). Besides, we use 67 mph as drone cruising speed (Raj, Murray, 2020). The average truck linehaul travel speed is set to 40 mph and inter-stop VRP delivery speed to 20 mph [3]. The electric cargo bike linehaul speed is 15 mph and inter-stop VRP speed is 10 mph [4]. The daily working hours per person is 8 hours, we use 6 hours as the maximum trip length limitation with extra 2 hours for trip preparation. For drone launch and recovery cost, we consider launching cost to the cruising altitude and landing cost. Under the regulations of the Federal Aviation Administration, 400 feet (about 122 meters) is the highest a small drone could fly to avoid interference with other aircraft. The unit distance cost ratio among takeoff, landing and cruising equals 2.04:1.53:1. 10 m/s and 5m/s are used as takeoff and landing speed respectively (Raj, Murray, 2020). The drone launch and recovery cost per trip can be calculated as takeoff and landing time multiplying drone operational cost coefficient, which is $0.02/trip.

Results of five delivery models are compared in Table 5. Note that drone cost in the table includes both drone operational cost and drone launch and recovery costs. For scenario 3, we consider four onboard drones on each truck. For the first three single echelon network scenarios, delivery models with multiple modes have less total cost than the truck only scenario. Under this specific idealized network design and parameter settings, handling cost is a dominant component over all costs. Compared to trucks, drones have less handling cost and unit operational cost, but need longer travel time because of their limited loading capacity. The tradeoff is captured by the mode decision results of scenario 2 in Figure 8. The red spot represents the warehouse location, and light grids are delivery zone served by drones and by trucks otherwise. The maximum drone flying distance is 10km, but the decision boundary is three grids away from the warehouse. Grids farther than the threshold will need very long total drone travel distance causing much higher travel cost than trucks.

For two-echelon scenarios, we consider 4 local transshipment centers located in the middle of four square sub-regions (see green dots in Figure 8). We also consider the extreme cases for two-echelon network with the same number of local transshipment centers as the number of grids. The local transshipment centers are located in the middle of each grid delivery zone. The 4 centers scenarios are named as ‘4-4L’ and ‘5-4L’, while the extreme cases are named as ‘4e’ and ‘5e’ respectively in the table. The extreme cases have the smallest truck cost over other cases with different numbers of local transshipment center, since each zone will be served by the local transshipment center in its own zone and trucks travel directly from hub warehouse to the zone. The extreme cases reveal the total cost lower bound of two echelon network delivery strategies. In general, two echelon networks have higher total cost than that of single echelon network, even for extreme cases. Two echelon network calculates handling cost twice at both levels and additional parcel transfer cost. Besides, the total travel distance is longer with a detour to the local transshipment centers before arriving at delivery zones. However, the two-echelon network can reduce the number of truck trips dramatically, by comparing the truck cost between the first three scenarios and last four. In our setting with handing cost dominated, the benefit is not obvious in total cost. The benefit will also increase if the warehouse is located further from the study region. In addition, the two-echelon network removes truck traffic from road network and reduced congestion from delivery traffic and double-parking activities. The two-echelon network may be more efficient when congestion effect is considered. The mode decision and local transshipment center assignment results of scenarios 4 and 5 are presented in Figure 8. In scenario 4, grids are evenly assigned to four predetermined local transshipment centers even though the warehouse is located on one edge. The second-echelon travel times by cargo bikes dominates the total travel time cost as each grid is divided into 16 smaller zones for bike VRP tours in the experiment. Choosing the closest local transshipment centers to the delivery zone results in smaller total travel time cost when there are many cargo bikes VRP tours at the second level. In scenario 5, with same local transshipment center assignment as scenario 4, closer grids are served by drones while farther by cargo bikes.

Table 5. Delivery Models Results Comparisons

Scenario	Total cost $	Handling cost $	Truck cost $	Drone cost $	Bike cost $
1	177447	140800	36647	/	/
2	161704	137488	21662	2553	/
3	175334	140800	29409	5125	/
4 – 4L	250401	150400	8726	/	88075
5 – 4L	250207	150016	8726	1390	86875
4e	211056	150400	23270	/	15493
5e	177210	140800	23270	3539.72	/

