Optimization of Multi-package Drone Deliveries Considering Battery Capacity

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ABSTRACT

Drone delivery has been tested by private companies around world. With advanced safety and reliability features, such as automated flight and sense-and-avoid technology to prevent collisions, it appears that deliveries by drone will soon be practical. This paper deals with an automated drone delivery system, rather than cooperative delivery by drones and trucks. The study assumes that a drone can lift multiple packages within its maximum payload and serve recipients in a service area of given radius. Battery capacities, the primary energy sources for drone operation, are analyzed to relate parcel payloads and flight ranges. Numerical analysis is used to optimize the drone fleet size for a service area, by minimizing the total costs of the delivery system. Four variables are explored to show the sensitivity of system outputs to input parameters: working period, drone operating speed, demand density of service area, and battery capacity. Extended daily working periods are shown to benefit both service providers and users. Increased drone operating speed reduces overall costs, but increases operating and investment costs for suppliers. The study indicates that drone deliveries are more economical in areas with high demand densities. Lastly, the large amount of energy storage resulted from battery improvement can reduce the number of drones satisfying all demands in a service area.

INTRODUCTION

Drones are already widely used in industries, leisure activities and academia (1). These drones are equipped with various sensors, including GPS and wireless communication, which enable them to perform special functions, such as automated flight, object tracking, and collision avoidance.

One of the promising drone applications in transportation fields is parcel delivery service, either solely by drones or in collaborative operation with trucks. This application is largely investigated in the private domain, and recent achievements have shown its feasibility. For example, several companies, including Amazon.com, Inc. in the U.S., DHL in Germany, and Alibaba in China have been working on deliveries by drones. Amazon, an electronic commerce company, announced the latest prototype of its Amazon Prime Air drone in November, 2015. The prototype drone can fly up to 15 miles with a maximum speed of 50 miles/hour (MPH) and carry packages weighing less than five pounds. (1 mile = 1.61 km, 5 lb = 2.27kg.) Amazon announced that over 86 percent of its items can be delivered by drones. In addition to delivery by drones, ground robots have been introduced for deliveries. In March 2016, Domino's pizza introduced the autonomous ground delivery vehicle as a world first for delivering a maximum of ten pizzas to customers located within 12 miles. Thus, for such applications, autonomous delivery service is expected to be practical.

In comparison to ground delivery services, deliveries by drones are considerably restricted by drone range and payload because most drones are powered by lithium-ion batteries, which currently only allow about a half hour of flight. It is crucial to consider those characteristics and examine the operating variables in the overall operation process. Otherwise a decision may result in overestimating or underestimating capital requirements. Improvements in batteries or larger drones can improve performance, i.e. range and/or payload.

The study focuses on parcel delivery service solely served by drones simultaneously lifting multiple lightweight packages and optimizes the number of drones to satisfy a desired service level. For analysis purposes, characteristics of drones and the baseline for service properties and service area are preset. All demands are served from a single distribution depot. The specified variables are explored through sensitivity analyses. These tests identify the critical factors contributing to total costs of a drone delivery system. Several factors that may affect actual applications, such as weather conditions, government regulations, and safety issues (e.g. drones should fly below 500 feet and below 100mph), are not yet considered here.

Figure 1 Drone Delivery and Robot Delivery

(Left: Amazon Prime Air, Right: Domino's Robotic Unit)

The following section briefly summarizes the relevant research on drone applications in transportation and delivery services. In the methodology part, variables are specified that describe service area and drones, as well as relations among flight range, payload, and battery capacity. Based on the initial settings, the drone delivery model is constructed, and numerical analysis is conducted. Then, tests are conducted to determine the sensitivity of results to some important factors. Finally, conclusions and future extensions for drone delivery research are presented.

LITERATURE REVIEW

Applications of drones in transportation have focused on collecting traffic parameters: traffic counts, queue lengths at the signalized intersections, incident detection (2) and estimation of vehicle speeds on freeways using computer vision algorithms (3). Since package delivery by drones has been discussed as a new business model since at least 2013, a few studies considered the characteristics of drones, individual drone movements supported by trucks, and environmental impacts.

Mathew et al (5) set two scenarios for drone delivery. A distribution depot dispatched drones supported by a truck, and delivery service was solely operated by drones departing from multiple centers. Each case was analyzed using the Traveling Salesman Problem (TSP) algorithm. Their results suggested that delivery supported by trucks reduced delivery time by 35 percent compared to a truck-only system.

