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Topology Effects in Drone Parcel Delivery

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Abstract

Despite the positive sustainability prospects of drones, their flight range is compromised due to their limited battery capacity and the payload of delivered parcels. An alternative to address this challenge is the placement of charging stations where drone batteries are recharged to expand their flying range. The aim of this work is determining the number and location of drone charging stations for topology-dependent scenarios: rural areas and densely populated urban areas. To the best of the researchers' knowledge, there is currently no existing study in the literature that specifically investigates the impacts of topology on drone-assisted delivery. This study focuses on designing drone assignment strategies through optimization-simulation, aiming at minimizing charging station installation costs and operational costs and as a novelty, drone battery consumption is considered in the model design. Drone delivery order instances with different sizes and spatial distributions are generated to simulate realistic scenarios of demand and evaluate the optimization model to allocate the customer demands to stations and dimensioning drones fleet. Results show that considering parcel weight and flight distance has a significant impact on the performance of drone allocation to stations and highlight the effects of topology in the implementation of a drone-assisted delivery network.

Keywords: Drone delivery; Charging station infrastructure; Facility Location Problem; Energy consumption

1. Introduction

The ongoing advancement in technology have expanded the mobility options of unmanned aerial vehicles (UAV), capturing the interest of the researchers worldwide. Even if last-mile delivery of goods made by drones is considered to be in its experimental phase, drones represent one of the most promising technologies with successful trials of international enterprises such as Amazon, that announced their newest Prime Air drones will deliver to customers by the end of 2024, in three U.S. locations as well as cities in Italy and the UK (Amazon, 2023). As Zou et al. (2023) highlight in their work, compared with conventional delivery vehicles, drone delivery offers higher delivery speeds, avoiding traffic jam problems, flexible throughput capacity by adjusting fleet sizes and lower operating costs than courier delivery systems.

Drones often represent the unique option to reach distant areas and, thus, drones have an increasing potential to be used from surveillance and monitoring to transportation applications to widen the accessibility to rural and isolated areas. As Sham et al. (2022) mention in their research, accessibility is a fundamental prerequisite for sustainable development and people living in rural areas face major challenges due to long distances between the community and the nearest facility. Logistic processes become complicated in these areas and as a consequence, these areas suffer from inadequate access to basic services, transport and facilities, resulting in territorial and socioeconomic marginalisation.

Thus, having in mind the previous considerations, the aim of this work is to design a simulation-optimization model which finds the optimal number of drone hubs for two scenarios: (i) densely populated urban areas and (ii) sparse rural areas. The problem considers the following drone delivery system aspects: (a) limited battery and payload capacity of drones, (b) limited flight endurance and range and (c) volatile delivery order scenarios. Therefore, the novelty of this research is that our model considers battery energy consumption during UAV movement. Moreover, we identify the location and size of the stations, dimensioning the drone fleet needed to attend the demand of the customers assigned to each station. To the best of our knowledge, there is currently no existing study in the literature that specifically investigates the impacts of topology on drone-assisted delivery.

Next section presents a review of relevant literature about UAV technology, and optimization and simulation approaches. Section 3 describes the proposed methodology and displays the computational experiments and Section 4 reveals the obtained results. Finally, Section 5 highlights the main findings, and concludes the analysis.

2. State of the art

Drone applications extend over a wide range, from monitoring such as in previously published researches (Praschl and Schedl, 2023; Farina et al., 2021), or humanitarian logistics as in Ghelichi et al. (2022), to urban transportation and delivery, as regards to this study. The primary challenge faced by UAVs is related to battery limitations. As showcase in the existing literature, this limitation can be mitigated through at least three methods: Firstly, the drone-truck collaboration (Gonzalez-R et al., 2024); secondly, the dynamic landing zones, which employ public transportation vehicles, such as roof-top of buses, for drone assistance (Moadab et al., 2022). For instance, Deng et al. (2023) propose a novel routing and scheduling algorithm for drone delivery considering the fixed schedules of public vehicles. As proposed in this paper, the last approach is the placement of charging stations (CSs) or service centers where drone batteries can be replenished. Given a large amount of customers that has to be served in a large area, a battery charging need will show up. Charging stations guarantee longer flying time and are utilized as platforms where drones land and have their batteries changed or recharged Raivi et al. (2023).

