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Full Length Article

Replacing urban trucks via ground–air cooperation☆

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ABSTRACT

The advent of drones is leading to a paradigm shift in courier services, while their large-scale deployment is confined by a limited range. Here, we design a low-cost product that allows drones to drop parcels onto and pick them up from the roofs of moving passenger vehicles. With this, we propose a ground-air cooperation (GAC) based business model for parcel delivery in an urban environment. As per our case study using real-world data in Beijing, the new business model will not only shorten the parcel delivery time by 86.5% with a comparable cost, but also reduce road traffic by 8.6%, leading to an annual social benefit of 6.67 billion USD for Beijing. The proposed model utilizes the currently “wasted or unused” rooftops of passenger vehicles and has the potential to replace most parcel trucks and trailers, thus fundamentally addressing the congestion, noise, pollution, and road wear and tear problems caused by trucks, and bringing in immense social benefit.

1. Introduction

Urban logistics has been one of the biggest issues for freight transportation since it requires the movement of goods in cities, where road network is complex, traffic congestion is severe, and population is dense. Meanwhile, the recent booming of e-commerce, accelerated by the pandemic, makes urban logistics a fast-growing problem. It is expected that in the world's top 100 cities, urban deliveries will grow by 78% by 2030, leading to 36% more delivery vehicles.1 This certainly imposes tremendous costs to cities, e.g., carbon emissions and traffic congestion. It is expected that without interventions, the growth of urban logistics needs will cause emissions to rise by more than 30% and add approximately 11 min to each passenger's commute (Hillyer, 2022). Therefore, we must move fast before the problem becomes intractable.

The problem of urban logistics is essentially the trucking problem. Scattered customers in cities lead to massive detours of trucks for collecting, shipping, and delivering parcels. The extra mileages induced by these detours undoubtedly contribute to more emissions and worse traffic jams. Fleet electrification has been an attractive solution for tackling the emission issue. However, electric vehicle adoption in heavy-duty vehicles, is exceedingly sluggish, with less than 1% market penetration, and the main reasons span that heavy-duty lithium-ion batteries needed for tucks are still extremely expensive, and vast up-front investments are needed for new charging infrastructure for electric trucks and new technicians for fleet maintenance and repair (Liu et al., 2021). Nevertheless, fleet electrification cannot eliminate the detours. Various operational techniques, e.g., routing optimization for trucks, have been proposed to minimize the detours (Cattaruzza et al., 2017), but they cannot significantly curtail that by any order of magnitude, because the root cause of the trucking problem is that trucks must carry all parcels to the next job.

Drone delivery is poised to change the traditional distribution pattern that relies on ground transportation, especially for parcel deliveries of 5 kg or lighter (Carlsson and Song, 2018). In the U.S. and Europe, the existing urban logistics pattern relies completely on trucks to deliver parcels from depots to customers’ doors, and in China, trucks are mainly used to transport parcels between regions, and low-speed vehicles (e.g., three-wheeled trailers) are used for the last-segment for better accessibility within a region. Nevertheless, these patterns will be challenged and increasingly replaced by flexible and fast aerial mobility systems, similar to the services trialed by giant online retailers or logistics service providers, like Amazon, FedEx, UPS, and DHL (Cary and Bose, 2016; Hartmann, 2019). Such a trend will provide tremendous benefits, e.g., reducing truck traffic, road congestion, and, most crucially, transportation emissions (Reed et al., 2022).

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To replace the ground-based parcel delivery vehicles with electric drones, the primary need is to solve the mileage anxiety of drones. This requires a new network of urban warehouses or waystations to make a wide coverage of drone delivery possible (Gaitan and Health, 2014), while the dramatic cost of establishing such a network is not viable for urban logistics (Perera et al., 2020). As a result, the current wave of delivery drones is only able to augment existing truck-centric delivery modes for "last-segment" problems, using a truck as the drone carrier and charger via a moving hub-and-spoke system (TechCrush, 2017; Antunes, 2021). Although this system partially solves the range limitation, it inherits all the shortcomings of a typical hub-and-spoke style one-to-multiple system, such as the long distances traveled by trucks and the vulnerability of the system in case of "hub" failure (Azizi et al., 2016). As a result, although researchers have been actively studying hub-and-spoke operations of trucks and drones since 2015 (Murray and Chu, 2015), the truck-drone approach has not received enough attention in real business practices (Antunes, 2021; Gaille, 2019).

Inspired by the booming sharing economy in transportation, we shift drone carriers' vision from exclusively freight trucks to existing passenger vehicles on the road. At the early stage, these vehicles could be taxis or buses that can be easily coordinated, which will be extended to all passenger vehicles (as for the ridesharing business model) for massive adaption. As such, we can replace the entire fleet of medium and large trucks with light-duty (electric) vehicles contributes, contributing to the reduction of emissions. We redesign the roof-racks for passenger vehicles and the roof-racks allow drones to drop off and pick up parcels while vehicles are in motion, as shown in the upper left of Fig. 1(a). If possible, drones can also stay in the roof-racks for charging.

