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Point-to-point drone-based delivery network design with intermediate charging stations

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ABSTRACT

Drone-based delivery represents a possible way of performing last-mile logistics activities with potential benefits on process efficiency, traffic congestion, and pollution emissions. However, many technological and legislative challenges still have to be overcome. From the technology perspective, the operating range of drones represents a critical aspect. This paper addresses the problem of extending the drones operating range from a network design perspective, in which there is the possibility (already technically feasible) to recharge drones on their journey to their final destinations using suitably located charging stations. This paper proposes a mathematical model and a heuristic method for a network design problem that combines two objectives regarding infrastructural investments (i.e., the number of charging stations to be deployed) and service aspects (i.e., minimizing the travelled distances). The proposed model and the developed heuristic delineate a strategic-level approach to the delivery process using drones.

1. Introduction

The increasing residential demand for urban freight transportation, generated and supported by the flourishing of e-commerce, along with pervasive technologies, urbanization and demographic growth, has spurred the quest for innovative delivery processes (Perboli and Rosano, 2019). Due to the demand upsurge and the chronic traffic congestion affecting modern cities, with its consequences in terms of CO_2 emissions, the interest of the research is moving increasingly towards alternative transport modes as sustainable development of cities must necessarily foresee a reduction of the environmental impact of transport (Gatta et al., 2019). Since CO_2 emissions are directly proportional to the amount of fuel consumed by a vehicle (Bielaczyc et al., 2014), the scenario of using battery-powered unmanned aerial vehicles (UAV or drones for short) for parcel delivery has been stipulated as a possible future development (Hong et al., 2018). This innovation could bring benefits in delivery efficiency and effectiveness, fuel and workforce costs, reduction in transportation-related pollutant emissions, and flexible capacity (Chiang et al., 2019; Shen et al., 2021). One of the first and perhaps most well-known initiatives in this regard is Amazon Prime Air, which promised to deliver parcels via drones (Amazon, 2016).

Among the many challenges to be addressed to establish an effective drone-based delivery service, such as shorter range compared to other vehicles, long recharging time, limited payload, and limited availability of charging stations (Kınay et al., 2021; Kchaou Boujelben and Gicquel, 2019), this paper focuses on the issue of drone's operating range (i.e., the maximum distance that a drone can travel to deliver a parcel to a customer), determined to a large extent by the batteries autonomy and the energy consumption. The

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technological evolution in this area has allowed extending the range of the drone to reach up to 16 km (Hong et al., 2018). However, this range could drop when carrying relatively heavy packages. Several solutions can be devised in order to extend the drone's range. For example, it is possible to locate several departing hubs (i.e. warehouses where goods are stored and from which the drones depart), each covering a delivery area with a size corresponding to the drone operating range (Fig. 1.a). However, this solution may result in a large number of warehouses to fully cover the demand, with conspicuous fixed and inventory costs. Alternatively, it is possible to extend the range of drones by combining them with trucks (Ferrandez et al., 2016; Murray and Chu, 2015), effectively representing moving hubs. Following a similar perspective, Amazon filed a patent for an airborne fulfilment centre (i.e. a flying hub) utilizing UAVs for items delivery (Berg et al., 2016). These examples aim to extend the range of operations of drones and are all based on one or more (moving or stationary) hubs, each carrying inventory. Although the hub-based solutions can represent a viable approach, they imply implementing and managing several hubs with the related inventory.

1.1. Contribution and structure

Similarly to Hong et al. (2018) and Huang and Savkin (2020), this paper addresses the problem of extending the drones operating range from a network design perspective, leveraging on technology advancements that allow for recharging the drones' batteries on-field, when necessary (see Section 2.3 for a discussion about the contribution with respect to the extant literature). In a network with on-field recharge capability, a drone can leave the hub and travel towards the final destination: if the destination is beyond the operating range of the drone, it can land at the charging stations where it can be recharged or the battery automatically substituted with a charged one. Such stations can consist of autonomous structures or equipment integrated into existing structures such as streetlamps or buildings. By strategically deploying a number of these charging stations, it is possible to extend the operating range of the drones to reach farther sites from fewer departing hubs than in the case with only direct deliveries from the hubs (Fig. 1.b).