In the literature, a great range of works tackles the last-mile delivery problem with drones addressing vehicle routing problems for small sized and uniform drone fleets. Nevertheless, in practice, delivery companies assemble fleets of drones considering heterogeneous configurations and characteristics (speed, endurance and energy supply technique) to satisfy various customer package demands as Wang et al. (2023) presents. Thus, this study aims to in-depth research on how to deliver packages via drones efficiently through charging station (CS) deployment taking into account the varying flight endurance and load. Similarly, Bruni et al. (2023) introduce the Drone Latency Location Routing Problem, which combines Logistic Fulfillment Center selection and drone routing considering load-dependent drone energy requirements.

3. Materials and Methods

3.1. Problem formulation

This section presents the integer problem (IP) to determine the configuration of the drone hubs, determining their location, the allocation of customer demand to stations and the fleet of drones in each CS. We extend the classic Coverage Facility Location Problem (CFLP) by optimally deploying the drone hubs in a parcel distribution system with a fleet of drones operating with different payloads and maximum flight ranges.

This model is defined over the set of nodes $i \in \mathcal{I}$ and $j \in \mathcal{J}$ representing the potential locations for drone CS infrastructures and the potential customer demand points having demand w_j (measured in kg), respectively. The notation, variables, and parameters are described in Table 1 whereas the mathematical model is contained in the Equations (1) - (6).

Table 1. Model variables and model parameters.

Variable	Description
y_i	Binary variable valued 1 if CS $i \in \mathcal{I}$ is open, 0 otherwise
x_{ij}	Binary variable valued 1 if customer $j \in \mathcal{J}$ is assigned and served by station $i \in \mathcal{I}$, 0 otherwise
u_{ij}	Binary variable valued 1 if customer $j \in \mathcal{J}$ is unattended and not assigned to station $i \in \mathcal{I}$, 0 otherwise
Parameter	**Description**
sc_i	Set up cost of a charging station $i \in \mathcal{I}$
M	Penalty for unattended demand
pe	Price of electricity in euro per kwh
r_j	Flight range of drone for demand of customer $j \in \mathcal{J}$
w_j	Weight of demand of customer $j \in \mathcal{J}$ measured in kg
eu_j	Energy consumption per km traveled in Wh/km
d_{ij}	Distance from customer $j \in \mathcal{J}$ to a CS $i \in \mathcal{I}$ in km
c_{ij}	1 if distance $d_{i,j}$ from customer node $j \in \mathcal{J}$ to a charging station $i \in \mathcal{I}$ is smaller than r_j, and 0 otherwise
ND_i	Maximum number of drones that a CS $i \in \mathcal{I}$ can host

$$Min \quad \sum_{i\in\mathcal{I}} sc_i \cdot y_i + \sum_{\substack{i\in\mathcal{I}\\ j\in\mathcal{J}}} M \cdot u_{ij} + \sum_{\substack{i\in\mathcal{I}\\ j\in\mathcal{J}}} pe \cdot eu_j \cdot d_{ij} \cdot x_{ij} \tag{1}$$

subject to

$$\sum_{i\in\mathcal{I}} (c_{ij} \cdot x_{ij} + u_{ij}) = 1, \qquad \forall j \in \mathcal{J} \tag{2}$$

$$c_{ij} \cdot x_{ij} \le y_i, \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} \tag{3}$$

$$\sum_{j\in\mathcal{J}} c_{ij} \cdot x_{ij} \le ND_i \cdot y_i, \qquad \forall i \in \mathcal{I} \tag{4}$$

$$\sum_{i\in\mathcal{I}} w_j \cdot c_{ij} \cdot x_{ij} \le p, \qquad \forall j \in \mathcal{J} \tag{5}$$

$$x_{ij}, u_{ij}, y_i \in \{0,1\}, \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} \tag{6}$$

The objective function (1) defines the minimization installation and operational costs together with minimizing unattended demand, that is, maximizing demand coverage. Restrictions considered in the optimization problem sum up to station capacity (4), drone payload capacity (5) and assignment (2, 3) constraints. Expressions (6) define the decision variable ranges.