In what follows, we present a business model that takes full utilization of currently "unused" vehicle roof resources of passenger vehicles via Ground-Air Cooperation (GAC) to extend the drone flying range with negligible extra costs and energy consumption. In this mode, we divide the city area into different catchments, with a depot at the center of each catchment. Drones fly with parcels within each catchment and passenger vehicles carry parcels between catchments, where note that we do not intervene in the trips of passenger vehicles, but just take a ride on ongoing trips. The purpose is to minimize the deadhead distance of drones and thereby increase their utilization. When a target vehicle enters the boundary of the catchment (represented as the green squares in Fig. 1), the drone makes a parcel handover with it by either dropping the parcel taken from the depot onto the roof-rack or taking the parcel from the roof-rack to the end-user. After the current task is completed, the drone moves to other tasks within the catchment.

Now, a natural question is: in real-world urban logistics systems, compared with the traditional truck-based system and the truck-drone hub-and-spoke system, how would the new GAC solution perform in terms of logistics cost, delivery time, and energy consumption, and social benefit? To answer this question, we consider a courier provider that delivers parcels from a warehouse to a set of customers. A total of three modes of delivery are compared as follows:

Mode 1 (M1): Truck + trailers (see Fig. 1(b)) (Anderluh et al., 2017). A truck loads parcels from all the customers at the warehouse, visits a sequence of satellites that are a set of predefined transfer points housing several trailers and returns to the warehouse. At each satellite, a portion of the parcels are unloaded from the truck and reloaded onto the trailers (usually small three-wheeled vehicles that can easily access residential and commercial buildings and are responsible for the last-segment delivery). Each trailer will travel from the satellite, deliver parcels to customers, and return to the satellite. This is how most of the current courier services work, or how they expect to work.

Mode 2 (M2): Truck + drones (see Fig. 1(c)) (Perera et al., 2020; TechCrush, 2017). A truck equipped with a drone charging facility loads parcels to all the customers at the warehouse and carries a fleet of drones, then makes a sequence of temporary stops based on customer

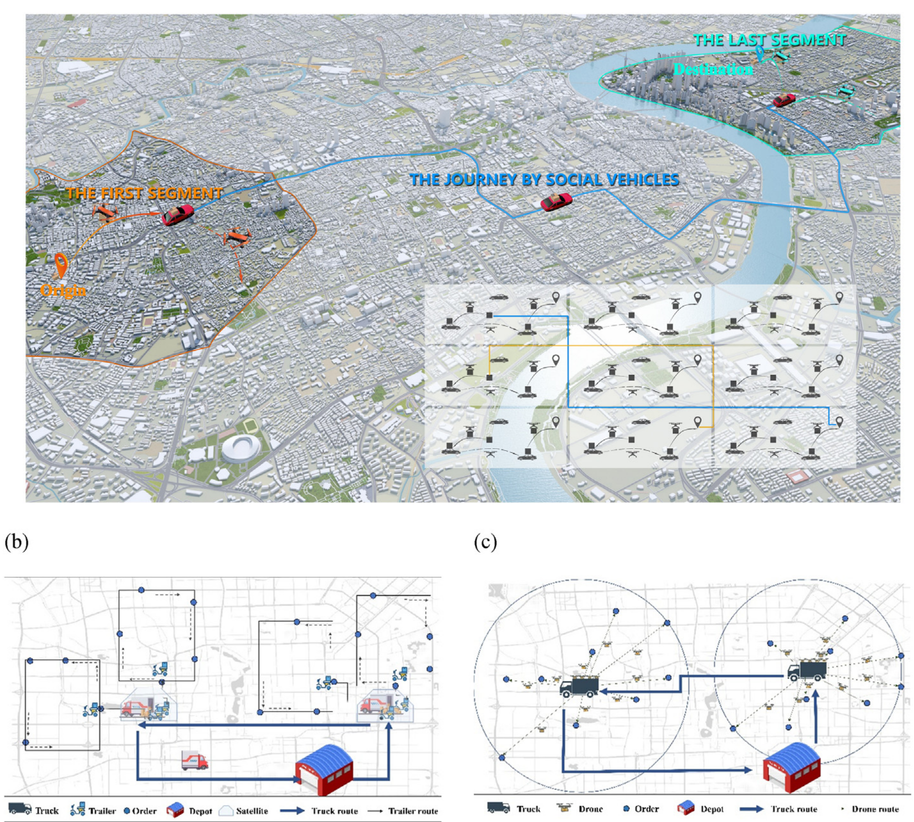

Fig. 1. Business models for coordinated urban logistics. (a) The proposed model (GAC mode), where drones are for the first and last segments, and passenger vehicles are for the long-distance transportation from one catchment to another; (b) Truck + trailers mode; (c) Truck + drones mode.

distribution before returning to the warehouse. At each stop, drones are responsible for the last-segment delivery to customers. When all the drones have finished delivering and returned to the stop, the truck will travel to the next stop, during which the truck also charges the drones.

Mode 3 (M3): Drone + passenger vehicle (GAC mode). We innovatively design this new business mode in this paper. For each catchment, a drone picks up a parcel for a customer from the warehouse and flies to and drops the parcel onto the roof-rack of a passenger vehicle. The parcel is carried by the vehicle to the catchment where the customer is located, and another drone in the catchment flies to the vehicle, picks up the parcel, and delivers it to the customer.

