

Article

Sizing of the Drone Delivery Fleet Considering Energy Autonomy

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Abstract: One of the most innovative solutions treated in the literature in order to reduce the environmental impact of urban parcel delivery logistics is the use of drones for delivery on the last kilometer. Consequently, nowadays, the primary challenge is essentially related to the drones' fleet sizing according to its means of support for the urban delivery of parcels. In this paper, we will discuss the issue of dimensioning from a forecast of deliveries of an urban perimeter, the size of the fleet, the stock of battery to dispose of and the strategy of battery charging. We will present an analytical model expressing the proposed problem of the optimal drones' delivery mission taking into account the issues of autonomy and energy consumption related to the drone's technical specification. According to the developed analytical model, two optimization policies will be proposed. The first policy consists of planning missions under reducing distance. The second policy tries to make a compromise between the distance and the number of drones. A case study will be presented in order to compare the two policies based on the overall cost of a plan. The main objective of the study is to create a decision-making tool for the design of a drone fleet in the case of forecast deliveries over a time horizon under operational constraints.

Keywords: sustainable delivery; parcel delivery; drone delivery; fleet dimensioning; drone autonomy; energy consumption

1. Introduction and Literature Review

1.1. The Last Mile Delivery: New Challenges

As a final ring in the chain distribution logistics, last mile delivery represents a significant challenge with the expanding of e-commerce. E-commerce activities boost companies to modernize their transportation service. Hence, delivery services are increasing due to the just-in-time management. In 2014, e-commerce reached \$1.9 trillion [1]. As a consequence, new express delivery services have appeared such as: same-day delivery, one-hour or two-hour delivery, which are backed by a high level of urbanization. The express service offers day and time-definite transit [2] and is essentially destined for the business-to-business (B2B) segment. Moreover, the express service has expanded to business-to-customer (B2C). We count about 382 million express parcels delivered in 2012 [3].

E-commerce represents the key to a successful urban delivery market especially when 54% of the world population lives in urban areas [1]. As such, improving this sector and offering a delivery service with high quality seem the main challenges that the pioneer companies of e-commerce like Amazon or Google are facing. These companies are endeavoring to be closer to their customers and to adapt their service to the client's behavior. As an example, Amazon has over 10 million Amazon

Prime Members [4], and they propose a new delivery format for same-day or two-hour delivery. The new delivery service requires rapidity and customer satisfaction to meet the just-in-time demands. However, urban transportation can face many problems related to delivery area [5] or route traffic. These constraints represent major obstacles in urban transportation activities.

In the literature, we find many studies that propose solutions to overcome many obstacles related to urban delivery. Oliveira et al. [6] focused on bicycles, tricycles and light commercial vehicles as attractive delivery alternatives to reduce accessibility issues faced by the trucks in the urban area due to some road restrictions. Other studies have focused on the energy efficiency for last mile delivery. In fact, taking the energy constraint into consideration is very important, especially in urban area that are impacted by pollution and congestion issues, as developed in the paper of Bányai et al. [7]. In the same vein, the paper of Luigi et al. [8] sheds light on externalities' cost reduction as an innovative strategy in last mile delivery sector. The authors concentrated on the factors with a high potential of externalities' cost reduction. One of those factors is new vehicles. Electric or hybrid vehicles are highly-regarded in supporting sustainable evolution in urban areas. However, the autonomy constraint and infrastructure network limit larger exploitation. Indeed, these vehicles yield to traffic congestion and parking zone constraints. Morganti et al. [9] showed through their study, in France and Germany, that alternative parcel deliveries are in continual growth with the evolution of e-commerce. According to them, pick-up points' networks are developing and increasing the number of successful deliveries the first time. Zhang et al. [10] treated another delivery transportation means and structure using cargo bicycles and pick-up points. The article showed that delivering parcels with cargo bikes reduces delivery cost and pollution. It is important to note, however, that to reroute parcels, the customer should move toward the pick-up point. Iwan et al. [11] presented another delivery alternative, which consists of using parcel lockers, as they have an interesting potential if used as a delivery location. This delivery location is available 24 h for the customer, but also involves customers displacements. Zhou et al. [12] proposed simultaneous home delivery and customers' pick-up to be used in the context of online shopping. This solution may help to overcome the problem of the customer's mobility. Nevertheless, this delivery/pick-up solution is restricted by the vehicle capacity. Those studies identified multiple transportation means and delivery infrastructures as an alternative to enhance urban delivery and satisfy customers' needs. However, each of those alternatives has its own limit (autonomy, congestion impact, additional customers' displacement, partial availability, etc).

Customers expect their parcels to be delivered quickly and tend to avoid displacing to collect them. For these reasons, companies delivering to individuals are experimenting with new delivery services using drones as a means of transportation [4,13,14]. In fact, exploring the use of drones for commercial applications is the result of their successful usage in military application given that drones (also called UAV (Unmanned Aircraft Vehicle)) do not need a pilot and do not have congestion constraints that affect their functioning. Accordingly, customers do not need to move compared to the way they do when it comes to other delivery services (pick-up point or parcel lockers). In addition, this transportation solution overcomes road restriction constraints. These arguments are encouraging drone designers to consider using them for various public applications (As an example, drones are already used as a transportation means for health services [15]. Besides, Haidari et al. [16] showed that the use of drones to transport vaccines increased their availability with minimum cost.). The use of drones has seen an incessant progress from its use in the military field to its use for scientific and civilian purposes. The paper of Watts et al. [17] highlighted the transition of the drone from military to civilian uses. In addition, during the last decade, parcel deliveries have been developed, as well as the civilian use of UAV. The combination of these two aspects creates a new domain, which the same leaders of parcel delivery or e-commerce have started to test and explore. We can cite for example Amazon [4] or DHL [18], which are testing these delivery services through drones. Drone delivery may overcome the difficulties that commercial activities have with one-day or same-hour delivery in order to meet the high availability level of expectation and ensure an economic advantage, making this form of delivery more and more appealing. Managing a fleet of drones, in the context of urban

delivery, requires the application of routing problem models to ensure the different delivery missions. These methods take into account the exploitation constraints and the technical characteristics related to the drones.