Murry and Chu (6) applied TSP to cooperative deliveries by drone and truck. Two scenarios were set: the first scenario was a truck with a drone, where the drone was launched from the truck when demand points were located further or packages exceeded the drone's allowable payload. The second scenario analyzed deliveries by drones serving demand points near a distribution center. Murry's team showed how the operating speed of drones reduced delivery times.

Welch (7) conducted a cost and benefit study of drone delivery service with a numerical analysis using demographic and geographic information from the city of Chattanooga in

Tennessee. The author concluded that a package delivery by drones required 17 times less capital investment than delivery solely by truck.

Toy and Goodchild (8) compared delivery-by-drone with delivery-by-truck in terms of CO2 emissions and VMT (Vehicle Miles Traveled). The authors used the U.S. county network database for representing the customer's location. Emission rates for truck were estimated by vehicle year and speed. The rates for drones were transformed from the amount of energy required for a battery charge into CO2 emissions from electricity power generation. Drone delivery emitted less CO2 than trucks when service zones were located close to the center or had few customers, while VMT's were higher for drones than trucks. The authors suggested that drones and trucks collaborate in deliveries for the environment's sake, where drones deliver parcels to nearby recipients while trucks deliver to more remote customers.

In summary, most of the studies found have considered drone delivery as a partly automated service in which trucks are responsible for line-haul and heavyweight packages. This is mainly because today's technologies are not fully ripe for autonomous delivery in terms of parcel payload and drone flight range. However, difficulties also exist for hybrid delivery services. For instance, they may require the synchronization of drone landings on moving trucks. This process requires highly accurate sensors, which may increase the costs of drones. Some researchers tried to incorporate battery capabilities within their models, but no studies treated battery power as a way of expressing physical constraints, such as flight range. These motivate the present paper, which analyzes fully autonomous drones delivering multiple packages, while considering battery capacity.

METHODOLOGY

The following sections discuss the characteristics of drones and their service properties. We formulate a total cost function for this delivery system and find the number of delivery vehicles that minimizes the system's total cost. A service area is the region in which demands are generated and served by a fleet of drones, each of which can lift multiple packages, from a single distribution facility. Most input variables for delivery vehicles are adapted from specifications provided by drone manufactures. Other baseline numerical values, such as the service zone size and drone operating speed, originate from Amazon.com (13).

Baseline Numerical Values

Symbol	**Variable**	**Units**	**Baseline Value**	**Range**
C_t	Total Cost	$ / day	-	-
C_{cp}	Capital Cost	$ / day	-	-
C_{op}	Drone Operating Cost	$ / day	-	-
C_{udc}	Delivery Waiting Cost	$ / day	-	-
N_{dr}	Number of Drone	vehicle	-	-
$N_{battery}$	Number of Batteries	units / vehicle	-	-
N_{pack}	Number of Packages	package / vehicle	-	1 - 13

		(1 package = 0.5 kg)		
N_{trip}	Daily Trip	trips / (vehicle·day)	-	-
D	Average TSP distance	km	-	-
L	Line-haul Distance	km	8	-
A	Zone Area	km^2	196π (16km radius)	-
Q	Demand Density	packages / km^2 / hr	1	0.1 – 5
W	Working Period	hrs	6	3 - 24
V	Drone Speed	km / hr	50	30 - 110
T_{rt}	Average Round-trip Delivery Time	hrs / vehicle round-trip	-	-
T_{dwell}	Dwell Time	hrs / parcel	0.03	-
$T_{replenish}$	Replenishment Time	hr / trip	0.5	-
uc	Unit Delivery Cost	$ / package	-	-
dr	Drone Cost	$ / vehicle	3000	-
bcc	Battery Charge Cost	$ / battery	0.012	-
bc	Battery Cost	$ / unit	150	-
in	Indirect Cost	$ / package	0.5	-
hd	Handling Cost	$ / package	1	-
wgt	Drone Weight	kg	10	-
v	User Value of Time	$ / (package · hr)	1	-
I	Interest Rate	%	6.5	-
Y	Life Span for Drone	year	3	-
cyc	Life Cycle for Batteries	time	500	-