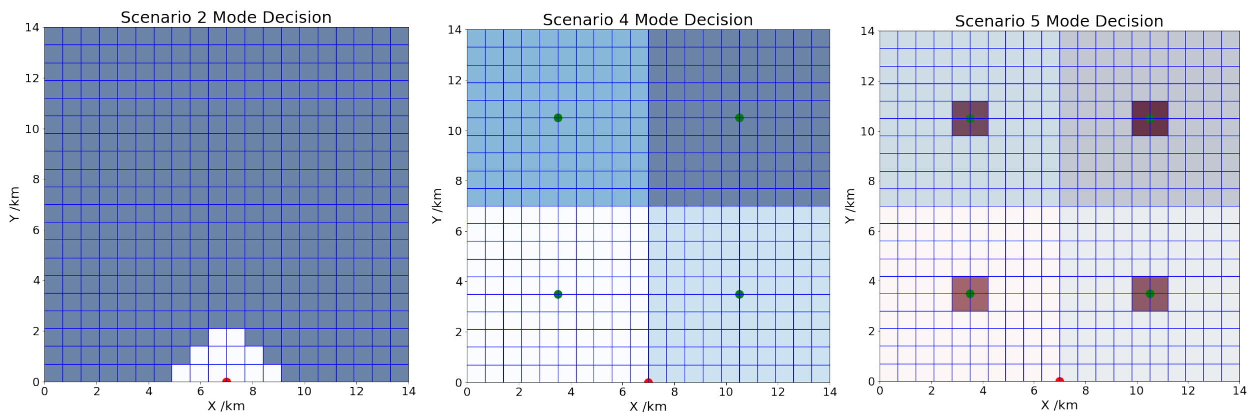

Figure 8. Multimodal delivery models results

d) Conclusions

Multimodal delivery models with different combinations of vehicles are summarized and compared in this work. Especially two-echelon delivery network with cargo bikes or drones are proposed. We consider both the facility assignment and mode decisions under scenarios. We explicitly calculate the delivery costs mainly including parcel handling cost and vehicle operational costs. From our specific experiments, we found that single echelon delivery model generates less cost than that of two-echelon. Our models do not include or focus on the inventory benefit of a two-echelon delivery network for faster parcel arriving time, or the benefit of reducing road traffic congestion by removing truck traffic and double-parking activities in two-echelon network. Taking into the consideration above, the two-echelon network may be more efficient. In addition, delivery models with multiple vehicles modes in both single- and two- echelon networks are more efficient in terms of total delivery cost than truck only scenario. The results suggest that we can take advantage of synergistic operation among emerging vehicle types, especially nonmotorized vehicles, and drones for more efficient parcel delivery.

For future research, one direction can be performing sensitivity analysis with different parameter settings and network design, and compare delivery models under various scenarios. Besides, it would be interesting to apply the delivery models to real-world case studies, and compare the multimodal delivery efficiency with idealized situations. In addition, we can improve the current multimodal delivery models considering congestion effects results from delivery traffic, and evaluate the benefit of integrating multiple vehicle modes.

2.1 Congestion Models

The proposed multimodal strategies in the previous section optimize facility choice, mode selection, and delivery routing for synergistic operations without consideration of congestion effects. In the following two sections, we take congestion into consideration and integrate it into the multimodal strategies. In our congestion model, we will capture both the road congestion impacts on delivery traffic, and the congestion externalities of delivery traffic imposed on the road system. For road congestion impacts on delivery traffic, we focused on the delay cost of delivery traffic that results from the reduced truck speed in congested situations. For congestion externalities by delivery traffic, we evaluate the impacts through calculating the additional total system delay of non-delivery traffic.

Integrating these congestion effects with the proposed optimization models for multimodal strategies requires an analytical formulation between congestion costs and truck traffic. The analytical congestion cost functions need to be simple and compatible with the optimization model to maintain computation tractability. We developed the congestion model through a series of procedures using Macroscopic Fundamental Diagrams (MFD), micro-level traffic simulations, and regression fitting. Figure 9 presents the workflow for congestion model. We take into account the traffic dynamics over a day in the system. It is assumed that daily traffic demand trends for both non-delivery traffic and truck traffic are given. Knowing the MFD profile of the road network, we can conduct traffic simulation to calculate the system accumulation trend based on trip information and average system travel speed. Then the total system delay for delivery traffic and non-delivery traffic can be calculated.