The power consumed by a drone in a delivery action from facility $i \in \mathcal{I}$ to demand point $j \in \mathcal{J}$ is estimated with statistical methods as described in Equation (7), adapted from Figliozzi (2017), where the relevant parameters are explained in the Table 1:

$$eu_j = \frac{(w_j + m_t) \cdot g}{2 \cdot ld \cdot \eta} + \frac{m_t \cdot g}{2 \cdot ld \cdot \eta} \tag{7}$$

Note that the binary parameter $c_{i,j}$ is used to force the CFLP to only assign potential CS nodes to client nodes that are within the range of a drone r_d, since this is the maximum distance the drone can travel depending on the carried package load (w_j) and the battery capacity (bc) such that:

$$r_j = \frac{bc \cdot V}{eu_j} \tag{8}$$

In order to avoid unfeasibility, a penalty function is added to the objective function consisting of a penalty coefficient M (sufficiently large number) multiplied by an artificial variable $u_{i,j}$, that stands for the unattended deliveries. The travel distances of drones is considered Euclidean. This assumption is employed to estimate the energy consumption of each round trip done by a drone, which is used to calculate the last term of the objective function taking into account the electricity price pe. The price of electricity is fixed to one of the values obtained in March 17th 2024 of €0.1228 per kWh consumed in Spain. The number of drones a station can host is limited to 10 for experimentation for all the stations ($ND_i = 10$).

Finally, the drone-assisted delivery system has the following features:

- If a drone is launched from a node $i \in \mathcal{I}$, it must return to the same point $i \in \mathcal{I}$ after the order delivery.
- A drone can only carry one order per flight, thus it can only go to a customer $j \in \mathcal{J}$ and return back to its home station $i \in \mathcal{I}$ without visiting other customer.
- Drones fly at a constant speed and energy consumption attributed to take off and landing for order preparation and serving are neglected.

3.2. Computational Experiments

In this section, we generate the instances to simulate drone-assisted delivery scenarios under different conditions of demand spatial distribution. All experiments are conducted on a Windows 11 desktop with Intel Core i7-10750H CPU 2.60GHz, and 16 GB of RAM and are solved using IBM®ILOG CPLEX 12.6.2 API for the Java Environment solver in the Anylogic simulation software.

3.2.1. Simulation of Topology Cases

To study the effect of demand dispersion in a drone-assisted delivery system, we simulate various instances of customer orders that will differ in spatial distribution. Two settings will be considered. On the one hand, rural area instances are simulated, considering three cases: small, medium sized, and high populated rural areas. On the other hand, instances simulating urban demand will be created, distinguishing between low-, medium-, and high-density urban areas.

Following the methodology proposed by Tao et al. (2022), the instances of demand nodes and potential locations for drone hubs will be defined as instance (n, m, s, d) and will be generated in a grid $2dx2d$ around a central point, being $2d$ the edge length of the squared grid. The parameter n corresponds to the number of CSs generated in the instance. Stations coordinates will follow a uniform distribution $\mathcal{U}(-d, d)$. These locations will be taken as focal points to generate the customer nodes, where m is the number of customer nodes generated around each station. Customer coordinates follow a normal distribution centered on the focal point and with a standard deviation s.

3.2.2. Parameter Setting

Payload is one of the key factors affecting the flight duration and, therefore, it should be considered in drone scheduling as it impacts on the battery endurance. Note that there will be m orders to be attended. Thus, there are m payloads to be delivered, which are randomly generated from a continuous normal distribution with mean 1 kg and standard deviation 0.4 kg $-\mathcal{N}(\mu = 1, \sigma = 0.4)$. Similarly, the set up cost values for each of the n facilities are also randomly generated, considering a uniform distribution $\mathcal{U}[500, 1000]$.

Drones considered for experimentation are multi-rotor type, which are predominant for delivery purposes. In this particular study, Wing delivery company's (Wing, 2022) commercial drone specifications are applied to the model. Parameters characterizing the drone are shown in the Table 2. Gravity is taken as $g = 9.81\ m/s^2$ for experimental calculation.

To simulate the scenarios of demand, we set the parameters $n, m, sandd$ according to the situation. For rural scenarios, three instances are presented: small $-(50, 1, 1.5, 30)$, medium $-(35, 2, 2, 30)$, and large $-(21, 5, 3, 30)$. The first instance corresponds to the most

Table 2. Wing drone parameters considered for experiments.