Table 1. Variable Definitions

Demands of a service area are determined by multiplying demand density (Q), zone area (A), and time unit, where the time unit is set as one day. Those demands are served during the working period and assumed to be uniformly generated over time and space. Payload refers gross weight of parcels, and each parcel weights 0.5kg in this study. The number of packages (N_{pack}) is the average number of packages lifted by delivery vehicles within the maximum allowable payload, where the combined mass of battery and parcels should be less than 2/3 of the total vehicle mass (wgt) (4); this value is set for multi-package drones. More details about the baseline value for N_{pack} are discussed in the next section. Next, dwell time (T_{dwell}) includes a series of operations in delivering parcels, such as take-off, landing, unloading, accelerating, and decelerating, and these take several minutes per demand point. After the deliveries are completed, the vehicle must return to the depot and go through a series of processes ($T_{replenish}$), such as battery replacement or recharge, inspection, and parcel replenishment for the next trip. Daily trips (N_{trip}) is the average number of tours made by the vehicle during the daily working period,

which is derived using equations (1) and (2). The required number of batteries per drone year ($N_{battery}$) can be estimated by considering battery cycles for a lithium-ion polymer battery (*cyc*) times. T_{rt} is the amount of time spent by individual vehicle for completing a tour. Then, $N_{battery}$ is determined with equation (3).

$$T_{rt} = \frac{D+2L}{V} + T_{dwell} \times N_{pack} + T_{repleinsh} \tag{1}$$

$$N_{trip} = \frac{W}{T_{rt}} \tag{2}$$

$$N_{battery} = \frac{365cyc}{N_{trip}} \tag{3}$$

Battery capacity is set to allow a drone to fly a round trip across the service area ($2\sqrt{A/\pi}$) while carrying a single parcel; this is the minimum required energy for delivering a parcel to a recipient located at the edge of the service area. Battery charge cost is proportional to electricity use. The average electricity cost is $0.10 / kWh according to a 2016 U.S. consumer report (9). The charge can be varied depending on drone battery capacity. Purchasing costs for delivery vehicles (*dr)* and batteries (*bc*) are gathered by averaging prices of high-end commercial drones, such as DJI Inspire 1. While indirect cost and handling cost, such as monitoring drone operation are considered, facility construction cost is not considered here.

Preprocessing Inputs Variables

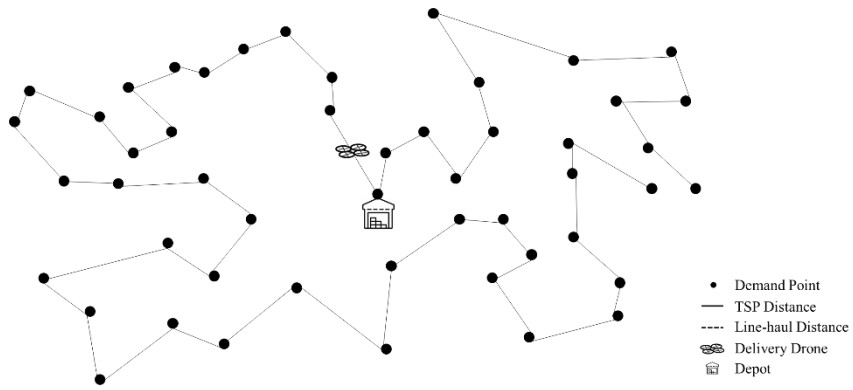
Some variables from the baseline should be preprocessed for easier computation. First, an approximation is derived for the travel distance from a depot to each demand point by drones. Second, battery capacity is represented with constraints on payload and flight range.