In order to manage the different missions of the drone fleet, the routing problem should be solved. In the literature, this problem is categorized as VRP (Vehicle Routing Problem), and many studies discuss VRP related to drones in civilian applications. In addition, the capacity of the UAVs and the time windows of the delivery are also considered to be constraints that should be addressed. Combining all of those constraints is called the CVRPTW problem. This issue was treated by many studies [19–24]. For example, Figliozzi [19] focused on the problem of congestion in urban area, especially the vehicle speed variation. Other studies are available and have focused on UAVs' routing, but in the military context. For example, Shetty et al. [25] organized target assignment and the path of a fleet of Unmanned Combat Aerial Vehicles (UCAVs). Russel and Lamont [26] treated a problem of UAV routing with a genetic algorithm to schedule routing as dynamic routing, which depends on fast adaptation to respect flight regulation in changing routes. In another case of the application of UAVs in military use, Savuran et al. proposed a route optimization method for carrier-launched UAVs [27]. For the public use and in the search and rescue domain, Kurdi et al. [28] treated the task allocation problem of multiple UAV with a bio-inspired algorithm. Boone et al. [29] were interested in Multiple TSP (MTSP) involving many UAVs with a new clustering approach. In a paper focusing on UAV missions, Mathew et al. [30] discussed task scheduling and patch planning for cooperating heterogeneous, autonomous vehicles (UAV and UGV) in a context of urban delivery. Recent papers showed an interest in the delivery with the drone. These studies highlight a tandem truck and drone transport for parcel deliveries [31–33]. They proposed multiple approaches to solve this problem as a mixed integer linear programming problem or heuristics. Sawadsitang et al. [34] presented a new framework of cooperative supplier for a drone delivery fleet. The Table 1 regrouped those works and included others that treated the issue of drone routing in both civilian and military applications with different routing formulations.

Table 1. Various formulation of UAV problems.

Paper	Military Use	Civilian Use	Formulation
Russell et al., 2005	X		GVR
Shetty et al., 2008	X		<i>m</i> TSP
Kurdi et al., 2016		X	Multi-UAV task allocation
Murray et al., 2015		X	FSTSP
Agatz et al., 2015		X	TSP-D
Ha et al., 2015		X	Column Generation
Boone et al., 2015	X	X	MTSP
Mathew et al., 2015		X	HDP/MWDP
Savuran et al., 2015	X		VRP
Sawadsitang et al., 2018		x	MIP + merge-and-split algorithm

1.2. Motivation and Target Contribution

This paper, which is based on the work of Troudi et al. [35], presents a configuration of a drone operator that delivers parcels with drones. In this context, we are describing the delivery process of the drone delivery activities. This process helps to understand how the drone operator manages the parcels' delivery process, as presented in Figure 1.

After the reception of the parcels, the operator programs through a CVRP-TW (Capacitated Vehicle Routing Problem with Time Windows) the different missions to perform. Then, the operator assigns UAVs from the available fleet: a drone that belongs to the available fleet is a drone that can perform missions. Once the loading task is done, the operator selects a runway to start the mission. Figure 1 represents the different possible statuses of the UAV fleet and the condition changes of each fleet status. The active fleet regroups all the UAV already inspected, and after every mission, each UAV

will be in a standby status for its inspection and control. When a UAV starts its mission, it is considered as an active vehicle.

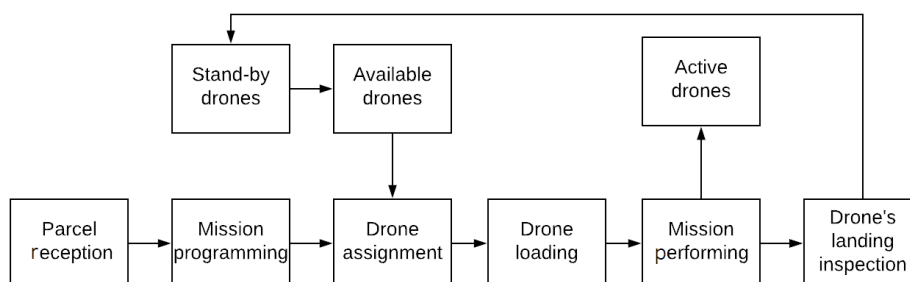


Figure 1. Presentation of delivery process in a context of drone delivery application.

Through the logistics analysis approach discussed in [35], the authors focused on the importance of analyzing the activity in order to support the evolution of the fleet with an appropriate logistics support system. The approach is based on the standard of logistics support analysis MIL-STD-1388-1A [36] and the extension of the same tasks in this analysis in the post-production phase. In fact, in order to implement an appropriate support system for a drone delivery fleet, we should determine the system dimensioning and its evolution as a function of various parameters like delivery time, the number of customers to deliver to, etc. In addition, the modification of equipment may have an impact on the functional capacity of the system and, as a consequence, may result in the change of the mission plan. Through this analysis, we conclude that, in order to update the logistics support of a drone fleet, we should study the impact of every modification in the operation management and the dimension of the support system instantaneously. These types of services require a high level of availability and an economic advantage to make them appealing.

Our primary purpose is to manage a park of a large fleet of drones, which is ready to deliver parcels to costumers. The majority of researchers have focused on military UAVs or ground package delivery with a routing problem formulation. However, in this work, we intend to focus on modeling the routing problem in a package delivery context with civilian UAVs.