Such a network of charging stations must be designed considering the costs and constraints implied. In particular, the network design implies the decisions about the number of charging stations and their locations concerning the area to serve. Therefore, this paper proposes an exact, mixed-integer optimization model and a heuristics method to address the design of a drone-based, point-to-point delivery network for parcel delivery with intermediate charging stations (regardless of the technology implemented for charging the batteries) in order to reach all the potential delivery points served by a parcel company. As point-to-point delivery networks arise in numerous applications settings, such as package and mail delivery, communication network, and rail freight shipping (Leung et al., 1990), the ideas proposed in this paper can be extended to other areas as well to provide policy-makers with appropriate methods and models supporting planning processes involving different stakeholders (Le Pira et al., 2017).

This paper explores a speculative scenario that can open new perspectives in the delivery process using drones (as well as other battery-operated vehicles), although not imminent due to technology and regulatory constraints. Indeed, the interest in the broad subject of drone-based delivery networks, which may lead to the possibility of their extensive adoption in the future, requires to be addressed under different, yet currently abstract, perspectives. To this end, the paper is organized as follows: Section 2 analyses the previous research deemed relevant to position this paper's contribution, while Section 3 presents the problem addressed, along with the assumptions and the problem's objectives. Section 4 and 5 illustrate two different approaches to solve the bi-objective models, and compare them on some randomly generated instances. Finally, Section 6 reports on the conclusions.

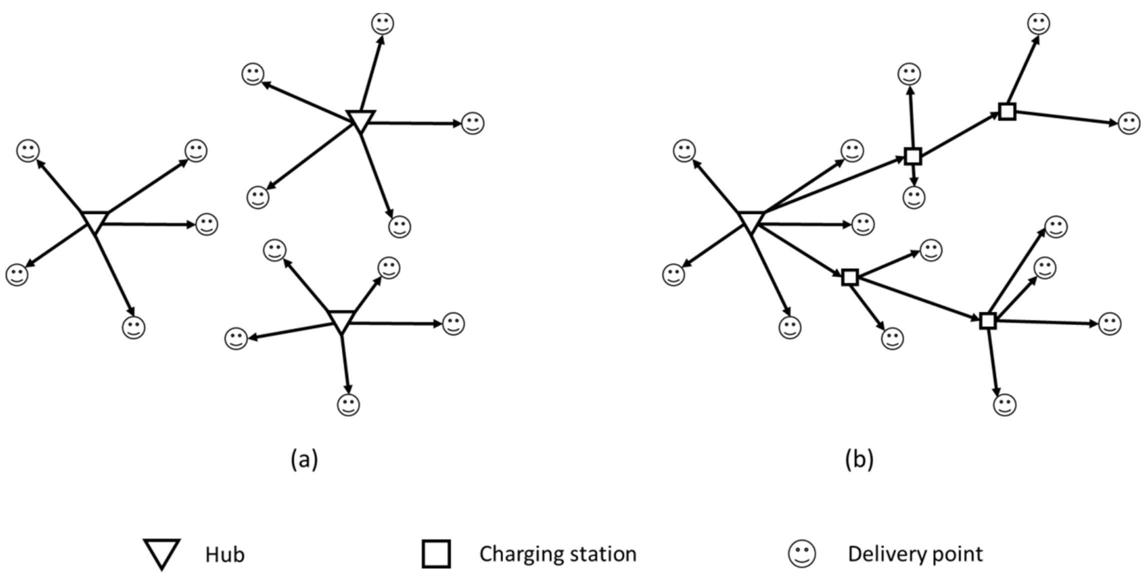

Fig. 1. (a) Drone-based delivery network with direct connections between three hubs and delivery points; (b) Same delivery points network with recharging stations and one single hub.

2. Background and literature review

This section aims at providing the background of the addressed problem, thereby supporting the positioning of this research contribution. To this end, Section 2.1 provides an overview of drone-based delivery models, whereas Section 2.2 concerns charging station location models. The former topic is relatively more recent than the latter, which has been extensively studied, especially for electric vehicles (i.e., cars, buses, freight vehicles) when considering long distances. Finally, Section 2.3 positions the research contributions.