2. Experimental procedures

We elaborate on the models for the three modes of operations: mode 1: truck + trailers, mode 2: truck + drones, and mode 3: drone + passenger vehicle (GAC mode). The logistics service provider schedules the fulfillment of orders received during the past $\widehat{T}$ min (e.g., $\widehat{T} = 15$). Denote by I the number of orders received. All orders have the same origin o, which is a warehouse (also called depot) operated by the logistics service provider. Order $i = 1, \ldots, I$ has a destination d_i. Denote by N the set of nodes in the network, $o \in N$, $d_i \in N$, $i = 1, \ldots, I$. The travel time by truck from node $n_1 \in N$ to node $n_2 \in N$ is $T_{n_1 n_2}$, the travel time by a trailer is $\tau_{n_1 n_2}$, and the flying time by a drone is $t_{n_1 n_2}$.

Mode 1: A truck picks up packages for all the customers from the warehouse, visits a set of pre-defined satellites S, $S \subset N$, and returns to the warehouse. Each satellite $s \in S$ has a set K of trailers for last-segment delivery. The transfer of packages from the truck to the trailers at each satellite takes T' min. A trailer can carry packages for at most L customers and the cumulative travel time of the trailer is limited by the maximum working time denoted by $\tilde{T}$. The set and the sequence of customers to serve by each trailer are determined by a nearest unvisited heuristic. Suppose the total number of orders covered by the k th trailer at satellite s is $\overline{L}_{s,k}$ and the trailer visits customers $i^1_{s,k}$ (i.e., the ID of the first customer visited) $\rightarrow i^2_{s,k} \rightarrow \ldots \rightarrow i^{\overline{L}_{s,k}}_{s,k}$ and returns to satellite s.

The traveling cost of a truck when carrying cargo, when traveling empty, and the waiting cost of a truck for cargo transfer to trailers per minute are C_1, C'_1, and C_0, respectively, and the cost of a trailer traveling per minute is C_2. The amount of energy consumed by a truck per unit time of traveling is $\overline{e}_1$ when carrying cargo and is $\overline{e}_0$ when not carrying cargo, where $\overline{e}_1 > \overline{e}_0$, and the value is e for a trailer. The average delivery cost per order of mode 1 is $\mathrm{Cost}_1 = \frac{1}{I}\left\{[C_1 T_{o,1} + C_1 \sum_{s=2}^{|S|} T_{s-1,s} + C'_1 T_{|S|,o}] + C_0 T' |S| + C_2 \sum_{s \in S} \sum_{k \in K} [\tau_{s,d_{i^1_{s,k}}} + \sum_{l=2}^{\overline{L}_{s,k}} \tau_{d_{i^{l-1}_{s,k}}, d_{i^l_{s,k}}} + \tau_{d_{i^{\overline{L}_{s,k}}_{s,k}}, s}]\right\}$, where the average delivery cost consists of three costs incurred during three steps, i.e., traveling of trucks, waiting for cargo transfer, and traveling of trailers. The average delivery time per order of mode 1 is $\mathrm{Time}_1 = \frac{1}{I}\left\{(T_{o,1} + T')I + \sum_{s=2}^{|S|}(T_{s-1,s} + T')\left(I - \sum_{s'=1}^{s-1} \sum_{k \in K} \overline{L}_{s',k}\right) + \sum_{s \in S} \sum_{k \in K} [\tau_{s,d_{i^1_{s,k}}} \overline{L}_{s,k} + \sum_{l=2}^{\overline{L}_{s,k}} \tau_{d_{i^{l-1}_{s,k}}, d_{i^l_{s,k}}} \cdot (\overline{L}_{s,k} - l + 1)]\right\}$, where the average delivery time consists of three times spent in the above-mentioned three steps. The average energy consumption per order of mode 1 is $\mathrm{Consumption}_1 = \frac{1}{I}\left\{[\overline{e}_1 T_{o,1} + \overline{e}_1 \sum_{s=2}^{|S|} T_{s-1,s} + \overline{e}_0 T_{|S|,o}] + e \sum_{s \in S} \sum_{k \in K} [\tau_{s,d_{i^1_{s,k}}} + \sum_{l=2}^{\overline{L}_{s,k}} \tau_{d_{i^{l-1}_{s,k}}, d_{i^l_{s,k}}} + \tau_{d_{i^{\overline{L}_{s,k}}_{s,k}}, s}]\right\}$, where the average energy consumption involves traveling trucks and traveling trailers.

Mode 2: A truck loads packages from all the customers at the warehouse and carries a fleet of Q drones, visits a list of temporary stops determined by the distribution of orders, and returns to the warehouse. At each stop, the drones are responsible for the delivery to customers near the stop. Each drone delivers cargo to at most one customer and then returns to the truck. The truck will travel to the next stop when all the drones have returned.