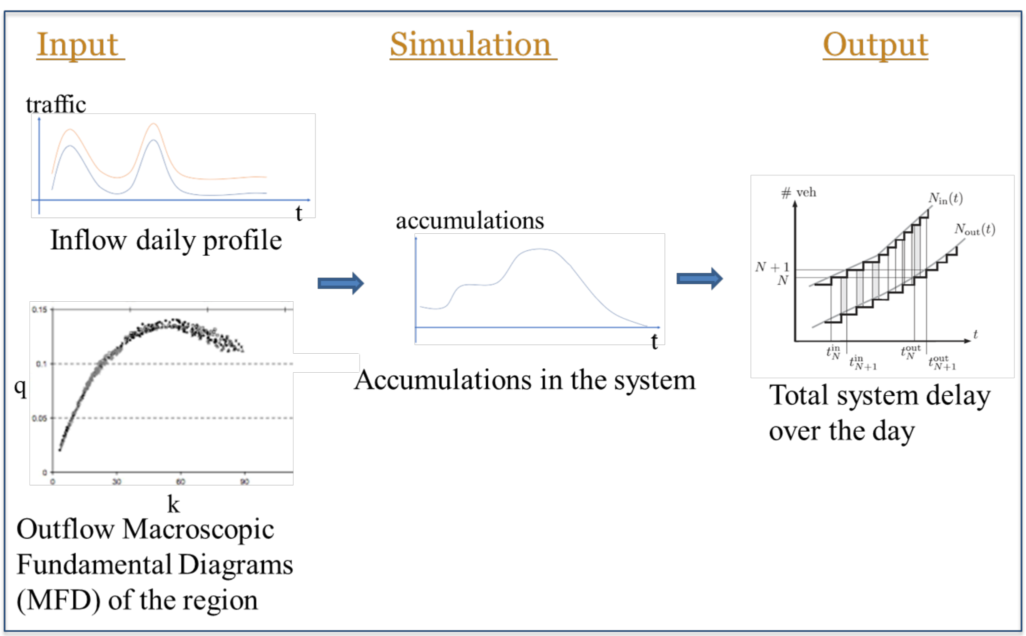

Figure 9. Congestion model workflow

2.2.1 Congestion Model Inputs

Daily traffic demand dynamics and the network MFD profile are needed for the congestion model. Figure 10 presents an example of daily inflow profile in the road network, with both delivery and non-delivery traffic demand trends over the day. The inflow profile captures the morning and afternoon peak-hour demand, and has low-demand midnight hours for delay dissipation.

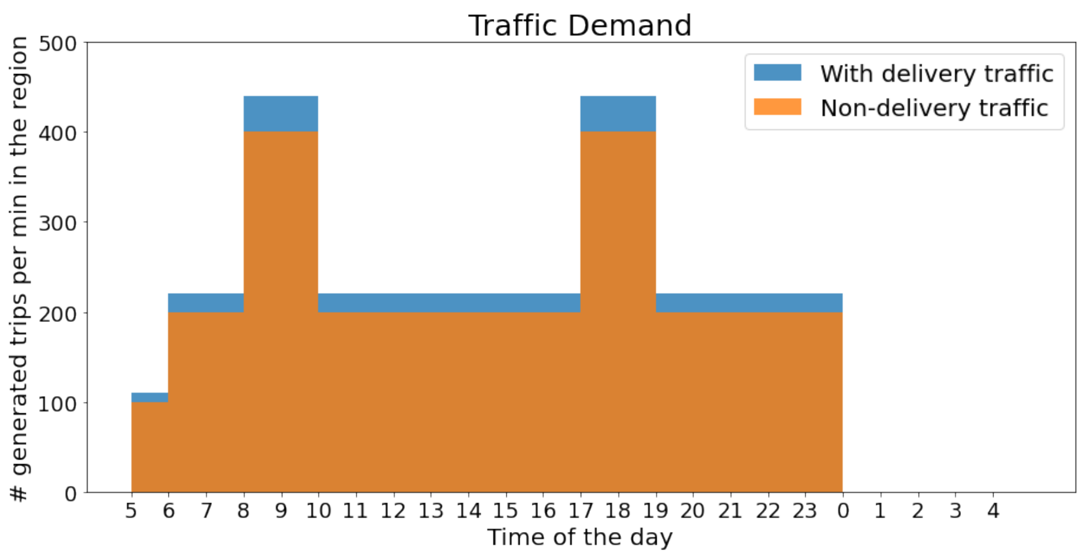

Figure 10. Daily traffic demand dynamics

The Macroscopic Fundamental Diagram (MFD) is a graph relating an average network flow to the average density of the entire studied network region. The graph can also be represented by speed vs density. It is usually used to predict the performance of a road system, or its response when applying inflow regulation or speed limits. We use a developed MFD profile of a virtual road system from [39] in our congestion model. The MFD is constructed in a virtual 4 km by 4km road system with 200-meter roadblocks. Trip origins and destinations were uniformly distributed over the network. Twenty distinct demands were examined, such that different network conditions ranging from free flow to gridlock are considered. Ten simulations were performed for each demand level. (See [39] for more details). Figure 11 presents the MFD profile with speed versus density.

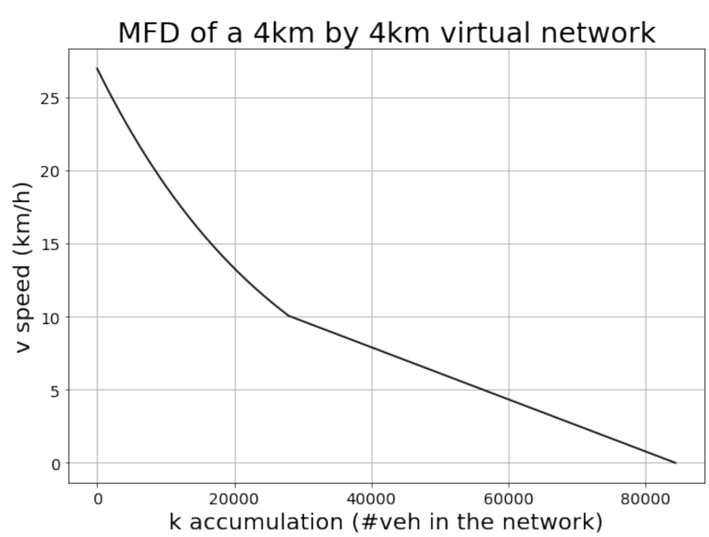

Figure 11. Macroscopic Fundamental Diagram (MFD) of a virtual network [39]