2.1. Drone-based delivery

Modern drones have been used over the years in many fields of application: from large scale metrology applications (Franceschini et al., 2010) and disaster management (Adams and Friedland, 2011) to disease control (Amenyo et al., 2014), from traffic monitoring (Kanistras et al., 2014) to law enforcement and surveillance (Clarke, 2014). Thanks to the spread of e-commerce, many companies have started proposing UAVs for last-mile parcel delivery and, with the growing commercial use, many academics have focused their attention on the topic. The research in this area has been developed in several directions: reliability (Schenkelberg, 2016; Torabbeigi et al., 2018), security (Seo et al., 2016), optimal routing and scheduling (Murray and Chu, 2015; Wang et al., 2017), energy efficiency and battery ageing (Park et al., 2016), inventory management (Xu et al., 2018) to name a few. In recent years, many researchers have also focused on sustainability. For example, Chiang et al. (2019) proposed a mixed-integer green routing model to exploit the sustainability aspects of the use of UAVs for last-mile parcel deliveries, studying the impact in terms of CO_2 emissions. Figliozzi (2017) analyzed UAV and conventional ground vehicles emissions during their lifecycle, showing that UAV deliveries are not more CO_2 efficient than diesel vans when customers are grouped in a delivery route. For these reasons, several recent studies focus on minimizing the long-term operational cost in environmental terms considering the technologies for the recharge swapping (Cokyasar et al., 2021) and calculating the drones energy consumption as a function of the drone speed (Dukkanci et al., 2021).

The general idea is to deliver packages from one location to pre-selected destination points with a fleet of drones. Deliveries can be made via drone-only fleets or multi-modal transport, where UAVs cooperate with traditional ground vehicles (Torabbeigi et al., 2019; Ferrandez et al., 2016). Several papers have proposed this latter mode (i.e., drone-truck systems), where delivery trucks operate as mobile depots from which drones depart for the last-mile delivery. Agatz et al. (2015) studied the traveling salesman problem with drones, where drones must follow the same road network as the trucks. Murray and Chu (2015), instead, formulated an optimization parcel delivery problem, which first constructs travelling salesman truck routes and then substitutes drones that deliver packages to customers and return to the truck down-route, coining the term “flying sidekick travelling salesman problem”. In their paper, Ha et al. (2018) considered a variant of the traveling salesman with drones, where the objective is to minimize operational costs, including total transportation cost and wasting time. By combining theoretical analysis with real-time numerical simulations on a road network, Carlsson and Song (2018) found that the efficiency improvement due to the truck-drone collaboration is proportional to the square root of the ratio between the two vehicles speeds. Raj and Murray (2020) addressed the trade-offs between speed and range considering a single truck and a UAVs fleet. UAV power consumption is a non-linear function of both speed and parcel weight, and flying at high speeds can dramatically reduce flight ranges. The authors addressed this problem by treating speeds as decision variables. A recent survey on drone-truck combined operations can be found in Chung et al. (2020).

Concerning models focusing on the drone-only strategy for delivery, although it has become increasingly attractive for delivery in recent years, there are two critical limits to its practical use: limited battery autonomy and limited payload. Recent literature is addressing these issues. Dorling et al. (2017) proposed a vehicle routing problem that addresses both issues, demonstrating that energy consumption varies approximately linearly with payload and battery weight. Sundar and Rathinam (2014) developed an approximation algorithm and heuristics to solve the fuel constrained UAV routing problem where a drone can refuel/recharge at multiple depots located throughout the delivery region. In their paper, Troudi et al. (2018) discussed the issue of dimensioning the size of the drone fleet, the stock of batteries, and the battery charging strategy based on the delivery forecast. These studies focus on characterizing the energy consumption of drones and fleet sizing, but not in the context of recharging station location.

The network design problem represents an essential yet under-investigated aspect of the drone-based delivery approach. At the strategic level, the design of such a network aims at shaping the strategic supply chain structure, locating the resources required and the main links among them (Song and Sun, 2017), potentially involving high investments. The strategic level refers to the design of a “static” network (Manzini, 2012) (i.e. not time-dependent) where design decisions are not meant to be changed frequently. This decision process is usually performed a few times during the business’ lifecycle or is triggered by substantial changes in the internal and external environments. For example, from a network design perspective regarding last-mile delivery, Deutsch and Golany (2018) have considered the problem of designing a parcel lockers network as a solution to the logistics last mile problem. Instead, considering a drone-based delivery network, Pinto et al. (2020) proposed an optimization model addressing the trade-off between the number of departing stations and the coverage of the demand for a drone-based meal delivery network.