We use a clustering scheme to determine the stops and the customers to be served by drones at each stop. We perform clustering of orders by first selecting the destination of the order that is the closest to the warehouse as the center of the first cluster p_1 (i.e., the first stop). All unvisited customers are then sorted by their distances to the cluster center. Therefore, the nearest Q customers are selected as the ones to be covered by the first stop, as long as these customers are within the mileage range of the drones. The set of orders in the cluster is denoted by N_1. If all the customers have been clustered, i.e., $|N_1| = I$, we can stop. Otherwise, we proceed to determine the second cluster. The center of the second cluster, p_2 (i.e., the second stop), is the destination of the $(N_1 + 1)$ st nearest customer to the first stop p_1. The nearest Q customers to p_2 are selected as the ones to be covered by the second stop, as long as these customers are within the mileage range of the drones. The set of customers in the second cluster is denoted by N_2. The clustering process ends when all customers are clustered. We denote the number of clusters as J, and the set of customers in each cluster as N_j where $j = 1, \ldots, J$, and the truck stops at the cluster center $p_j \in N$ when it visits cluster j.

The amount of energy consumed by a drone per unit time of flying is e_1 when carrying cargo and is e_0 when not carrying cargo; $e_1 > e_0$. The flying cost per unit time for a drone has two components: one is the component that is unrelated to the electricity cost, denoted by c, and the other is electricity cost. We assume that when a drone returns to the truck after completing a delivery, the truck will immediately charge it to full battery capacity and the charging cost per unit amount of energy is α_1. The average delivery cost per order of mode 2 is $\mathrm{Cost}_2 = \frac{1}{I}\left\{C_1(T_{op_1} + \sum_{j=2}^{J} T_{p_{j-1}p_j} + T_{p_J o}) + C_0 \sum_{j=1}^{J} \max_{i \in N_j} 2t_{p_j d_i} + (c + \alpha_1 e_1) \sum_{j=1}^{J} \sum_{i \in N_j} t_{p_j d_i} + (c + \alpha_1 e_0) \sum_{j=1}^{J} \sum_{i \in N_j} t_{d_i p_j}\right\}$, where the average delivery cost consists of three expenditures incurred throughout three phases, namely truck trips, truck waiting for drone delivery, and drone journeys. The average delivery time per order of mode 2 is $\mathrm{Time}_2 = \frac{1}{I}\left\{T_{op_1} I + \sum_{j=2}^{J}\left(\max_{i \in N_{j-1}} 2t_{p_{j-1} d_i} + T_{p_{j-1}p_j}\right)\left(I - \sum_{j'=1}^{j-1} |N_{j'}|\right) + \sum_{j=1}^{J} \sum_{i \in N_j} t_{p_j d_i}\right\}$, where the average delivery time is made up of time spent in the three preceding phases. The average energy consumption per order of mode 2 is $\mathrm{Consumption}_2 = \frac{1}{I}\left\{(\overline{e}_1 T_{op_1} + \overline{e}_1 \sum_{j=2}^{J} T_{p_{j-1}p_j} + \overline{e}_0 T_{p_J o}) + (e_1 + e_0) \sum_{j=1}^{J} \sum_{i \in N_j} t_{p_j d_i}\right\}$, where the average energy consumption consists of truck and drone trips.

Mode 3: We divide the area of interest into grids of 1 km * 1 km, and each grid is represented by its centroid (if the centroid is not in the road network, then it is replaced by its nearest node $n \in N$). We assume that at any time, there is a passenger vehicle that travels from one centroid to another centroid. Suppose we have a total of O centroids. The travel distance and travel time by a passenger vehicle from node $n_1 \in N$ to node $n_2 \in N$ are $l_{n_1 n_2}$ and $\tau'_{n_1 n_2}$, respectively. Suppose further that all drones will return to the depots in their catchments by time $T^{\#}$. Thus, we need to consider a total of $V = O^2 T^{\#}$ passenger vehicles: a vehicle starts to travel from one centroid to another centroid (can be the same centroid, meaning the vehicle does not travel) at each time $t = 0, \ldots, T^{\#} - 1$. The arrival time at the destination centroid depends on the travel time of the passenger vehicle. To simplify the notation, we let vehicle $v = 1, \ldots, V$

travel from node n_{1v} at time w_{1v} to node n_{2v} and arrives at time $w_{2v} = w_{1v} + \tau'_{n_{1v}n_{2v}}$.

After a drone drops a package onto a vehicle or delivers a package to a customer, it does not have to return to its depot; instead, it will fly to a location to carry out other tasks. We divide the whole area into different catchments of 3 km × 3 km, and drones belonging to their own catchment are responsible for different pickup and delivery tasks within the catchment. We define γ as the average efficiency of drones. For example, if $\gamma = 60\%$, then, on average, a drone will carry cargo for 60% of its flying time and will not carry cargo for 40% of its flying time. Drones are charged at the cost of α_0 per unit amount of energy.