Approximation of Distance Traveled by Drone

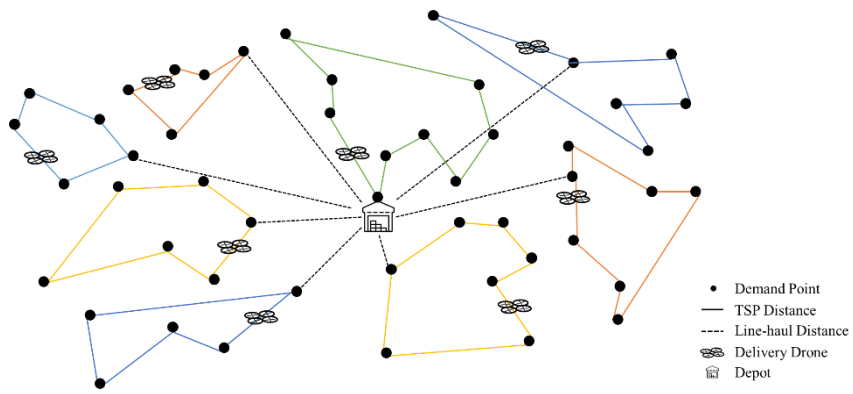
It is simple to measure a round-trip distance made by a vehicle delivering a single parcel. In contrast, an approximation of the travel distance is needed when multiple demand points are visited by a vehicle in one tour. Hindle and Worthington (10) have developed through simulation equation (4) for approximating the average Travelling Salesman Problem (TSP) tour length.

$$\text{Average TSP distance} = \text{a} \times \text{n} + b \times \ln(n) + c \tag{4}$$

where a, b, and c are constants. a = 3.63, b = 85.78, and c = 62.67



(a) Average TSP Trajectory with Single Delivery Drone



(b) Trajectories Allocated to Multiple Delivery Drones

Figure 2 Trip Distances for Delivery Drones

Equation (4) estimates average route distance travelled by a single vehicle visiting all demand points in Figure 2 (a). For drone delivery, the estimated distance should be divided by multiple delivery vehicles since limited battery energy storage restricts longer trips for the vehicles. Hence, flight distance for individual vehicles is derived by dividing average TSP distance by the number of drones (N_{dr}) as equation (5).

$$\mathrm{D} = \frac{\mathrm{a} \times \mathrm{n} + b \times \ln(n) + c}{N_{dr}} \tag{5}$$

Total flight distance estimated from equation (4) and (5) are not exactly the same in that the latter distance is longer. It is assumed that both distances are the equal.

Flight Range and Payload Associated with Battery Capacity

The Breguet range equation in the field of Aeronautics (11) specifies a relation between the flight range and payload of aircraft. This equation assumes that the weight of aircraft keeps decreasing as fuel is consumed, which is not applicable to battery-powered vehicles. For drones, the battery capacity determines the maximum flight range. Hence, we must define the relation between payload and flight range in terms of the capacity. D'Andrea (4) formulated drone

energy consumption considering various factors, such as air resistance, battery cost, life cycle, and cost of electricity usage, as shown in equation (6):

$$\text{Power consumption (in kW)} = \frac{(m_p + m_v)V}{370\eta r} + \text{p} \tag{6}$$

$$\text{Battery capacity} = \frac{(\text{Npack} + m_v)\text{V}t}{370\eta r} \tag{7}$$

where m_p is payload weight in kg, m_v is drone weight in kg, r is lift-to-drag ratio, η is power transfer efficiency for motor and propeller, p is power consumption of electronics such as sensors in kW, v is drone operating speed in KPH, and t is flight duration in hours.

According to equation (6), the energy consumption of drones increases proportionally with the combined vehicle and parcel weight. Battery capacity is expressed as energy consumption multiplied by duration, and flight range is proportional to the battery energy. Power consumption of electronics is assumed to be negligible. Since batteries for delivery vehicles store a fixed amount of energy, battery capacity can be treated as a constant. It should be noted that m_v, η, and r, are constants in equation (6). Then, the relation among $Npack$, drone speed (V), and flight duration (t) can be found. First, $Npack$ is inversely proportional to V. That is, vehicles can carry more parcels at lower speeds conserving the same amount of energy storage. Second, flight distance ($V \cdot t$) is inversely proportional to $Npack$ as shown in Figure 3. Using equation (7), it can be derived either $Npack$ or (D+2L) reciprocally once one variable is changed. In Figure 3, a relation between $Npack$ and (D+2L) is convex unlike concave shape resulting from the Breguet equation, mainly because battery weight does not change as energy is expended, unlike in fuel-using aircraft.