Modeling the drone parcel delivery fleet with VRP helps to solve the sizing the fleet problem. Taking into consideration the autonomy that characterizes drones is primordial. In addition, the sizing model is based on the battery charging policy. With different objectives, we will help the drone operator to identify their impact on some sustainability indicators like energy consumption or the number of used batteries.

The next section shows our sizing concept and the analytical model using the VRP formulation. Section 3 includes the result of the analytical model and the impact of different sizing objectives explained in Section 2.

2. Vehicle Routing Problem Approach for Drone Fleet Sizing

The drone delivery problem has an outstanding potential in terms of scientific development (Table 1). VRP, Vehicle Routing Problem.

In the parcel delivery sector, studies identified two ways to deliver parcels: only with a drone [29,30] or by combining a truck and a drone [31–33] (in this case, we consider the drone delivery as a complementary service). In addition, we noticed that all those papers found that the drone can carry only one parcel and did not take into account the energy consumption. As a consequence, our contribution in this section consists of proposing a new formulation for a drone delivery problem, Capacitated Vehicle Routing Problem with Time Windows (CVRPTW): multiple parcels to carry for each drone with adding the battery's energy constraint.

With an analytical model, we propose to size the drone fleet and establish the mission plan, which takes into consideration the energy consumption for and determines the number of the batteries, explained in Figure 2. The different objectives are introduced according to a defined battery charging policy. In this model, we opt for a full battery charging policy: every active drone has a full battery before every mission. It is also worth mentioning that a part of this model was introduced in a previous work [37].

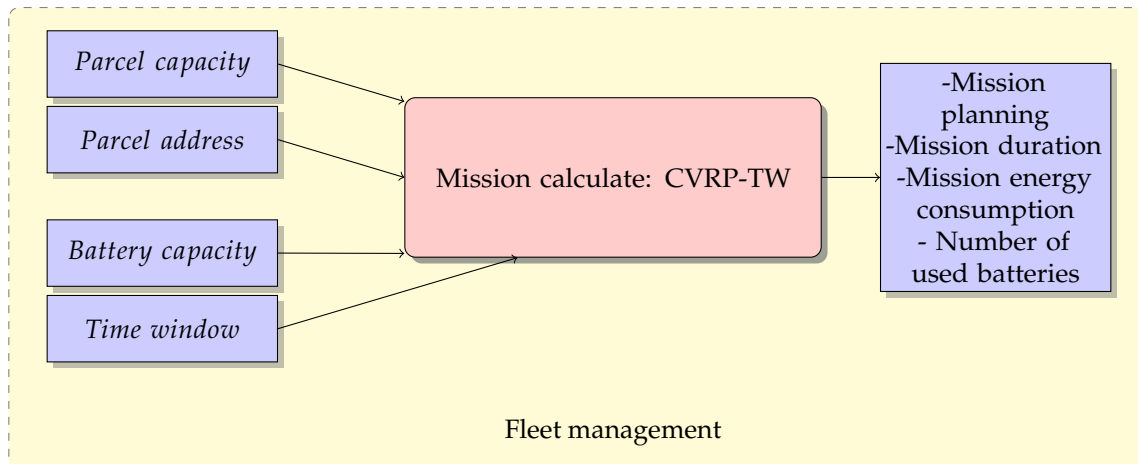


Figure 2. Sizing fleet concept. CVRP-TW, Capacitated Vehicle Routing Problem with Time Windows.

2.1. Assumptions and Parameters

In order to model the proposed problem analytically, we establish the following hypotheses:

- each point i represents a command to deliver;
- the maximum payload is unique for all the fleet;
- the same UAV could do more than one mission per day;
- the service time τ is the same for each client;
- every mission has a drone with fully-charged battery.

We consider a network N comprising a set of vertices $E_p : \{0, 1, i, j, \dots, C, C + 1\}$ and a set of arcs A , which interconnects the different vertices. C is the number of customers (or parcels to deliver). The vertices 0 and $C + 1$, in E_p , represent the depot. C is the number of addresses associated with the different parcels. The set E_c regroups all the parcels to supply with $E_c = E_p \setminus \{0, C + 1\}$. Each parcel is allocated to one address i and supplied by one UAV k . In this configuration, we have a homogenous fleet of UAVs E_v with K the UAVs' number. This fleet is able to do M missions, $E_f : \{1, 2, n, m, \dots, M\}$.

For our model, we introduce the following parameters and decision variable.

Parameters:

α, β, γ : integer coefficients between $[0, 1]$.

d_{ij} : distance between addresses i and j .

q_i : parcel's mass for address i .

Q_{maxk} : maximum charge carried by drone k .

c_{ijkm} : transport time between the vertices i and j using UAV k during mission m .

τ_{ikm} : the service time for parcel i supplied by UAV k during mission m .

e_i : the earliest time to serve address i

l_i : the latest time to serve address i

T : the allowed flight duration for a drone

A_k : autonomy of UAV k

Decision variables:

X_{ijkm} : binary variable; $X_{ijkm} = 1$ if parcel j will be supplied after parcel i by UAV k in mission m , and $X_{ijkm} = 0$ otherwise.

y_k : binary variable; $y_k = 1$ when drone k is used, or $y_k = 0$ otherwise.

D_{ikm} : the arrival time to address i with UAV k during mission m

θ_{nm} : binary variable; $\theta_{nm} = 1$ if mission m is before mission n , and $\theta_{nm} = 0$ if mission m is after mission n .

z_{ijkn} : the charge carried by the drone k between i and j .

2.2. Mathematical Model

In this part, it is imperative to remind that the proposed model respects the charging battery strategy that we propose: 100% battery for each mission. This means that, whatever is the rest of the battery capacity after a mission, the battery should be charged to 100% of its capacity for every mission. The drone operator should provide the sufficient battery items.

Through an analytical model, our objective consists of minimizing simultaneously the total distance resulting from served parcels, the total used drones and the total batteries used during these missions, in Equation (1).