For each order $i = 1,\ldots,I$, we choose a vehicle v_i to fulfill part of the delivery using the criterion of shortest delivery time. Thus, a drone will fly from the depot to vehicle v_i, drops the package onto the vehicle at node n_{1v_i} at time w_{1v_i}, the vehicle travels from node n_{1v_i} to node n_{2v_i}, another drone will pick up the cargo from the vehicle at node n_{2v_i} at time w_{2v_i}, and fly to d_i. The average delivery cost per order of mode $\mathrm{Cost}_3 = \frac{1}{I}\sum_{i=1}^{I}\left[\frac{c}{\gamma}\left(t_{on_{1v_i}} + t_{n_{2v_i}d_i}\right) + \alpha_0\left(e_1 + e_0\frac{1-\gamma}{\gamma}\right)\left(t_{on_{1v_i}} + t_{n_{2v_i}d_i}\right)\right]$, the average cost includes drone flying expenditures as well as drone charging fees. The average delivery time per order of mode $\mathrm{Time}_3 = \frac{1}{I}\sum_{i=1}^{I}\left(t_{on_{1v_i}} + \tau'_{n_{1v_i}n_{2v_i}} + t_{n_{2v_i}d_i}\right)$ which covers drone flight time and passenger vehicle traveling time. The average energy consumption per order of mode 3 is $\mathrm{Consumption}_3 = \frac{1}{I}\sum_{i=1}^{I}\left[\left(e_1 + e_0\frac{1-\gamma}{\gamma}\right)\left(t_{on_{1v_i}} + t_{n_{2v_i}d_i}\right)\right]$ which adds up and averages the back-and-forth consumption of each drone delivering the package.

The values of the parameters used in the numerical study on parcel delivery cost, delivery time, and energy consumption are listed in Table 1.

Social benefit: We define the annual average driving speed of all vehicles in a city as v_{city}, the annual driving mileage per vehicle as D_{city}, the value of time for a passenger as β_{city}, the percentage of truck flow as u_{city}, the number of passengers in each vehicle to be θ, and the total number of vehicles registered in the city as W_{city}.

Table 1
Values of the parameters (all cost in cost units).

Parameter	Value with unit
$\widehat{T}$	15 min
I	200
$T_{n_1n_2}$	Distance divided by the truck speed, assumed to be 6 m/s (21.6 km/h)
$\tau_{n_1n_2}$	Distance divided by the trailer speed, assumed to be 3 m/s (10.8 km/h)
$t_{n_1n_2}$	Distance divided by the drone speed, assumed to be 16 m/s (57.6 km/h)
$\tau'_{n_1n_2}$	Distance divided by the passenger vehicle speed, assumed to be 8 m/s (28.8 km/h)
$\lvert S\rvert$	4
$\lvert K\rvert$	4
T'	10 min
L	15
$\bar{T}$	180 min
C_1	2.04 per min
C_1'	1.968 per min
C_0	0.108 per min
C_2	0.558 per min
Q	25
$\bar{e}_1$	0.468 kWh/min
$\bar{e}_0$	0.396 kWh/min
e	0.014 kWh/min
e_1	0.042 kWh/min
e_0	0.038 kWh/min
c	0.672 per min
α_1	4.99 per kWh
O	196
$T^{\#}$	92 min
α_0	1.00 per kWh
γ	60%

We first check at which time the speed of the main roads in each city is equal to the average driving speed v_{city} based on real-time traffic data referred from Google Map. Then, we refer to the traffic count data reported in the literature and obtain the traffic flow volume corresponding to that time. Based on this flow volume and the percentage of truck flow u_{city}, we reduce the percentage of trucks by 100%, 75% and 50% to get the corresponding reduced traffic volume once the GAC model is used. Then, the time point at which the current traffic volume is equal to the reduced one is derived. Using Google Map, the adjusted speed (i.e., the speed given the reduced traffic volume once the GAC model is used) is obtained. We denote the adjusted speed as $\bar{v}_{\mathrm{city}}$, and the social benefit can be calculated as: $\mathrm{Socialbenefit}_{\mathrm{city}} = W_{\mathrm{city}}\,\theta\beta_{\mathrm{city}}\left(\frac{D_{\mathrm{city}}}{v_{\mathrm{city}}} - \frac{D_{\mathrm{city}}}{\bar{v}_{\mathrm{city}}}\right)$.

The values of the parameters used in the social benefit calculation are listed in Table 2.

3. Results

We use JD.com's parcel delivery data in our analysis (Straight, 2018). JD.com is one of the two giant B2C online retailers in China, along with Alibaba. The data consists of all of their customers located within the Third Ring Road of Beijing, approximately a square of 14 km × 14 km encircling the central part of Beijing. The locations of the warehouse and the customers are shown in Fig. 2(a) or 2(b) as numbered circles and solid squares, respectively. At present, JD.com uses delivery mode 1. The operational models for the three modes are presented later in the method section.

Fig. 2 shows the results for the three modes. As shown in Fig. 2(d), M3 has the lowest unit cost per parcel (21.6% lower than that of M2 and 3.7% lower than that of M1), because in M3 the expenses of truck operations and truck drivers are eliminated through passenger vehicle ride-hailing. The costs per parcel of M1 and M3 are comparable. The truck cost in M2 is higher not only because the truck travels for a longer distance but also because it must wait for drones to return at each stop, which contrasts with M1 in which the truck does not need to wait for the trailers. The drone cost in M2 is lower than the trailer cost in M1. The average delivery time of M2 is 27% shorter than that of M1. This is because, in M1, a customer must take two major detours before receiving a parcel—the detour of the truck to visit other satellites and the detour of the trailer to visit other customers, whereas in M2 there is only one major detour—the detour of the truck. M3 requires no major detour and reduces 86.7% and 81.7% of the delivery time compared to M1 and M2, respectively. M2 consumes the most energy, 42% higher than that of M1 or M3.