Beyond the drone-based context, the topic of locating the charging station for electric vehicles (more in general, for alternative fuel vehicles (AFV)) has been extensively addressed, as discussed in the next section.

2.2. Locating charging stations

One of the main issues for AFV (and electric vehicles (EV) in particular) is represented by the driving autonomy. For this reason, the optimal positioning of refueling (i.e. charging stations for EV) has been widely studied. Due to the focus of this research, in the remainder, we briefly address the literature concerning EVs, even though sometimes the ideas and findings are applied or discussed with reference to AFVs in general. Therefore, we use terms such as charging stations and battery autonomy in lieu of refueling stations and fuel autonomy.

Over the year, the consensus around *flow-based* facility location models (which represent the charging demand of EVs based on traffic flows on paths from an origin to a destination node) in lieu of *point-based* (or *node-based*) location models (which require the aggregation of charging demand in nodes) has grown significantly since the first work by Hodgson (1990), which introduced the uncapacitated flow-capturing location model (FCLM). The objective of the FCLM is to maximize the total flow demand passing by any one facility positioned on a node along a driver's shortest paths in a network. Subsequently, to include the possibility for multiple stops to complete the journey, Kuby and Lim (2005) developed the uncapacitated flow-refueling location model (FRLM) to optimally locates a set of *p* refueling facilities in a network maximizing the total flow volume captured by a combination of stations. A comparison between the point-based and flow-based approaches is discussed in Upchurch and Kuby (2010).

Concerning the intermediate stations network design, Capar et al. (2013), motivated by the need to develop infrastructure to facilitate the adoption of Alternative-Fuel Vehicles (AFVs), formulated the problem of locating a set of *p* facilities to refuel round trips between origin-destination (OD) pairs while considering the limited driving range of vehicles. Kchaou Boujelben and Gicquel (2019) aim at determining the best locations for a given number of EV fast-charging stations under driving range uncertainty, extending the Flow Refuelling Location Problem (FRLP) (Kuby et al., 2005) in which the EV range is assumed to be deterministically known. Arkin et al. (2019) address the problem of placing a minimum number of battery charging stations at a subset of network nodes so that battery-powered electric vehicles will be able to move between destinations using routes that are provably close to being shortest paths. A rather innovative approach is provided by Dong et al. (2019). They propose a two-step approach for defining the optimal locations of charging points by using a combination of spatial statistics and mathematical programming models. In particular, they associate the demand with workplace population density, travel flows, and densities of three point-of-interest categories (transport, retail, and commercial) and perform a maximal coverage location using a Bayesian spatial log-gaussian cox process model maximising the coverage of EV charging demand by locating a fixed number of charging stations.

A significant stream of research combines routing and location decisions, recognizing the potential that can be exploited if the two decisions are addressed simultaneously. Drexl and Schneider (2015) define the term *location-routing problem* (LRP) as a mathematical optimization problem where at least the following two types of decisions must be made interdependently: (i) Which facilities out of a finite or infinite set of potential candidates should be activated? (ii) Which routes should be built to perform a specific service to a set of customers/demanding points?

In this respect, Schiffer and Walther (2017) present a location routing approach simultaneously encompassing EVs routing and charging stations location to support the strategic decision-making process of logistics fleet operators. The authors discuss the problem from different planning perspectives represented by five different objective functions (i.e. from total driven distance to the number of used vehicles). Koç et al. (2019) developed a heuristic based on the adaptive variable neighbourhood search to solve a vehicle routing problem with shared charging stations to define the location and the technology of the charging stations used by different logistics companies, minimizing both fixed and drivers costs. In Kınay et al. (2021), a mathematical model is introduced to minimize the total cost of locating a given number of charging stations and en-route recharging so that every OD trip on a given transportation network is covered with respect to vehicle range. They introduce the possibility to take deviations from the considered shortest paths to complete the trip. Similarly, Hosseini et al. (2017) extend the FRLP to account for the possibility of customers deviating from their pre-determined shortest path to get refueling services from a network of limited capacity stations.