Parameter	Description	Wing
ld	Lift to drag ratio	3.5
η	Power transfer efficency	0.67
m_t	Tare weight of a drone without load in kg	3.8 kg
bc	Battery capacity from datasheet in mAh	17000 mAh
V	Voltage of battery from datasheet in V	22.2 V
p	Maximum payload of a drone in kg	1.2 kg

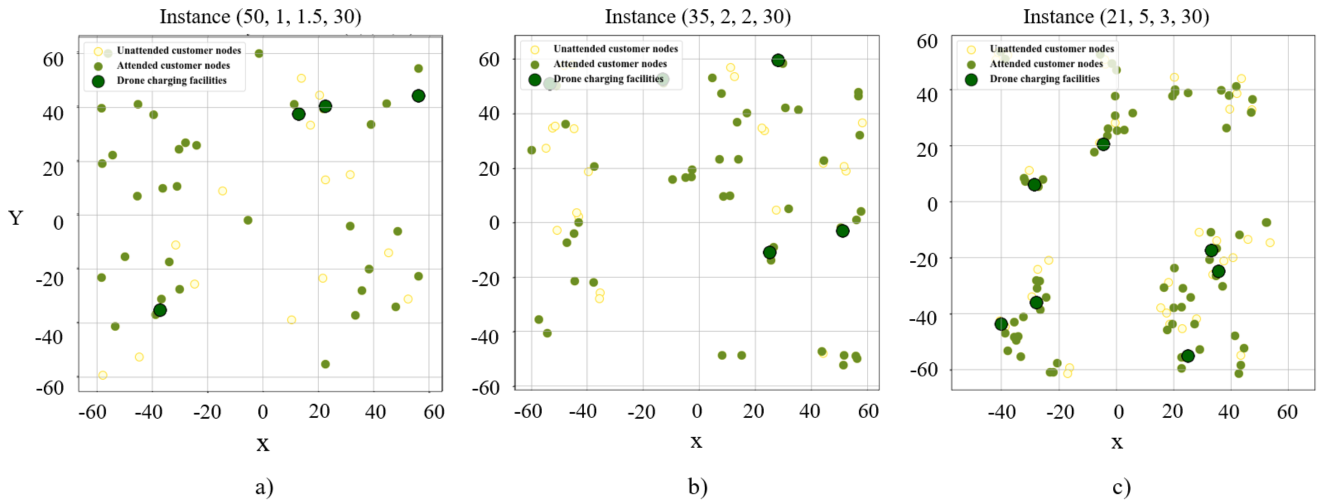

Figure 1. Drone-assisted rural delivery network for a singles run of a) instance (50, 1, 1.5, 30), b) instance (35, 2, 2, 30) and c) instance (21, 5, 3, 30).

sparse scenario, with dispersed towns with little demand, while the third instance corresponds to a scenario where demand is concentrated in towns. The area of the drone-assisted system generated is of 3600 km^2. In other hand, the three instances of urban scenarios are: small -(10, 5, 2, 4), medium -(10, 7, 2, 4), and large -(15, 7, 2, 4). In all cases a 16 km^2 area urban area is considered, and the number of customers and potential CSs is increased in each case, making each instance more populated.

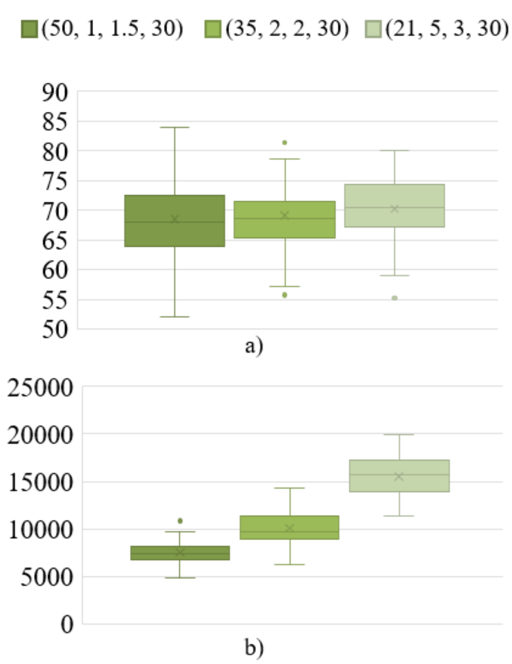

Figure 2. Coverage (a) and cost (b) boxplot for 50 runs of the rural instances

4. Results and Discussion

In this section instances are generated and run 50 times such that, for each demand scenario 50 demand and facility settings are generated and 50 solutions are reported. This section presents the statistics of the solutions obtained from running the model. In all cases, results show the optimal configuration of drone CSs for a given demand of parcels.