GAC delivery mode leverages currently "unused" vehicles' rooftop resources, with large-scale deployments capable of completely replacing trucks and trailers dedicated for last-mile delivery. We estimate the speed change of vehicles in the road network of Beijing under the traditional transport mode (mode 1) and the new mode (mode 3) with reduced road traffic based on historical traffic volume (Jing et al., 2016). We estimate the increase of speed to be between 0.48% and 8.83% (Fig. 3(a)), averaged at 3.90%. In this paper, we estimate the social benefit as the product

Table 2
Values of the parameters used in the social benefit calculation.

	v_{city} (km/h)	D_{city} (km)	β_{city} (USD/h)	u_{city}	W_{city} (10^6 veh)	θ
Beijing	25.0	15000	14.84	10%	6.57	1.54
Hong Kong	21.6	18035	24.13	12%	0.88	1.54
London	25.0	10944	38.34	12%	3.04	1.54
New York	12.0	10945	49.71	13%	2.19	1.54
Paris	15.0	12000	22.18	12%	5.00	1.54
Singapore	28.9	17500	31.14	16%	0.84	1.54
Shanghai	24.3	15000	14.06	10%	4.79	1.54
Tokyo	30.0	9,300	21.20	12%	3.11	1.54

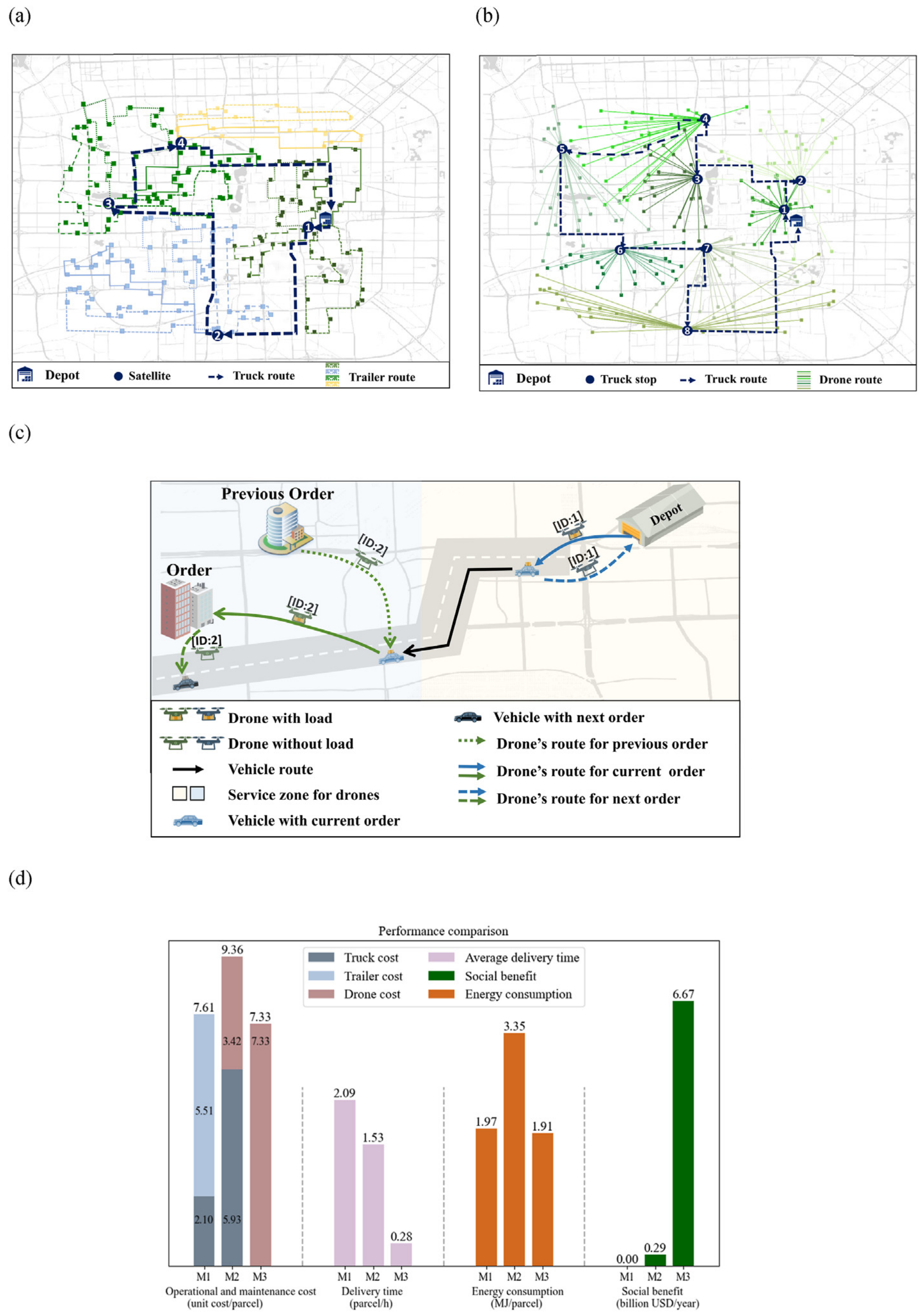

Fig. 2. Comparison of the three modes. (a) Optimal routes of mode 1; (b) Optimal routes of mode 2; (c) Illustration of routes of mode 3; (d) Cost, time, energy consumption and social benefit of the three modes.