2.2.2 Traffic Simulation

A micro-level traffic simulation process is developed as in Figure 12 to calculate the total system delay of delivery and non-delivery traffic. The traffic simulator iteratively updates the system vehicle accumulations and computes individual trip traveling information at each time step. Based on the trip start and end times from the simulation, we can extract the congestion cost from the cumulative diagrams of all traffic. For the road congestion impacts on delivery traffic, the congestion cost is calculated as the total delivery traffic delay when the non-delivery traffic presents, compared to the situation with free flow truck speed. The congestion cost delivery traffic imposed on the system, is calculated as the additional total non-delivery traffic delay after delivery traffic is added to the simulation.

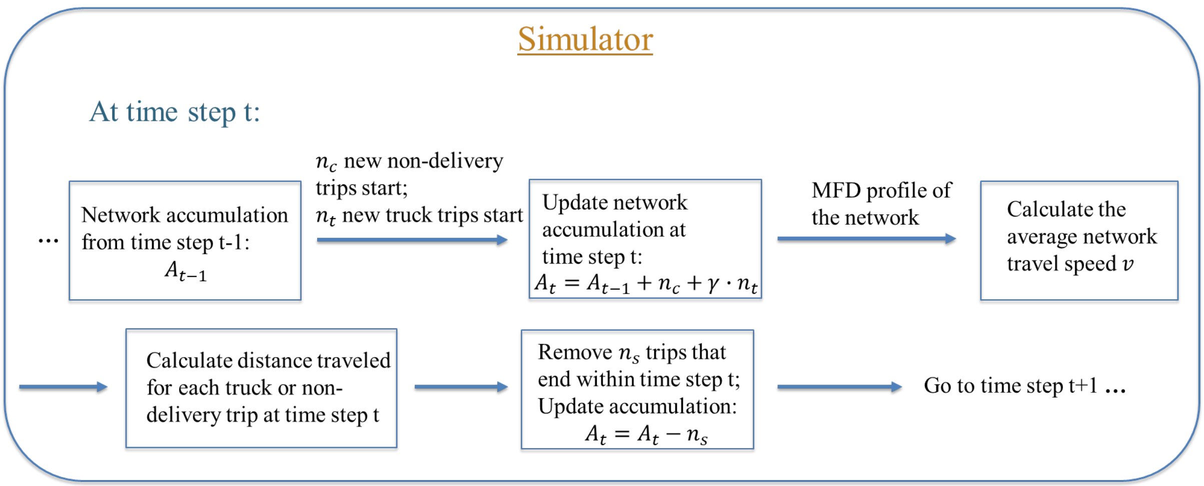

Figure 12. Traffic simulator

2.2.3 Congestion Cost Fitting

We perform the congestion model workflow in Figure 12 with different delivery traffic demand scenarios. The delivery traffic ranges from 0% to 5% of non-delivery traffic with 1% increment. In each delivery traffic demand scenario, we calculate the total delivery traffic delay and the total non-delivery traffic delay. Then linear regressions are used to fit analytical equations between the total delays and truck Vehicle Miles Traveled (VMT). Regression results in figure 13 and 14 shows high goodness- of- fit by linear fitting. The fitted analytical formations of two congestion costs will be directly integrated into the multimodal delivery strategies.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Cardelay   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 2.667e+06
Date:                Wed, 12 Apr 2023   Prob (F-statistic):               0.00
Time:                        11:54:06   Log-Likelihood:                -683.15
No. Observations:                 250   AIC:                             1370.
Df Residuals:                     248   BIC:                             1377.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.7944      0.460      1.726      0.086      -0.112       1.701
TruckVMT       0.0070   4.27e-06   1633.096      0.000       0.007       0.007
==============================================================================
```

Figure 13. Regression fitting results between system total non-delivery traffic delay and truck VMT

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Truckdelay   R-squared:                       0.991
Model:                            OLS   Adj. R-squared:                  0.991
Method:                 Least Squares   F-statistic:                 2.852e+04
Date:                Thu, 11 May 2023   Prob (F-statistic):          5.12e-258
Time:                        22:17:58   Log-Likelihood:                -1164.0
No. Observations:                 250   AIC:                             2332.
Df Residuals:                     248   BIC:                             2339.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -36.9929      3.150    -11.745      0.000     -43.196     -30.789
TruckVMT       0.0049   2.92e-05    168.886      0.000       0.005       0.005
==============================================================================
```

Figure 14. Regression fitting results between system total truck traffic delay and truck VMT

2.3 Multimodal Strategies with Congestion Effects

In this section, we integrate the congestion effects into the proposed five multimodal delivery strategies, using the analytical congestion cost formulation fitted in the previous section. Basically, we add two congestion cost components to the cost functions in the multimodal strategies. We consider both the congestion impacts of delivery traffic on the road systems, and the impacts of road congestion on the delivery traffic. We presented the new model formulation for each multimodal strategy as follows.