Lin and Lin (2018) examine the *p*-center flow-refueling facility location problems to locate *p* refuelling facilities such that, for the maximum percentage deviation of all drivers, the occurrence of the worst detour for any driver in a system is minimized. Li-Ying and Yuan-Bin (2015) present a hybrid heuristic incorporating an adaptive variable neighbourhood search to address a multiple charging stations location-routing problem with time windows and capacitated EV. The authors consider different types of charging infrastructures along with the location decision and routing plan. Schneider and Drexl (2017), Drexl and Schneider (2015), Prodhon and Prins (2014) have published literature reviews about location-routing problems and variants.

Finally, when the technology chosen for charging (e.g., slow recharging, fast recharging, partial recharges, battery swap, fixed charging, linear charging, non-linear charging, multiple technologies) have to be considered, the main models existing in the literature related to the location of the recharging stations refer to the recharging technologies and the routing strategies (Koç et al., 2019; Li-Ying and Yuan-Bin, 2015) with an increasing interest in sustainability, energy consumption, and power loss (Pal et al., 2021; Moupuri and Selvajyothi, 2021).

Concerning the specific problem considered in this paper, the most relevant contributions are arguably those by Hong et al. (2018) and Huang and Savkin (2020). In the former, the authors propose a new location model and a heuristic technique for optimally siting recharging stations to support commercial stand-alone drone delivery service in an area with obstacles, combining elements of the Euclidean Shortest Path (ESP), the flow refuelling problem, and the maximal cover location model. The latter proposes a computationally efficient, multi-phase approach to deploy a number of charging stations such that drones can serve a certain percentage of customers in the demand area. We further address these two contributions in the next section.

2.3. Research positioning with respect to the literature

Concerning the discussed body of literature, this paper focuses on a strategic level decision (as defined in Manzini, 2012, see Section 2.1) regarding the number and locations of charging stations required to support the operations of a fleet of drones in performing a parcel delivery service in a given area. The position of the intermediate stations would also determine the routings of the drones, which in turn will affect the objective function, thereby framing this problem as a location-routing problem. In particular, this paper defines the optimal number and location of charging stations that allow battery-powered drones to move between destinations beyond the battery autonomy following defined routes that cover all the demand nodes.

In our understanding, this paper follows and extends the ideas reported in the literature, especially with respect to the work by Hong et al. (2018) and Huang and Savkin (2020). In particular, it extends the former in considering an unknown number of intermediate stations and extends the latter by aiming at finding a compromise between the investment cost (i.e. number of intermediate stations) and the service time. To this end, this study formulates a bi-objective problem.

In summary, compared to the discussed literature, this paper:

- does not assume the number of stations known a priori. Differently from FRLP standard problem (Kuby and Lim, 2005) and related problems, the optimal number of stations is determined by the model;
- aims at defining a network of charging stations connecting customers delivery points to hubs minimizing the service costs (i.e., the total distance travelled by drones), the infrastructural investments (i.e., the number of charging points) or a combination of the two using a bi-objective optimization model;
- explicitly models the trade-off between the number of active charging stations and the lengths of the paths between departing points and destinations in the objective function;
- stipulates a demand coverage constraint, meaning that the demand for service raised by the delivery points must be covered (i.e., reachable) from a hub.

The combination of the above-mentioned points delineates an original contribution that, to our best knowledge, has not been yet addressed in the literature. The following sections of the paper elaborate these contributions.

3. Problem definition

Let us consider a set N of delivery points distributed in a known geographical region. The delivery points are served via a fleet of drones that depart from a set S of existing hubs (i.e., warehouse(s) or store(s) where goods are stored or urban consolidation centers (UCC) supplied by distribution centers in a two-tier network (Perboli et al., 2021)). The drones can either *i*) reach directly the delivery points that are closer to a hub and return, or *ii*) head to a farther delivery point that lies beyond the battery autonomy, thus requiring one or more stops for battery recharge (or substitution with a charged one) along the way to the final destination. Assuming that each hub hosts a charging station, this work focuses on the latter delivery points, explicitly excluding the formers that do not require any intermediate stop, as they can be served directly from a hub. In the remainder, for the sake of the discussion and without loss of generality, the paper refers to *battery recharge* and *charging stations*, regardless of the real technology implemented. The charging stations can be installed in a discrete number of pre-identified possible locations, represented by the set I; this would simplify the problem formulation and avoid issues with infeasible solutions that may arise considering a continuous space for the locations.