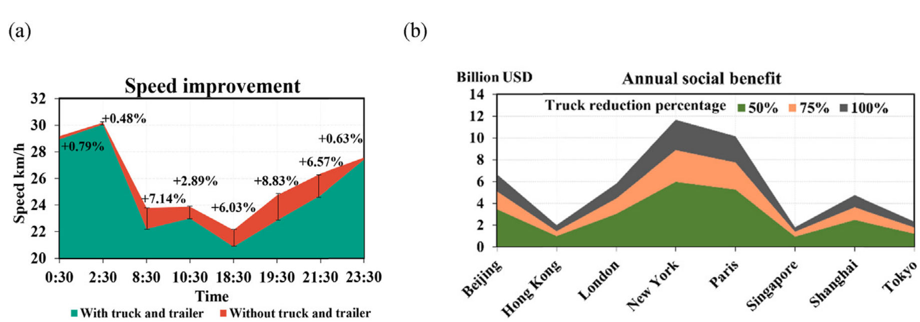

Fig. 3. Speed improvement and social benefit of GAC. (a) Increases in the average speed of passenger vehicles in Beijing using GAC; (b) Social benefit of GAC to major cities in the world.

Fig. 4. Time-sensitive deliveries (a drone-parcel hops among passenger vehicles towards its destination).

of passengers' annual travel time saved based on the average annual speed and the change in the fleet size of freight trucks, and the average value of time defined by the GDP per capita. With this estimation, M3 can bring in an annual social benefit of 6.67 billion USD to Beijing in comparison to M1 that is currently in operations and even replacing only the trailer would save 0.29 billion USD (Fig. 2(d)). Similarly, we estimate the social benefit of GAC to other large cities in the world, as shown in Fig. 3(b). We observe that New York has the largest social effect in the GAC mode and Paris ranks second, both due to high GDP per capita and large portions of freight traffic.

4. Discussion

With parcel delivery using the GAC mode, a huge ride-hailing market of “freight” will be opened up. With sufficient ground vehicles equipped with the roof-racks as drone carriers, the proposed GAC solution will fundamentally resolve the range limitations of drone delivery with negligible extra cost or energy consumption while having superior delivery time advantages as compared with the existing delivery mode. New business models may emerge with this paradigm shift. Once realized, the GAC solution will allow us to receive a gift from a friend in the same city or a parcel of products ordered from a warehouse in the same city within e.g., 1 h.

The GAC solution is not limited to the context of mode 3. A variant is that a roof-rack carries a drone with a parcel instead of a parcel alone; moreover, the roof-rack can charge the drone using the energy of the passenger vehicle. In this variant, a drone rides on one or more than one passenger vehicles before it delivers a parcel to a customer. This can be particularly useful for time-sensitive deliveries, e.g., medical parcels. As can be seen in Fig. 4, a drone-parcel can hop among multiple passenger vehicles toward its destination. When the drone-parcel faces a river, traffic jams, etc., it can fly for minimal travel time; when the drone-parcel needs to charge, it can land on a passenger vehicle with a similar route for charging while moving toward the destination. The design and operation of such a large-scale, complex system require sophisticated optimization techniques.

However, introducing such a new business model of GAC may lead to some practical issues, as the case when we introduce the ride-sharing business model, e.g., information privacy of passenger vehicles, safety issues of the cooperation between vehicles and drones, environmental concerns of flying drones over the city airspace, etc. All these issues would call for more in-depth research. Here, we provide some preliminary solutions. (i) Information privacy: GAC requires shared trip information from passenger vehicles, leading to privacy issues. On the one hand, the current design of GAC does not require detailed information on whole trips but rather aggregated and partial information, i.e., the times of the passenger vehicles arriving at the boundaries of catchment areas. On the other hand, at the early stage of GAC, we can only leverage taxis or buses, for which the trip information is less sensitive, and will open to passenger vehicles for those signed up for the agreement on trip information sharing. (ii) Safety issues: the handover of parcels between drones and vehicles is the main safety concern, especially considering that vehicles are in motion during the handover. Improving the reliability of drones on the mechanical engineering side is important, and we also need to leverage a stable traffic condition for the handover, e.g., we can use bus lanes for the handover or design handover zones on roads where we restrict the speed of ground vehicles. (iii) Environmental concerns: one of the major environmental concerns of flying drones is noise. This problem is inevitable for any mode of urban aerial mobility. Here, we can design fixed corridors for flying drones that should be far away from residential areas.