Scenario 1: All Truck

Two congestion cost components are added directly to the total cost formulation in the traditional all-truck scenario (see bold terms in equation 53). $\boldsymbol{w} \cdot (\boldsymbol{\alpha_1} + \boldsymbol{\beta_1} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z})$ represents the congestion impacts on the road system imposed by truck traffic, where $\boldsymbol{w}$ is value of time unit cost for non-delivery traffic users, and the fitted linear congestion equation is in bracket. $\boldsymbol{c_T^O} \cdot (\boldsymbol{\alpha_2} + \boldsymbol{\beta_2} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z})$ is the delivery traffic delay cost, which is the product of unit truck operational cost and additional travel time from road congestion. $\sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z}$ is the total truck VMT.

$$Total\ cost = \sum_z (c_T^H \cdot n_z \cdot \rho_z + \sum_z \frac{n_z \cdot \rho_z}{\Omega_T} \left(\frac{2d_z}{v_l} + \frac{D_z}{v_s} \right) c_T^O) + \boldsymbol{w} \cdot (\boldsymbol{\alpha_1} + \boldsymbol{\beta_1} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z}) + \boldsymbol{c_T^O} \cdot (\boldsymbol{\alpha_2} + \boldsymbol{\beta_2} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z}) \quad (53)$$

Scenario 2: Truck/Drone

The model formulation for truck or drone strategy with congestion effects are as follows.

$$Min\ \sum_z (H_z + O_z + L_z) + w \cdot P + c_T^O \cdot Q \quad (54)$$

s.t.

$$H_z = c_T^H \cdot n_z \cdot \rho_z \cdot I_z + c_D^H \cdot n_z \cdot \rho_z \cdot (1 - I_z) \quad (55)$$

$$O_z = c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot (\frac{2d_z}{v_l} + \frac{D_z}{v_s}) \cdot I_z + c_D^O \cdot n_z \cdot \rho_z \cdot \frac{2d_z}{v_D} \cdot (1 - I_z) \quad (56)$$

$$L_z = c_D^S \cdot n_z \cdot \rho_z \cdot (1 - I_z) \quad (57)$$

$$(2d_z + \varepsilon) \cdot (1 - I_z) \le U_D \quad (58)$$

$$I_z \in \{0,1\} \qquad \forall z \in Z \quad (59)$$

$$P = \alpha_1 + \beta_1 \cdot \sum_z 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot I_z \quad (60)$$

$$Q = \alpha_2 + \beta_2 \cdot \sum_z 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot I_z \quad (61)$$

Scenario 3: Truck with Drones on Board

Similar to scenario 1, two additional congestion terms are directly added to the total cost function for scenario 3.

$$Total\ cost = \sum_z (H_z + O_z + L_z) + \boldsymbol{w} \cdot (\boldsymbol{\alpha_1} + \boldsymbol{\beta_1} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z}) + \boldsymbol{c_T^O} \cdot (\boldsymbol{\alpha_2} + \boldsymbol{\beta_2} \cdot \sum_z \boldsymbol{2d_z} \cdot \frac{\boldsymbol{n_z \cdot \rho_z}}{\boldsymbol{\Omega_T}} \cdot \boldsymbol{I_z}) \quad (62)$$

Scenario 4: Truck and Cargo Bikes

In scenario 4, two congestion cost components are added to the objective function in equation 63, with specific definitions in equation 72 and 73.

$$Min\ \sum_z (H_z + O_z) + \sum_l R_l + w \cdot P + c_T^O \cdot Q \quad (63)$$

s.t.

$$H_z = (c_T^H + c_C^H) \cdot n_z \cdot \rho_z \tag{64}$$

$$O_z = \sum_l (c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \frac{d_l}{v_l} \cdot I_{zl} + \ c_B^O \cdot b_z \cdot (\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}) \cdot I_{zl}) \tag{65}$$

$$D_Z^C = 1.15 \cdot \sqrt{\frac{A_z}{b_z} \cdot \frac{n_z \cdot \rho_z}{b_z}} \tag{66}$$

$$R_l = \sum_z c_l \cdot I_{zl} \cdot n_z \cdot \rho_z \tag{67}$$

$$\sum_z I_{zl} \cdot n_z \cdot \rho_z \leq U_l \tag{68}$$

$$(\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}) \cdot I_{zl} \leq T \tag{69}$$

$$\sum_l I_{zl} = 1 \tag{70}$$

$$I_{zl} \in \{0,1\} \qquad \forall\, z \in Z \tag{71}$$

$$P = \alpha_1 + \beta_1 \cdot \sum_{zl} 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \ I_{zl} \tag{72}$$

$$Q = \alpha_2 + \beta_2 \cdot \sum_{zl} 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \ I_{zl} \tag{73}$$