4.1. Rural Area Scenarios

For the first instance a sparsely distributed rural demand is considered. This scenario is run for 50 samples to assess the effect of randomness in the input setting. The same methodology has been followed for the other rural scenarios, leading to the results displayed in Figure 2. In all cases, coverage lies around 65% and 75%, being the highest case the one with more concentrated demand nodes (21, 5, 3, 30) and the lowest the one with the most scattered framework. Note that in most cases the reason to leave a client unattended has to do with the payload limitation. Since the simulation of the weight of orders follows the distribution ($W \sim \mathcal{N}[\mu = 1, \sigma = 0.4]$), the probability to generate a weight below the considered drone's payload ($p = 1.2kg$) is of 69.14%, that is, $P(W < 1.2) = 0.6914$. Therefore, the coverage is constrained due to the payload capacity.

Similar trend can be seen in the computed cost of the delivery system, as the higher the population and concentration of demand, the more expensive the cost. Notice that the actual cost of the framework is computed from subtracting the unattended penalty cost from the objective function. These results agree with the number of facilities selected after solving the CFLP, which are featured in Table 3. For the first rural instance 50 runs, the mean of opened stations lies between 3 and 5. This means that out

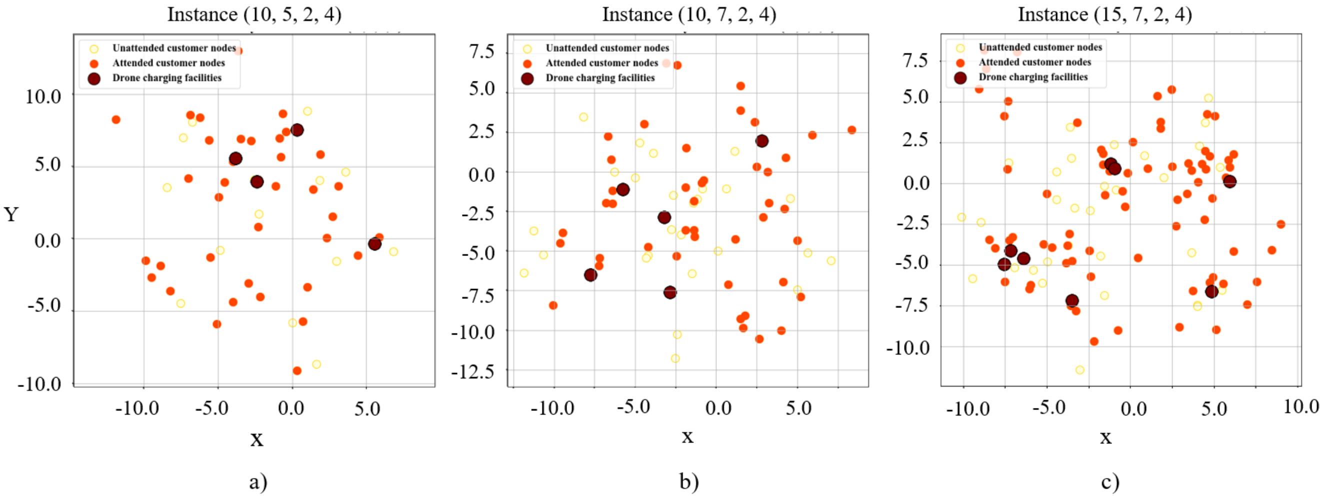

Figure 3. Drone-assisted urban delivery network for a singles run of a) instance (10, 5, 2, 4), b) instance (10, 7, 2, 4) and c) instance (15, 7, 2, 4).

of 50 potential CSs, these are enough to attend around 70% of the demand of the system. Similarly, for the instance (21, 5, 3, 30) the mean of opened felicities is 5, and for the instance (15, 7, 2, 4) that mean up to 8.