The analytical model is presented below:

$$\text{Min} : \alpha \sum_i^{C+1} \sum_j^{C+1} \sum_k^K \sum_m^M X_{ijkm} d_{ij} + \beta \sum_k^K y_k + \gamma \sum_j^C \sum_k^K \sum_m^M X_{0jkm} \quad (1)$$

$$\sum_{k=1}^K \sum_{i=0}^{C+1} X_{ijkm} \leq 1, \forall j \in E_c, i \neq j, \forall m \in E_f \quad (2)$$

$$\sum_{i=0}^{C+1} \sum_{j=0}^{C+1} q_i X_{ijkm} \leq Q_{maxk}, \forall k \in E_v, \forall m \in E_f, i \neq j \quad (3)$$

Constraint (2) ensures that one parcel (designed by vertex i) is supplied by only one UAV k . Constraint (3) indicates that the sum of the parcels' weights carried by one UAV k does not exceed its maximum capacity Q_{maxk} .

$$\sum_{i=0}^C X_{ijkm} = \sum_{i=0}^C X_{jikm}, \forall j \in E_c, \forall k \in E_v, \forall m \in E_f \quad (4)$$

$$\sum_{j=1}^C X_{0jkm} = \sum_{j=1}^C X_{jC+1km}, \forall k \in E_v, \forall m \in E_f \quad (5)$$

Constraints (4) and (5) eliminate sub-tours and guarantee that in every vertex, except Vertices 0 and $C + 1$, there is one entry and one exit.

$$\sum_{i=0}^{C+1} \sum_{j=0}^{C+1} (c_{ij} + \tau_i) X_{ijkm} \leq T, \forall k \in E_v, \forall m \in E_f \quad (6)$$

$$e_i \leq D_{ikm} \leq l_i, \forall i \in E_p, \forall k \in E_v, \forall m \in E_f \quad (7)$$

$$(D_{ikm} + ((c_{ij} + \tau_i) X_{ijkm})) \leq D_{jkm} + T(1 - X_{ijkm}), \quad (8)$$

$$\forall i, j \in E_p \text{ with } i \neq j, \forall k \in E_v, \forall m \in E_f$$

$$D_{C+1km} \leq D_{C+1kn} + 2T(1 - \theta_{nm}), \forall m, n \in E_f, \forall k \in E_v \quad (9)$$

$$D_{C+1kn} \leq D_{C+1km} + 2T(\theta_{nm}), \forall m, n \in E_f, \forall k \in E_v \quad (10)$$

With Constraint (6), the time required to realize a route must be lower than the maximum duration allowed to fly T per mission. Constraint (7) indicates that the arrival time to parcel address i must be within its time window $[ei, li]$ for each vertex i , and Constraint (8) indicates that the sum of the arrival time in i , service time τ_i and the travel time between i and j is at least equal to the arrival time to address j (the address served after i). To avoid a different UAV arriving at the same time to the depot, we add two constraints, (9) and (10). These constraints avoid the simultaneous arrival of the same UAV k . For this reason, we use the decision variable θ_{nm} to determine if mission n is before mission m and, as a consequence, the arrival time to the depot $(C + 1) D_{C+1kn}$.

$$X_{0jkm} \leq y_k, \forall k \in E_v, m \in E_f, j \in E_c \quad (11)$$

$$y_k \leq \sum_j^C \sum_m^M X_{0jkm}, \forall k \in E_v \quad (12)$$

Constraints (11) and (12) ensure that the decision variable y_k (which indicates if the drone k is used or not) is positive and must not exceed the sum of missions performed by drone k indicated by the sum of the departure arcs X_{0jkm} . They impact essentially the objective function in order to reduce the fleet size.

$$\sum_i^C z_{ijkm} - \sum_{l=1}^{C+1} z_{jlkm} = q_j \sum_{h=1}^{C+1} X_{jhkm}, \forall j \in E_c, k \in E_v, m \in E_f \quad (13)$$

$$z_{ijkm} \leq X_{ijkm} * (Qmax + 1), \forall i, j \in E_c, k \in E_v, m \in E_f \quad (14)$$

$$z_{ijkm} \geq 0, \forall i, j \in E_c, k \in E_v, m \in E_f \quad (15)$$

$$z_{i(C+1)m} = 0, \forall i \in E_c, k \in E_v, m \in E_f \quad (16)$$

To calculate the energy consumption during the mission, we should determine the cumulative load transported by the drone. We introduce a decision variable z_{ijkn} that calculates the cumulative charge that the drone transports between address i and address j .

When the drone visits address i , it delivers the parcel weighted q_i , as explained through Constraint (13). As a consequence, the load decreases during the mission, and the drone returns to the depot empty (16).

We make sure that the cumulative charge z is higher than zero (when we have a mission, we have a mandatory minimum of one parcel to deliver) and less than the maximum weight allowed for the drone $Qmax$, Equations (13)–(15).

The decision variable z helps us to determine the required energy to consume during a mission as shown in Constraint (17).

$$\lambda \left[\left(\sum_{i=0}^C \sum_{j=1}^{C+1} z_{ijkm} d_{ij} \right) + \left(\sum_{i=1}^C \sum_{j=1}^{C+1} m_{drone} d_{ij} X_{ijkm} \right) \right] \leq A_k * 0.8, \forall i \in E_c, k \in E_v, m \in E_f \quad (17)$$

The origin of the expression related to Constraint (17) comes from the following expression according to [19,38]:

$$\frac{(m_p + m_v) \vartheta * g}{(\eta r)} + p \quad (18)$$

This expression is an approximation of the power consumption in kW for a drone. This formulation highlights four parameters related to the UAV: the payload m_p represented by different parcels that the UAV can carry, the UAV speed ϑ in km/h, the gravity g , the lift-to-drag ratio r and the power transfer efficiency for motor and propeller η ; the consumption of the rest of the electrical equipment in the vehicle is insignificant in our study. The constant part of this formula is replaced by λ .