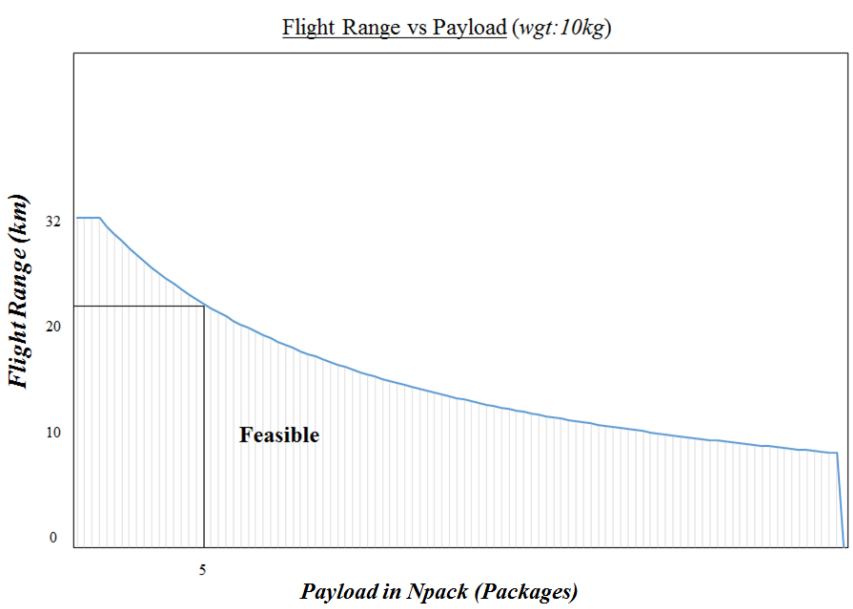


Figure 3 Relation between Flight Range and Payload

It is safe to operate a delivery vehicle until its battery only retains 20% of the full charge. This is called "the 80% flight rule", which is commonly used with lithium-ion polymer batteries for safety, maintenance and protection for drones (12).

Mathematical Formulation

Assumptions for Delivery System

1. *The tours of each delivery vehicle are routed on a 3-dimensional Euclidean network.*
2. *The demand does not vary with service quality.*
3. *The demand is uniformly distributed within the service area and uniformly generated over 24 hours / day.*
4. *All daily demands are served within a predetermined working period.*
5. *The size of delivery vehicles and their batteries are homogenous throughout a system.*
6. *Deliveries consist of one package per customer, i.e. per delivery point.*
7. *External costs, noise or system malfunctions, are assumed to be negligible.*
8. *From the distribution center to demand points, delivery vehicles travel a round-trip line-haul distance and a Travelling Salesman (TSP) tour at a specified operating speed.*

Cost Function of Drone Delivery System

The cost function consists of system cost and user cost. The system cost includes capital cost which satisfies peak-period demands and operating cost associated with the number of delivery vehicles, such as battery charge, management and maintenance. The user cost can be represented as the cost of the time when users wait for deliveries. It should be noted that this user wait would usually occur at a home, office, or other convenient place, with little disruption to other activities of the waiting users. Thus, the value of this user wait time is relatively low. The total cost is expressed as follows:

$$C_t = C_{cp} + C_{op} + C_{udc} \tag{8}$$

More specifically, each component is expressed as follows:

$$C_{cp} = \frac{(\mathrm{dr} \times N_{dr} + \mathrm{bc} \times N_{battery})}{365} \left[\frac{(1+i)^Y - 1}{i(1+i)^Y}\right] \tag{9}$$

$$C_{op} = \frac{W \times N_{dr}[bcc + hd + in]}{\frac{D+2L}{V} + T_{dwell} \times N_{pack} + T_{repleinsh}} \tag{10}$$

$$C_{udc} = 24QAv\left(\frac{2L+D}{2V}\right) \tag{11}$$

In equation (9), the capital cost refers to present worth of components, namely vehicles and batteries. It is noted that terminal costs for distribution depots, such as construction, rent, and warehouse, are not considered. Equation (10) includes the costs for system operation, which directly relate to the number of drones and their trips made in a day. Here, the operating cost, related to battery charging and handling, is proportionally increased as the number of flights

increases. Indirect costs, including marketing and insurance, are incorporated in drone operation. Equation (11) specifies the users' cost of waiting to receive packages.

Constraints in Drone Delivery System

The required battery capacity can be formulated based on the relation between payload and flight distance (shown in Figure 3).

$$N_{pack} \leq \frac{2}{3} wgt \tag{12}$$

$$D + 2L \leq 2\sqrt{A/\pi} \tag{13}$$

$$\frac{(D+2L)}{V} \leq W \tag{14}$$

Constraint (12) represents the maximum number of packages that each delivery vehicle can hold, while constraint (13) is the maximum delivery range. The sum of the TSP tour length and line-haul (letter "L"), i.e. total distance, is twice the service zone radius as described earlier. It is noted that right-hand side values from each equation can be varied according to battery capacity or vehicle specifications. Lastly, constraint (14) is the condition that deliveries should be completed before the end of the working period. Other conditions which may affect energy use are not considered, such as weather and altitude limit.