After the CFLP is solved, the model, developed in Anylogic simulatin software, generates a GIS map with the obtained framework of demand nodes and opened facilities. Figure 1 displays one sample of each of the rural area instances, depicting the potential locations for stations with bigger dots than the demand nodes. Once the CFLP is solved, the selected stations show up in dark blue and the ones not selected stay uncoloured. When a customer is going to be served by a station, its node turns blue, while when it is unattended the node shows up in red. The setting of the parameters n, m, s and d for generation of the topology of customers and CSs gives as a result the maps in Figure 1. It can be seen how the topology changes from a more sparse, low populated and more potential stations setting that corresponds to instance (50, 1, 1.5, 30), to a less stations and more concentrated situation for instance (21, 5, 3, 30). In particular, if we pay attention to this instance, we can see that there are 21 potential facilities, out of which 8 are opened and there are 5 customer nodes centered around each of these facilities.

4.2. Urban area Scenarios

For urban scenarios, the area of delivery considered is reduced to 16 km^2. In this case, the number of customers considered in each instance mimics the number considered in the rural instances, such that for the first rural and urban instances 50 clients are considered, for the second 70 and, for the third, 105. As seen in Figure 4, the coverage results obtained from running 50 samples of each urban instance follow a similar trend to the ones obtained for rural areas. For most of the runs, coverage results are ranged from 65% to less than 75% and it increases as the population and concentration of the considered demand increases. It should be pointed out that for the urban case, coverage for the small and medium instances has almost the same value and varies across the same range. Whereas, compared with the rural case, the coverage range changes significantly from the small to the medium instance. Note that the demand coverage corresponds to the percentage of attended customers and that depending on the instance the amount of customers to be attended is different and can be either 50, 70 or 105.

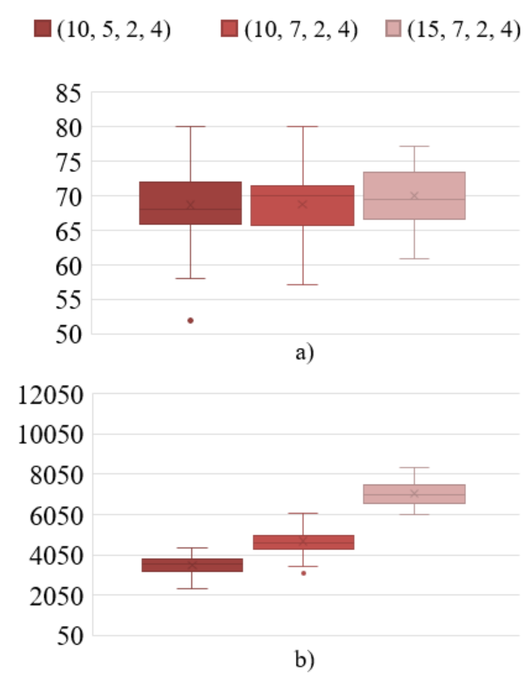

Figure 4. Coverage (a) and cost (b) boxplot for 50 runs of the urban instances

Table 3. Instances mean values

Instance	Time (s)	Cost (€)	Demand Coverage	Open CSs
(50, 1, 1.5, 30)	0.5	7586.52	69.06 %	4
(35, 2, 2, 30)	0.5	10071.51	69.07 %	5
(21, 5, 3, 30)	0.5	15547	70.29 %	8
(10, 5, 2, 4)	0.5	3543	68.72 %	4
(10, 7, 2, 4)	0.5	4761	68.74 %	5
(15, 7, 2, 4)	0.5	7101	70.02 %	8

When it comes to costs and number of selected facilities, it can be appreciated that despite following a similar trend, cost as significantly lower than the ones obtained from rural cases. While for the small urban instance the system cost ranges from €2,000 to €4,000 for small rural instances it lies between €5,000 and €10,000. For medium instances, in urban samples varies from €3,000 to €6,000 and in rural samples lies between €6,000 to €14,000 and finally, for large cases, ranges between €6,000 and €8,000 in urban and €11,000 and €20,000 in rural.