In the next section, we introduce the analysis realized from the analytical model with the drone MD4-1000 of Microdrones. We divide the objective function (1) into three sub-functions to highlight the different targets. This division treats the impact of the different sub-functions in the total of the traveled distance, energy consumption, fleet size and the battery set size.

- minimize the distance with $[\alpha = 1, \beta = 0, \gamma = 0]$
- minimize the number of used drones $[\alpha = 0, \beta = 1, \gamma = 0]$
- minimize the number of used batteries $[\alpha = 0, \beta = 0, \gamma = 1]$

3. Case Study: MD4-1000 Drone Fleet

3.1. The Instances Bound

In this part, we plan to set up the instances related to our analysis. Through this, we want to define the limit of numerical study. We will base our analysis on MD4-1000 technical data illustrated in Table 2 and computer data as inputs for customers' address, parcel weight, time windows, etc.

Table 2. Technical parameters of the drone MD4-1000.

Parameter	Value
Speed (m/s)	13
Range (km)	1
Structure mass (kg)	3.35
Maximal take-off mass (kg)	5.55
Maximal loaded mass (kg)	1.2
Battery	22.2 V, 6S2P 13.Ah LiPo
Endurance (min)	70

The distances:

Distances are managed randomly between each customer and the repository.

Therefore, we have a diagonal matrix (X, X) , where $d_{ij} = d_{ji}$ with $d_{ii} = 0$.

Referring to the laws that regulate the use of drones, the range of a drone must not exceed one kilometer, which means that customers should be within a radius of one kilometer. Our distances vary in the following interval: $[0, 1 \text{ km}]$.

From the technical characteristics of the MD4-1000 drone of the company Microdrones, we opt to apply the rule flying 80%. This rule summarizes that during each flight, the drone must consume only 80% of its autonomy.

According to the characteristics, the endurance of the battery is 70 min, and with the rule of 80%, the maximum flight time is 56 min. With an average speed of 13m/s, a drone can fly 43 km empty for 56 min.

This duration represents the maximum period of a clear mission.

We chose to use the average speed to make an approximation between the speed of climb and the cruising speed.

Indeed, this approximation comes to simplify the speed variation during the flight. Through the previously explained configuration, we can deduce that the maximum distance between two clients is 2 km. Using the maximum distance traveled empty, we can deduce at this point that a drone can visit 20 empty customers.

Time parameters:

Based on the shortest day of the year and referring to the regulation, the total flight duration allowed is around 6 h. We can, at this stage, determine the maximum number of missions. The drone can perform empty during a day: six empty mission per drone and per day.

In this analysis, we take the same time window for both customers and the deposit window. We suppose that the delivery service is performed during the day. However, the model presented below can consider, without any modification, different time windows, adding consequently more constraints, yet making the model more realistic.

The capacity of the drone:

By default, each drone can use a battery for each mission performed. The maximum number of batteries that could be on the site must respect the following formula with K is the number of the drones and M_k is performed missions by one drone during one day:

$$\text{nbr batteries}_{\text{maxi}} = K * M_k \quad (19)$$

For the md4-1000 drone model, the payload is 1.2 kg. This is the maximum capacity a drone could carry. The mass of the drone and the vacuum battery is 3.35 kg. During a mission, a drone could serve at least one client, whose capacity of charge can vary between $[0, 1.2]$ kg.

$$\sum_{i=1}^C m_i + 3.35 \leq 5.55 \text{ kg}, \quad \forall i \in E_c, k \in E_v, m \in E_f \quad (20)$$

This Equation (20) came to, in addition to Equation (3), supervise the loaded parcels. The most limited case is that the drone delivers to one customer with a 1.2-kg package during a mission.

The number of drones:

The number of drones made available must ensure the delivery to all customers without exception.

From the limit case, customers choose the delivery slots. This case is present in several sites like making medical appointments or reprogramming the delivery of parcels at home. The number of drones is based on the number of customers divided by six.

3.2. Numerical Results and Discussions

Here, we developed a program in FICO XPRESS to validate and explore the proposed mathematical model. We had five sets of $[5, 10]$ customers. We focused on the variation of the time windows from $[0.1, 0.5]$ h in order to evaluate three different objectives: the fleet size, the traveled distance and the energy consumption through different objectives shown in Equation (1). Our analysis highlights three parts of this sizing objective function independently:

- A, the minimization of the traveled distance with $[\alpha = 1, \beta = 0, \gamma = 0]$
- B, the minimization of the number of the drone used with $[\alpha = 0, \beta = 1, \gamma = 0]$
- C, the minimization of the number of the battery used with $[\alpha = 0, \beta = 0, \gamma = 1]$

The analysis will be based on the simulation of each objective and the discussion about the impact of time windows' variation in sizing the fleet, determining the number of the batteries that the operator should have.

3.2.1. The Impact of the Time Window with the Traveled Distance Minimization (Case A: $[\alpha = 1, \beta = 0]$ and $\gamma = 0$)

In this part of the analysis, we want to determine the impact of the time windows in the traveled distance performed by the fleet of drones to deliver parcels during a day.