Numerical Results

The number of delivery vehicles that minimizes the total cost function is found by differentiating the objective function (C_t) with respect to N_{dr}. The result must also satisfy the imposed constraints. Using baseline inputs, the obtained results are that 146 delivery vehicles costing $15,318/day should be used, as shown in the second row of Table 2. The total cost function is most affected by delivery waiting costs for users. Drones average 4.76 trips/day. All constraints, regarding average number of packages per drone, average delivery distance, and delivery time are satisfied. More details on system outputs are discussed in the following section.

SENSITIVITY ANALYSIS

Sensitivity analyses are conducted to explore how the system reacts to changes in inputs. Four cases are presented, analyzing the sensitivity to operating variables, service quality, demand pattern, and battery storage improvement.

Case I - Variation of Working Period

This case is intended to demonstrate whether delivery system is affected by changes in the working period; other variables, including demands in the area and vehicle speed, stay unchanged. It is noted that operation costs are assumed to be the same for days and nights and external costs of overnight operation, such as noise, are not considered.

W	N_{dr}	N_{trip}	N_{pack}	$D+2L$	T_{rt}	C_{cp}	C_{op}	C_{udc}	C_t	uc
3	299	2.38	11.41	25.99	1.36	1,807	7,481	10,529	19,816	1.03

6*	146	4.76	5.86	26.25	1.20	1,310	2,430	11,578	15,318	0.79
12	55	9.52	3.98	29.73	1.21	810	1,816	11,694	14,320	0.74
18	31	14.29	3.04	31.98	1.23	648	1,559	11,875	14,082	0.73
24	24	19.05	2.28	31.98	1.14	623	1,559	11,655	13,838	0.72

* baseline output

Table 2 Effects of Working Period

Values in Table 2 represent system outputs, including system constraints: average number of items shipped in vehicle (N_{pack}) and average flight distance ($D+2L$). Since the number of daily trips per vehicle (N_{trip}) increases as W is increases, the service area can be served with fewer vehicles (N_{dr}), thus reducing the service provider's cost for capital (C_{cp}) and operation (C_{op}). From the user's perspective, delivery waiting time cost (C_{udc}) shows no clear relation with W, because fewer vehicles serve the demands during a longer time window. C_{udc} does not include waiting costs for demands generated outside of W, where the users must wait for service until the following day. For example, if W has a baseline value of 6 and the service operates between 9:00am and 3:00pm, the customers who place an order after 3:00pm must wait at least until 9:00am the following day. This additional waiting costs decrease as W increases. Overall here, the extended working period is beneficial.

Case II – Variation of Operating Speed

Again, delivery vehicles can deliver more packages by lowering operating speed at the fixed amount of energy storage; the amount of energy saved by low speed flight enables vehicles to lift heavier payload according to equation (7), and the same is true in reverse. It can be possible that lower speed allows vehicles to deliver a larger service area, which exceeding the flight range constraint, but this case is not happened in this range of analysis.

V	N_{dr}	N_{trip}	N_{pack}	$D+2L$	T_{rt}	C_{cp}	C_{op}	C_{udc}	C_t	uc
30	182	3.56	8.38	26.97	1.65	1,368	2,272	15,919	19,559	1.01
50*	146	4.76	5.86	26.25	1.20	1,310	2,430	11,578	15,318	0.79
70	159	5.57	3.92	24.03	0.96	1,590	3,105	9,271	13,965	0.72
90	160	6.15	3.20	23.23	0.85	1,713	3,445	8,201	13,359	0.69
110	163	6.59	2.73	22.61	0.79	1,839	3,772	7,622	13,233	0.69

* baseline output

Table 3 Effects of Vehicle Speed

Although increased vehicle speeds (V) reduce total cost as well as unit package delivery cost (uc), this is not a favorable option here for a service provider because C_{cp} and C_{op} increase. The advantages of higher speed would increase if the assumed value of waiting time would increase.