Scenario 5: Truck and Cargo Bikes/Drones

Similar to scenario 4, the new model formulation for scenario 5 is presented.

$$Min\ \sum_z (H_z + O_z) + \sum_l R_l + w \cdot P + c_T^O \cdot Q \tag{74}$$

$$s.t.$$

$$H_z = \sum_{l,m} (c_T^H + c_m^H \cdot I_{zlm}) \cdot n_z \cdot \rho_z \tag{75}$$

$$O_z = \sum_{l,m} (c_T^O \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \frac{2d_l}{v_l} \cdot I_{zlm} + c_m^O \cdot T_{zlm} \cdot I_{zlm}) \tag{76}$$

$$T_{zl0} = b_z \cdot (\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}) \tag{77}$$

$$D_Z^C = 1.15 \cdot \sqrt{\frac{A_z}{b_z} \cdot \frac{n_z \cdot \rho_z}{b_z}} \tag{78}$$

$$T_{zl1} = \frac{2d_{lz}}{v_D} \cdot n_z \cdot \rho_z \tag{79}$$

$$R_l = \sum_{z,m} c_l \cdot I_{zlm} \cdot n_z \cdot \rho_z \tag{80}$$

$$\sum_{z,m} I_{zlm} \cdot n_z \cdot \rho_z \leq U_l \tag{81}$$

$$(\frac{2d_{lz}}{v_{Bl}} + \frac{D_Z^C}{v_{Bs}}) \cdot I_{zlm} \leq T \tag{82}$$

$$(2d_{lz} + \varepsilon) \cdot (1 - I_{zlm}) \leq U_D \tag{83}$$

$$\sum_{l,m} I_{zlm} = 1 \tag{84}$$

$$I_{zlm} \in \{0,1\} \qquad \forall\, z \in Z, l \in L, m \in M \tag{85}$$

$$P = \alpha_1 + \beta_1 \cdot \sum_{zlm} 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \ I_{zlm} \tag{86}$$

$$Q = \alpha_2 + \beta_2 \cdot \sum_{zlm} 2d_z \cdot \frac{n_z \cdot \rho_z}{\Omega_T} \cdot \ I_{zlm} \tag{87}$$

Experiments

In this section, five multimodal delivery strategies are compared in an idealized zone-based network under the scenarios of both with and without congestion effects. We work on a square network region divided into many grid squares, where each grid square is treated as a delivery zone in the model. We assume the hub warehouse is located on the middle point of the region edge (see red dot in Figure 15). Constant parcel demand density is assigned to the region using San Francisco data. In December 2019, around 100,000 packages are delivered in San Francisco daily [27]. Daily demand density is about 800 pkg/km^2, given San Francisco area is 121 km^2. The grid size of the idealized network is determined as the grid area contains daily parcel demand that can be delivered by exactly one full-loaded truck. Given truck loading capacity is 400 parcels [2], the grid width is set to be around 0.7 km. We work on a $8 \times 8\ km$ network with 12×12 delivery grid zones.

Comparisons of different multimodal delivery models require reasonable parameter settings. The parcel handling costs by different modes are calculated as the product of hourly labor cost and average handling time per parcel by the mode [28]. The parcel handling cost includes parcel preparation and sorting, loading and unloading. Hourly California blue collar wage $22.77 [27] is used as the labor cost. We assume 10s average handling time per parcel for all modes in the experiments. The parcel handling cost coefficient is $0.06. In the two-echelon network, we assume a $0.02 per parcel transferring cost from truck to second-echelon delivery vehicles.