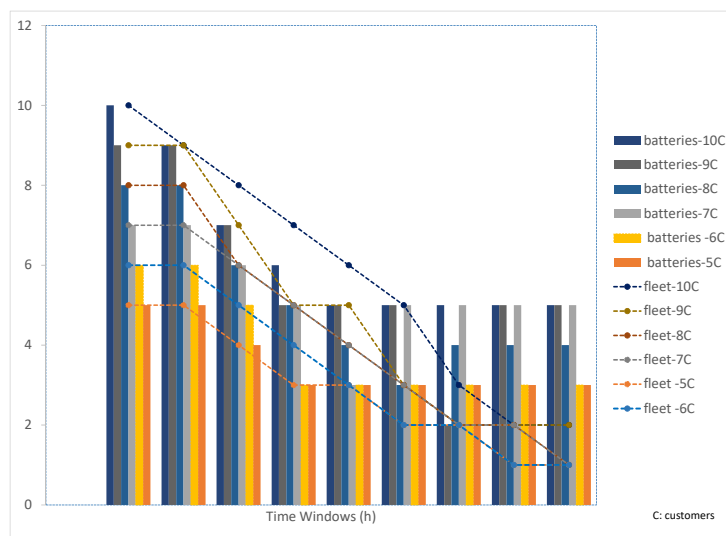
Through the simulation of different scenarios related to the different time windows, we concluded that the traveled distance decreases when the time windows increases.

In fact, during short time windows, the operator has to use the maximum of the drone to deliver parcels. As a consequence, the traveled distance is important, as well as the number of performed missions, the number of used batteries and also the global quantity of consumed energy.

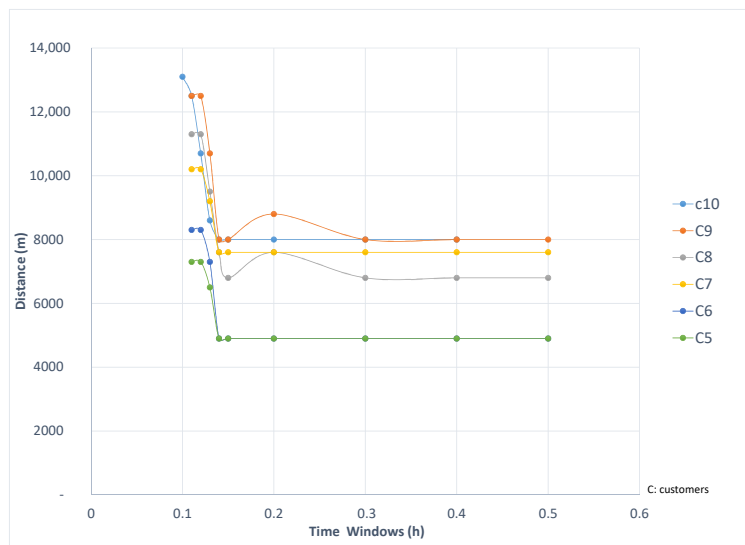
Starting from a certain value of a time window, the traveled distance and the energy consumption value have a stability phase with constant values. This value represents a minimum limit that the fleet of drones can have to deliver to a defined number of customers.

As shown in Figure 3, the evolution of the traveled distance and the energy consumption are correlated. It reflects the link between traveled distance and the energy. In fact, the energy formulation is proportional to the traveled distance and the mass loaded (Equations (16) and (17)). The expansion of those two parameters together impacts at the same time the energy consumed by drones in the delivery missions.

We conclude that delivering in a short time windows requires an important number of batteries in accordance with the battery charging strategy setup: 100% charge for each battery by a drone and by a mission. This analysis helps the drone operator to provide a minimum of the number of drones and how many batteries he/she should have at his/her disposal.

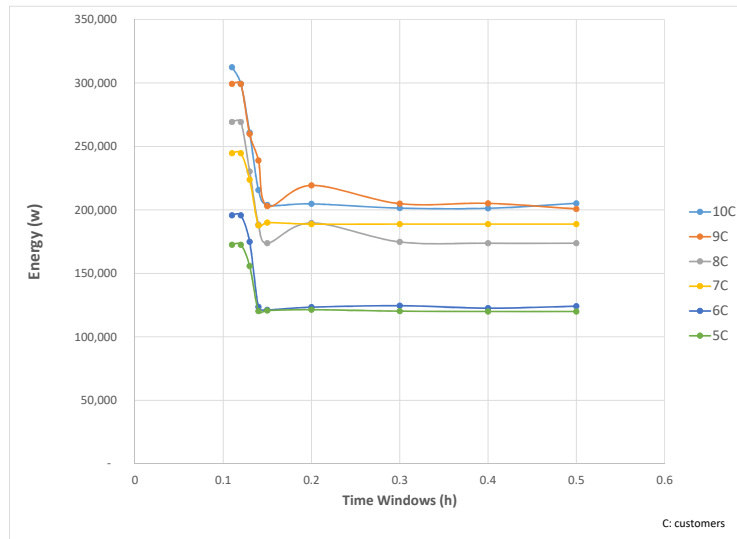


(a)



(b)

Figure 3. Cont.



(c)

Figure 3. Traveled distance minimization: the impact of the time windows on the fleet size, traveled distance and energy consumption. (a) Fleet and batteries’ size; (b) traveled distance; and (c) energy consumption.

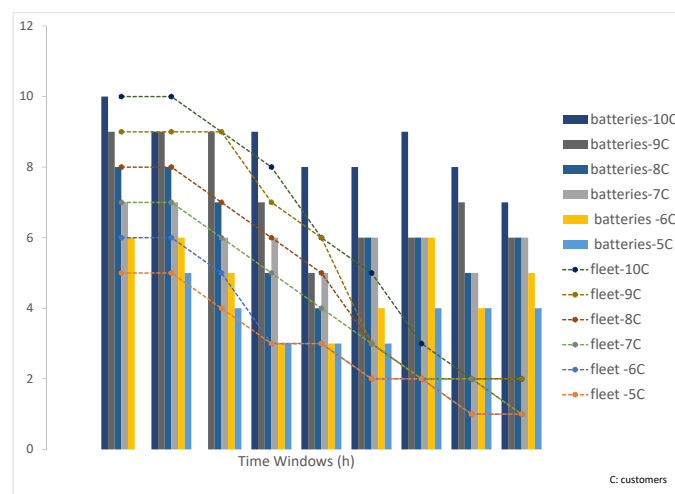
3.2.2. The Impact of the Time Window with Fleet’s Size Minimization (Case B: $[\alpha = 0, \beta = 1$ and $\gamma = 0]$)

In Case B, we focus principally on the minimization of drones to deliver a set of customers in a defined time window. This time window is unique for the delivery operator and all the customers. Counter to the previous simulation, the traveled distance and the energy consumption do not have the same evolution as in Case A.