Figure 3 gathers three examples of the obtained CS and customer network from solving the CFLP for the urban instances. Instance (10, 5, 2, 4) corresponds to the less populated city example, with 50 customer demands and 10 potential sitting locations for drone hubs. The solution presented opens 4 stations to serve 37 customers, leaving 13 orders unattended. Instance (10, 7, 2, 4) serves 55 orders out of 70 customers with 6 operative stations. Finally, for the most densely populated instance the solution of the optimization problem leads to 8 open facilities to attend 76 out of 105 customers.

4.3. Analysis of Energy Consumption

The drone adopted for the study is the Wing delivery company's commercial model. The results obtained from running the proposed experiments give that the average energy consumed per km travelled is around 18 km, calculated from equation 7. Similarly, considering the battery capacity of these commercial drones, with equation 8 it can be drawn that the maximum flight range is on average 21 km for these drones, which coincide with the specifications from commercial drone specifications shared by Wing. In this context, Wing announced the introduction of a new prototype to their drone fleet catalogue by the end of 2024 (Wing, 2024). The motivation for designing this new aircraft was that 70% of all US orders can be delivered by one Wing aircraft, while 30% are delivered by two. To optimize their business, they have doubled the capacity of their drone from 1.2 kg to 2.2 kg. This brings new possibilities for future analysis and research, as existing fleets could be complemented with different drone capacities to develop heterogeneous fleet models.

This study considers the optimization of parcel delivery by drones with the integration of charging stations. By formulating an optimization problem aimed at minimizing costs associated with the system setup, operational energy, and customer order fulfillment, we design a cost-effective network of drone hubs. Our model accounted for the limited battery and payload capacities of drones, flight range constraints, and different delivery scenarios, incorporating the selection of optimal charging station locations and demand allocation. Major players in the delivery sector, including Amazon, Google, UPS, and DHL, are heavily investing in advancing their UAV technologies for everyday operations. Our research aims to support these efforts by providing insights into establishing operational frameworks conducive to widespread adoption of drone-powered delivery solutions. Thus, we introduce an optimization model designed to support decision-making processes in crafting distribution strategies leveraging existing drone technologies.

5. Conclusions

In this study, a Facility Location Problem has been posed to address the design of a drone charging stations network according to the requested parcel demand. There are two major conclusions to be drawn from our work. Firstly, in terms of results, we have found that considering parcel weight and flight distance has a significant impact on the performance of drone allocation to stations, as it has a direct effect on the battery consumption and therefore, the flight range. These findings highlight the importance of adjusting operational parameters based on drone payload and range to optimize the delivery system. Secondly, our research highlights the effects of topology in the implementation of a drone-assisted delivery network. Two different settings have been considered, with the aim to analyze the effect of the demand and facility topology in the delivery system performance. While the majority of existing studies focus on minimizing completion time or total travel distance, considering demand into models presents a significant advantage. Apart from demand dispersion, our model also includes parcel demand estimation, emulating the uncertainty in demand. Lastly, as renewable energy continues to develop towards a low-carbon profile, alternative sustainable transport emerges as a potential solution to this environmental transition. The proliferation of electric vehicles in all their ways (road or air) is leading to a challenge for charging infrastructures and creates the need for expansion to meet the future charging demands of these vehicles.

While our model proved effective in optimizing delivery, certain limitations must be acknowledged. Data limitations, potential inaccuracies, and omitted factors like climate impact and traffic circumstances may have affected our analysis. Future research should focus on overcoming these limitations by acquiring primary data sources and conducting in-field surveys to enhance the accuracy and reliability of models. It must be noted that parameter values selected for our experiments could be easily adjusted according to other scenarios that could be posed in future works. As Dukkanci et al. (2023) emphasize, considering uncertainty generally increases computational difficulty, as in related delivery and location problems. Nevertheless, our model is able to obtain a real-time solution. As drone-assisted deliveries are already being implemented, drone hub facility location considerations are necessary not only for economic purposes, but also for social interest, since drone deliveries play a crucial role in medical supplies and humanitarian relief supply. These deliveries are often time-sensitive and may be affected by uncertain weather conditions and any uncertainty related to delivery logistics. For that, future work will focus on creating a model on which time is also included. In particular, the uncertainty of daily demand will be considered through a simulation framework that estimates the demanded packages that must be delivered in the urban area during a given period of time, such that the number and location of CSs are optimally established to maximize coverage according to the optimization results.

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