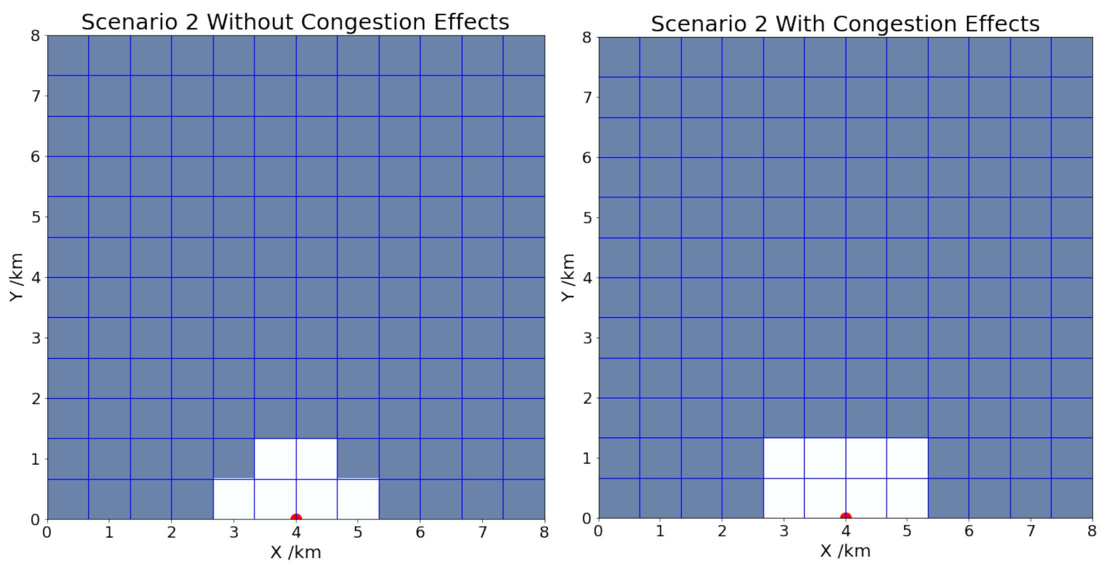

Figure 15. Multimodal assignment results of scenario 2

Notes: white grids are delivered by drones and blue grids by cargo bikes

Truck time-based operational cost coefficient includes two components, driver costs $30/hr and vehicle costs $37/hr [29], in total $67/hr. Driver costs include driver wages and benefits, and vehicle costs include fuel, truck lease or purchase payments, repair and maintenance, truck insurance premiums, permits and licenses, tires, tolls. The operational cost coefficient for electric cargo bike includes $30/hr driver cost and $9/hr vehicle costs [9]. For drone operational costs, we take into account $0.34/hr initial investment [30], $20/hr labor costs [31], and $0.94/hr vehicle costs [31], with total $21.28/hr. The initial investment per drone including software is $4000, and the drone has a lifespan of 5 years with 9-hour daily operation time and 5 days per week [30]. The drone vehicle costs include insurance, maintenance, and electricity for battery recharging. We assume each drone operator can monitor 12 drones at the same time [33]. The loading capacity of each truck is 400 parcels, and 40 parcels for electric cargo bikes [2]. Besides, we use 67 mph as drone cruising speed [34]. The average truck linehaul travel speed is set to 40 mph and inter-stop VRP delivery speed to 20 mph [3]. The electric cargo bike linehaul speed is 30 mph and inter-stop VRP speed is 15 mph [4]. The daily working hours per person are 8 hours, we use 6 hours as the maximum trip length limitation with extra 2 hours for trip preparation. For drone launch and recovery cost, we consider launching cost to the cruising altitude and landing cost. We use 180 feet as typical drone flying altitude according to Amazon Prime Air [35]. 10 m/s and 5m/s are used as takeoff and landing speed respectively [34]. The drone launch and recovery cost per trip can be calculated as takeoff and landing time multiplying drone operational cost coefficient, which is around $0.01/trip.

Results of five multimodal delivery models are compared in Table 6. Note that drone cost in the table includes both drone operational cost and drone launch and recovery costs. For truck with drones on board scenario, we consider three onboard drones on each truck. In uncongested situations, single echelon delivery strategies with multiple modes have less total cost than the all-truck scenario. Truck-with-drones-on-board model is more efficient than trucks or drones operated individually for different zones. Compared to trucks, drones have smaller unit operational cost, but need more trips to deliver same amount of packages because of their limited loading capacity. Such tradeoff is captured by the mode decision results of truck/drone scenario in Figure 15. The white grids are delivery zones served by drones, while blue grids are served by trucks. The one-way maximum drone flying distance is set to 10 km, but the decision boundary is two grids away from the warehouse. Grids farther than the threshold will need a very long total drone travel distance resulting in higher travel cost than trucks.

For two-echelon scenarios, we assume many local transshipment center candidates, and the model will optimize the selected facilities. The results are shown as the last two scenarios in Table 6. The more local transshipment centers selected, the less use of second-echelon vehicles traveling from local transshipment centers to the center of delivery zones, and the more facility costs required to open local transshipment center. In Table 6, two echelon network scenarios have higher total cost than single echelon network scenarios. Two echelon network requires additional parcel transferring cost between first- and second- echelon vehicles. Besides, the total travel distance is longer with a detour to the local transshipment centers before arriving at delivery zones. However, the two-echelon network can reduce the number of truck trips dramatically, and mitigate congestion from truck traffic and double-parking activities.