Since the objective is only to minimize the fleet size, the distance, as well as the energy do not decrease and stabilize as represented in Figure 4.

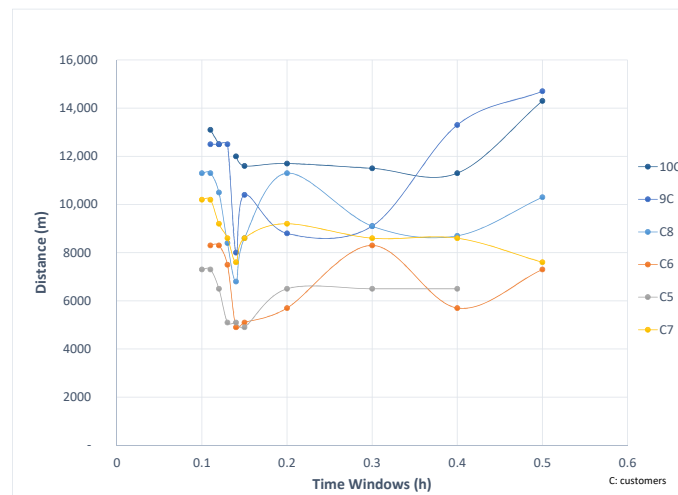
Minimizing the fleet of the drone does not automatically mean the minimization of the number of battery sets for the energy consumed to deliver customers.

In fact, the minimization of the fleet size forced the different drones to perform many missions. Thus, the number of used batteries will be more important than in Case A.

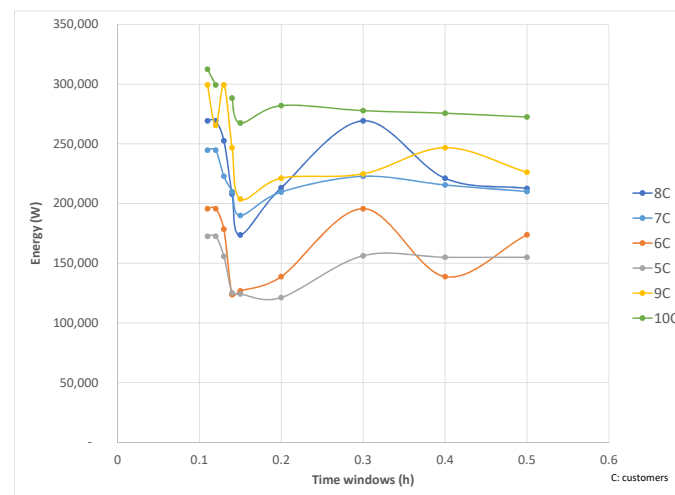


(a)

Figure 4. Cont.



(b)



(c)

Figure 4. Fleet size minimization: the impact of the time windows in the fleet, batteries' sizing, traveled distance and energy consumption. (a) Fleet and batteries' size; (b) traveled distance; and (c) energy consumption.

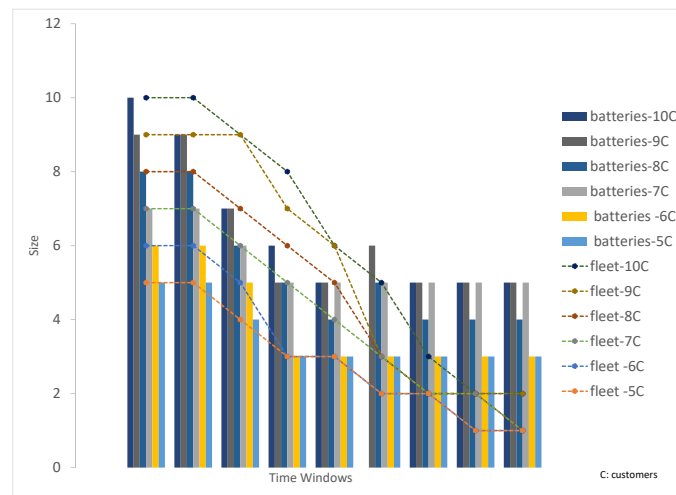
3.2.3. The Impact of the Time Window with Batteries' Size Minimization (Case C: [$\alpha = 0$, $\beta = 0$ and $\gamma = 1$])

In this part of the simulation, we are targeting to reduce the number of batteries needed to perform the delivery missions.

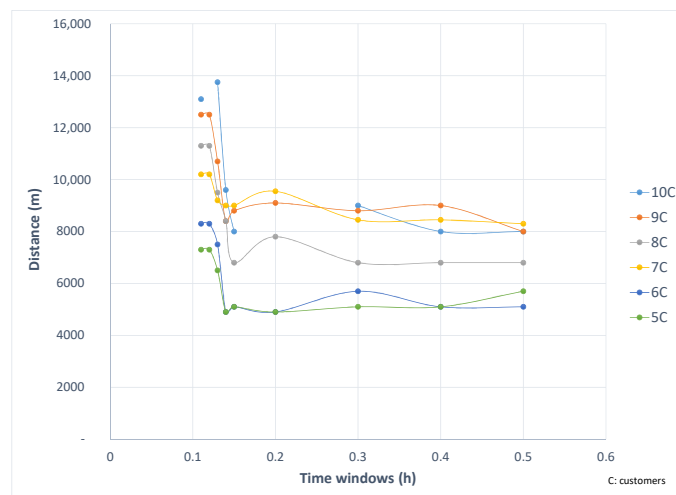
In this scenario, minimizing distance or drones is not a priority. According to the battery charging strategy, batteries are linked to the minimization of the number of missions to perform.