Case III – Variation of Demand Density

This case is designed to explore the effects of demand density on system performance. Lower demand density (Q) can be interpreted as rural areas, while higher density may represent urban

areas. It is noted that the case does not consider multiple deliveries made to the same recipient, which potentially decreases the travel distance.

Q	N_{dr}	N_{trip}	N_{pack}	$D+2L$	T_{rt}	C_{cp}	C_{op}	C_{udc}	C_t	uc
0.1	17	4.76	5.19	25.77	1.17	150	277	1,150	1,577	0.82
0.5	74	4.76	5.77	26.19	1.20	666	1,236	5,800	7,702	0.80
1*	146	4.76	5.86	26.25	1.20	1,310	2,430	11,578	15,318	0.79
1.5	217	4.76	5.89	26.27	1.20	1,954	3,624	16,908	22,486	0.78
5	716	4.76	5.95	26.31	1.20	6,452	11,969	57,888	76,308	0.79

* baseline output

Table 4 Effects of Demand Density

As Q increases, more parcels are generated within the service area, thus increasing N_{dr}; both N_{pack} and $D+2L$ for the vehicles are increased. A service area with lower demand density, e.g. a rural area, yields the highest uc. For more detailed analysis of how density affects the system performance, a microscopic analysis may be conducted with a TSP algorithm to determine the desirable combinations of tour frequency and payload per vehicle tour.

Case IV – Battery Performance Improvements

The last case is designed to explore how battery energy storage affects a delivery system. In general, more energy storage enables vehicles to carry greater payloads or extend flight range. Note that the right-hand side value for constraint (13) is now ignored. Since there are numerous combinations of payload and flight range with the enhanced battery capacity, we select combinations in which two factors are proportionally increased. Batteries with 10%, 50%, and 100% enhancement from the baseline are analyzed. It is assumed here that increased battery storage does not increase vehicle weight.

Battery Capacity	N_{dr}	N_{trip}	N_{pack}	$D+2L$	T_{rt}	C_{cp}	C_{op}	C_{udc}	C_t	uc
100%*	135	4.76	5.00	27.06	1.19	1,215	2,255	11,871	15,341	0.80
110%	121	4.76	7.08	28.42	1.28	1,083	2,009	12,355	15,447	0.80
150%	84	4.76	10.18	33.83	1.48	753	1,398	14,298	16,449	0.85
200%	61	4.76	14.02	40.59	1.73	549	1,018	16,677	18,244	0.95

* baseline output

Table 5 Effects of Battery Capacity

Unlike results from case II, the enhanced battery energy storage is preferable for service providers, as C_{cp} and C_{op} decrease significantly. From the users' perspective, C_{udc} increases because fewer vehicles serve the same numbers of recipients with increased N_{pack} and $D+2L$. Note that there are additional cost-saving factors for the providers which are not considered, such as rent or investment in facilities.

CONCLUSIONS AND FUTURE STUDIES

The drone delivery industry is mostly led by private companies, and their achievements indicate that such services are becoming practical. Apart from technical difficulties, many concerns must be overcome exist regarding security, regulations, noise problems and operating conditions, including weather. This paper analyzes fully automated drone delivery services, rather than drones supported by trucks, as found in most related studies. The study considers delivery vehicles which can lift multiple packages within the predefined shipment weight and flight range. Battery capacities, the primary source of drone flight, are included in the model in order to realistically analyze vehicle capabilities.

Four cases are presented for demonstrating how system outputs are affected by changes in inputs. It is found that extended working periods are shown to benefit both service providers and users. Increased drone operating speed, beyond the baseline, reduces total cost, but increases operating and investment costs for suppliers. Deliveries by drones are more economical in areas with high demand densities. Lastly, the large amount of energy storage resulted from battery improvement reduces the number of drones meeting all demands in a service area.

Future extensions can deal with location of facilities, economic analysis, and consideration of operating conditions. First, facility location requires large amounts of capital investment, such as the purchase of land, warehouse, and labor. For this reason, constructing distribution depots based on drones' present ranges may yield inefficient solutions for future drone capabilities. Therefore, it may easier to effectively increase present ranges by shifting parcels among drones at relay nodes. Second, from the economic perspective, it is worth examining whether delivery by drones outperforms ground delivering vehicles, including robots. Lastly, cybersecurity and operating conditions, such as weather, might be considered, possibly by translating them into costs.

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