Nevertheless, the potential social benefit of GAC is immense—as high as billions of U.S. dollars per annum for a big city—due to the removal of truck traffic from the city. Although truck traffic has increasingly been criticized, with opponents citing noise, pollution, congestion, and road wear and tear, trucks remain the dominant mode of freight transportation. The proposed GAC mode takes advantage of the currently “unused” roof spaces of passenger vehicles and has the potential to replace most, if not all, parcel trucks and trailers, thus fundamentally addressing the problems associated with the use of trucks.

Replication and data sharing

The data and code used in this research can be found at: https://doi.org/10.26599/ETSD.2022.9190010.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Anderluh, A., Hemmelmayr, V.C., Nolz, P.C., 2017. Synchronizing vans and cargo bikes in a city distribution network. Cent. Eur. J. Oper. Res. 25 (2), 345–376.

Antunes, J., 2021. Amazon's new patent wants to combine drones with trucks for deliveries. Commercial UAV News 2021. https://www.commercialuavnews.com/drone-delivery/amazon-s-new-patent-wants-to-combine-drones-with-trucks-for-deliveries. July 29.

Azizi, N., Chauhan, S., Salhi, S., Vidyarthi, N., 2016. The impact of hub failure in hub-and-spoke networks: Mathematical formulations and solution techniques. Comput. Oper. Res. 65, 174–188.

Carlsson, J.G., Song, S., 2018. Coordinated logistics with a truck and a drone. Manag. Sci. 64 (9), 4052–4069.

Cary, N., Bose, N., 2016. UPS, FedEx and Amazon gather flight data to prove drone safety. https://venturebeat.com/2016/09/24/ups-fedex-and-amazon-gather-flight-data-to-prove-drone-safety/.

Cattaruzza, D., Absi, N., Feillet, D., González-Feliu, J., 2017. Vehicle routing problems for city logistics. EURO J. Transpor. Logistics 6 (1), 51–79.

Gaille, L., 2019. 18 delivery drones pros and cons. February Vittana 11, 2019. https://vittana.org/18-delivery-drones-pros-and-cons.

Gaitan, D., Health, R., 2014. Drones being developed to deliver medical aid, not bombs. Reuters August 15, 2014. https://www.reuters.com/article/us-medical-drones/drones-beingdeveloped-to-deliver-medical-aid-not-bombs-idUSKBN0GF17I20140815.

Hartmann, S., 2019. DHL launches its first regular fully-automated and intelligent urban drone delivery service. Deutsche Post DHL Group. https://www.dpdhl.com/en/media-relations/press-releases/2019/dhl-launches-its-first-regular-fully-automated-and-intelligent-urban-drone-delivery-service.html, 16 May 2019.

Hillyer, M., 2022. Urban deliveries expected to add 11 minutes to daily commute and increase carbon emissions by 30% until 2030 without effective intervention. World Economic Forum 10, 2020. January. https://www.weforum.org/press/2020/01/urban-deliveries-expected-to-add-11-minutes-to-daily-commute-and-increase-carbon-emissions-by-30-until-2030-without-effective-intervention-e3141b32fa/.

Jing, B., Wu, L., Mao, H., Gong, S., He, J., Zou, C., et al., 2016. Development of a vehicle emission inventory with high temporal–spatial resolution based on NRT traffic data and its impact on air pollution in Beijing–Part 1: development and evaluation of vehicle emission inventory. Atmos. Chem. Phys. 16 (5), 3161–3170.

Liu, H., Kaewunruen, S., Ahmad, W.N.K., Shamsuddin, A., Ayetor, G.K., Hansson, J., Bräunl, T., 2021. A net-zero future for freight. One Earth 4 (11), 1517–1519.
Murray, C.C., Chu, A.G., 2015. The flying sidekick traveling salesman problem: optimization of drone-assisted parcel delivery. Transport. Res. C Emerg. Technol. 54, 86–109.
Perera, S., Dawande, M., Janakiraman, G., Mookerjee, V., 2020. Retail deliveries by drones: how will logistics networks change? Prod. Oper. Manag. 29 (9), 2019–2034.
Reed, S., Campbell, A.M., Thomas, B.W., 2022. The value of autonomous vehicles for last-mile deliveries in urban environments. Manag. Sci. 68 (1), 280–299.
Straight, B., 2018. From bikes to drones, how JD Logistics built its delivery network. FreightWaves, March 30. https://www.freightwaves.com/news/asia/china/jd-logistics-builds-last-mile-efficiency, 2018.
TechCrush, 2017. UPS tests residential delivery via drone. YouTube. https://www.youtube.com/watch?v=P5hQHBNpd7s.

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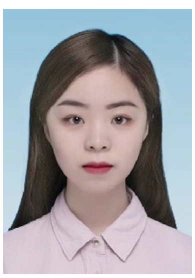

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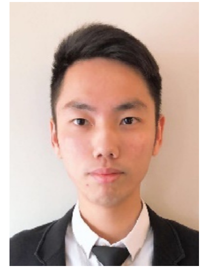

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