In this step, the operator will have to deliver to a maximum of customers by a mission in order to reduce the performed missions and consequently used batteries.

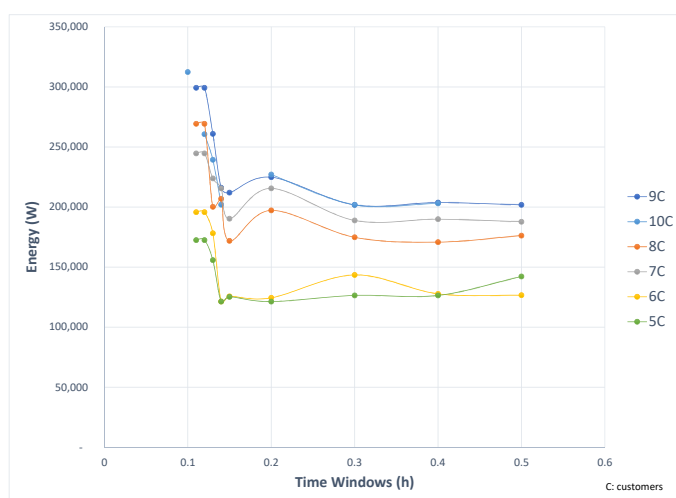
We noticed through the results (see Figure 5) that the number of batteries needed may exceed the fleet's size. As an example: to deliver in 30 min to five customers, the operator should have, at a minimum, one drone and three batteries. These requirements respect the defined charging strategy previously mentioned (each drone should have a 100% charged battery before every mission). In addition, we remarked that minimizing the battery set does not impact the minimization of the energy consumption. Thereby, missions should deliver to a maximum of customers, which increases the loaded charge per drone and the traveled distance (see Equations (16) and (17)).



(a)



(b)



(c)

Figure 5. Battery set minimization: the impact of the time windows in the fleet, batteries' sizing, traveled distance and energy consumption. (a) Fleet and batteries' size; (b) traveled distance; and (c) energy consumption.

3.2.4. Classification of the Different Sizing Objectives

After analyzing the three cases, we classified them based on their impact on different indicators: traveled distance, fleet size, energy consumption and battery set size. We defined a ranking scale from 1–3 to determine the impact of each case: 3 means that the impact is important, while 1 means that the impact is minor. As an example, Case B has the longest traveled distance compared to Cases C and A, while Case A has the smallest energy consumption. Table 3 summarizes this classification.

Case A shows that, by minimizing the traveled distance, the energy consumption is reduced compared to the other cases, while Case B shows that, by reducing the fleet size, the energy consumption is at its highest value. While reducing the fleet size may be advantageous in the short term, especially at the beginning of the activity, the operator will have a significant cost related to energy consumption and the large size of the battery set in the long term. In addition, new issues will arise if Case B is chosen: high frequency for the recycling and purchase of batteries.

The classification approach helps the drone operator to decide on the cases that should be kept in order to handle sustainable issues like energy consumption or limiting the number of batteries used.

Table 3. Classification of the sizing objectives according to sustainability indicators.

	Traveled Distance	Battery Set Size	Energy Consumption
Case A	1	1	1
Case B	3	3	3
Case C	2	2	2

4. Conclusions and Perspectives

The potential that the delivery with drones for the last kilometer is developing encourages investors to establish a new form of delivery. For this reason, in this paper, we have presented a sizing problem related to civilian drone delivery activity in an urban area. Treating this new issue will eventually help investors to better promote their activities.

We have also presented an analytical model, which resolves a capacity delivery problem with a time window constraint. The integration of an energetic formulation represents the particularity of this model, and based on it, the drone operator can determine the quantity of needed energy to provide together with the number of batteries to use.

The model is based on three different objectives joined together: the minimization of the distance, the number of drones and the number of batteries used. This model is based on a defined battery strategy that we propose: 100% of battery capacity for each mission performed by a drone. According to this strategy, the drone operator tries to minimize the three objectives in order to reduce as much as possible the cost. To highlight the impact of these parts, we proposed to divide our analysis into three cases focusing on each objective separately.

The first Case A shows that the minimization of the traveled distance as a function of the time window decreases the fleet size, while the batteries' size remains important. The energy consumption, as well as the traveled distance, has a stabilization phase, which represents the minimum requirements.

In the second Case B, we chose to reduce the number of drones. This option does not especially decrease the traveled distance or the energy consumption. Besides, the number of needed batteries is still important compared to the first case for the same time window delivery. We have many missions per drone with a maximum of customers to visit. As a consequence, the operator charges many sets of batteries, and the traveled distance is no longer reduced.

The last Case C aims at minimizing only the number of used batteries. According to the charging policy, every mission requires one fully-charged battery. Therefore, during one mission, the drone visits a maximum of customers. The traveled distance and the energy consumption have approximately the same evolution as the first case of the analysis.

Through these different simulations, the drone operator can evaluate his/her fleet and battery sizes and the necessary energy consumption to deliver a defined set of customers during a defined time window.

Once all the different cases were analyzed, we presented a classification approach to evaluate which case was more advantageous in terms of energy consumption or also in terms of the number of batteries used. This approach helps to show the impact of each objective and guide the operator to choose his/her goals to resolve sustainable exigencies.

For future works, addressing a balance between the three different objectives seems to be interesting especially in terms of costs. Comparing the charging strategy with other strategies will help the operator to choose the adequate way to charge the batteries and if the allocation of batteries should be reviewed to release a minimum charging task. In addition, using real data will help to have a more realistic cost evaluation.

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