When congestion effects are considered, shown in the bottom part of Table 6, the multi-echelon network can significantly eliminate congestion cost by reducing truck traffic. The all-truck scenario has more than double the congestion cost from our two-echelon multimodal strategies. The congestion cost is around 8% of total cost in traditional truck-only delivery, but only 3% in two-echelon truck and bike delivery. In Figure 15, we find that our multimodal strategy assigns a slightly larger drone delivery range in congested situation, compared to the without congestion effects situation. Note that Table 6 only presents results for a specific set of parameters. The results show that two-echelon scenarios outperform single-echelon scenarios in congested situation. The multimodal two-echelon delivery strategies can reduce congestion significantly by reducing truck traffic and double-parking activities. Sensitivity analysis will be performed in future work to reveal the change of optimal delivery strategy in more highly congested situations. It is necessary to consider varying cases with different delivery demands, road congestion levels, relative costs of different modes and other parameters. The work in this section can provide delivery service providers with suggestions of the most efficient network design and multimodal delivery strategy based on the congestion levels of the interested area.

Table 6. Delivery Models Results Comparisons

Without Congestion Effects						
Scenario	Total cost	Handling cost	Truck cost	Drone cost	Bike Cost	Facility Cost
All Truck	20782	14400	6382	/	/	/
Truck/drone	20745	14400	6177	168	/	/
Truck with drones on board	19512	14400	4005	1107	/	/
Truck+bike	25898	18029	1705		4610	1554
Truck+bike/drone	24582	18029	1795	3574	/	1184

With Congestion Effects								
Scenario	Total cost	Handling cost	Truck cost	Drone cost	Bike Cost	Facility Cost	Congestion Cost for car	Congestion Cost for truck
All Truck	43378	14400	6382	/	/	/	19306	3290
Truck/drone	41702	14400	5811	640	/	/	17815	3036
Truck with drones on board	35541	14400	4005	1107	/	/	13695	2334
Truck+bike	34672	18029	1396	/	6347	1184	6592	1123
Truck+bike/drone	32817	18029	947	8013	/	592	4473	762

Chapter 3. Contributions and Impacts

3.1 Research Findings and Contributions

Multimodal delivery models with different combinations of vehicles are summarized and compared in this work. Especially two-echelon delivery network with truck, cargo bikes and drones are proposed. We consider both the facility assignment and mode decisions under scenarios. We explicitly calculate the delivery costs mainly including parcel handling cost and vehicle operational costs. From our specific experiments, we found that single echelon delivery model generates less cost than that of two-echelon. Considering the benefit of reducing road traffic congestion, the two-echelon network may be more efficient. In addition, delivery models with multiple vehicles modes in both single- and two- echelon networks are more efficient in terms of total delivery cost than truck only scenario. The results suggest that we can take advantage of synergistic operation among emerging vehicle types, especially nonmotorized vehicles, and drones for more efficient parcel delivery. Then, we propose congestion models that analytically evaluate the congestion impact of different multimodal delivery strategies. Macroscopic Fundamental Diagrams (MFD) and simulations are used to develop the congestion models. Simulations are performed under various scenarios and the results are fitted to analytical expressions with high goodness of fit. The developed multimodal delivery models and analytical congestion models can be the basis of future studies. By integrating the analytical congestion models into multimodal delivery models, we are able to reduce costs and increase the efficiency of the delivery systems. This work provides delivery service providers and public transportation sectors with benefits of cooperations among different vehicles modes and the importance of congestion sensitivity.

3.2 Impact Statement

Online delivery has become a global market worth more than $150 billion. Especially during the Covid-19 pandemic, the market has more than doubled in the United States (Ahuja et al., 2021). Delivery service providers have said they are optimistic the expansion will continue despite a gradual return to normality from coronavirus restrictions because Covid-19 has changed people’s dining habits (Liu, 2022). To meet the enormous delivery demand, efficient delivery operations are necessary in transportation systems. The delivery system has incorporated new types of vehicles, including drones and auto robots. Amazon first proposed drone delivery in 2013. Wing operated drone deliveries on three continents. And Walmart is backing several drone startups to experiment with delivering its products. Meituan started to offer drone delivery in very challenging environments: dense urban neighborhoods (Yang, 2023).

The project developed efficient system operations and planning strategies for multimodal delivery by utilizing recent advances in operations research and data analytics. Such operations and planning strategies provide delivery service providers with a rigorous plan for vehicle routing, scheduling, mode assignment, and facility location problems. So that the delivery service providers can manage and operate delivery trips more efficiently to reach an optimal system. Our project team invited stakeholders (e.g., delivery companies like Walmart) to review the proposed system operations and planning strategies to enhance their pertinence and applicability for real-world implementation by arranging a board meeting. In addition, the theoretical framework for delivery system optimization and solution approaches can be tailored to solving similar service planning problems.

In long-term, as part of the transportation systems, delivery traffic causes problems, including generating air-polluted emissions and contributing to road congestion. Systematic strategic planning helps the city and government promote an efficient and green transportation system. The strategic planning strategies helps provide not only the delivery service provider but also the city planner with efficient infrastructure design and planning in transportation systems. Proper land use and infrastructure design help improve system efficiency and sustainability.

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