The goal is to define the optimal number and location of the charging stations in such a way that it would be possible to connect

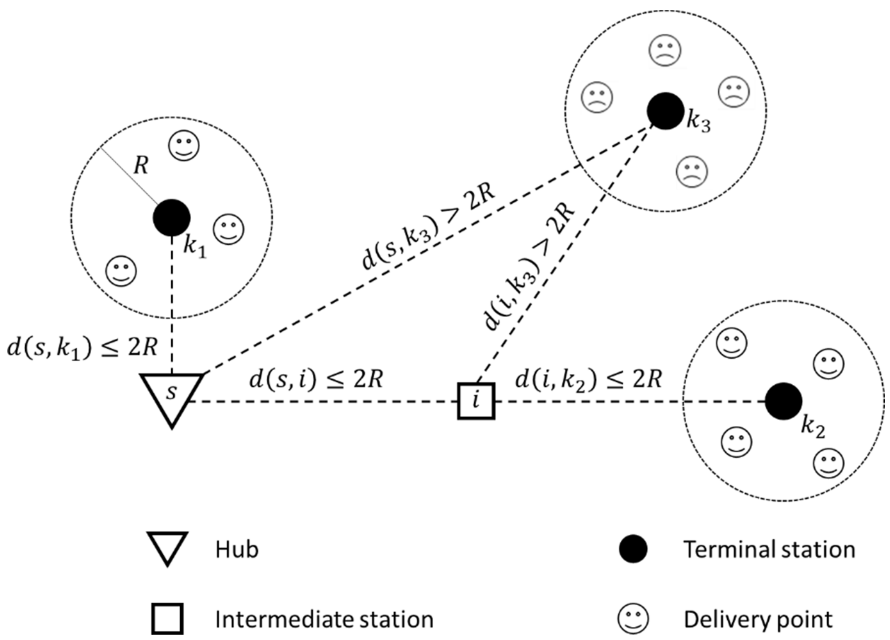

Fig. 2. Network exemplification with one intermediate station (distances not to scale).

each delivery point in N to a departing hub in S via a path traversing one or more charging stations. A path between a hub and a delivery point is defined as a sequence of edges: i) starting at a hub, ii) ending in the delivery point, and iii) passing through (visiting) one or more charging stations. A subset $K \subseteq I$ of locations operate as *terminal charging stations* from which the delivery points are reached directly, while others operate as *intermediate* (or *transit*) *stations* (Fig. 1).

3.1. Assumptions

In designing the network of charging stations, we assume the following operating conditions. Delivery points in N are served from terminal stations in K: the dotted circles of radius R centred in the terminal stations represent the coverage area of the stations, that is, the area reachable from the station under the battery limitations. Each terminal station is connected directly to a hub (i.e. terminal station k_1, excluded in the remainder as previously discussed) or via an intermediate station (i.e. terminal station k_2 via station i). The terminal station k_3 in Fig. 2 is not reachable with the current configuration of the network as it lays beyond the operating range of drones, being $d(s,k_3). > 2R$ and $d(i,k_3). > 2R$ (i.e. the drone does not have sufficient battery autonomy to reach k_3 from s or i). It would require the repositioning of station i or the location of another intermediate station j: for example, a new candidate location j can be identified between s and k_3 such that $d(s,j) \leq 2R$ and $d(j,k_3) \leq 2R$. Notice that in Fig. 2, all distances are considered rectilinear for the sake of simplicity, so covering areas are represented by circles of radius R; however, such an assumption is not required for our proposed approach.

Each drone has an operating range $2R$ allowed by the battery autonomy: that is, with a charged battery, a drone can fly up to a distance $2R$ from the departing point (hub or charging station). Thus, R is the distance of the non-returning point: up to this distance, the drone can fly to the destination and get back to the departing point without recharging. For the sake of this study, the battery discharge is assumed proportional to the distance travelled (Capar et al., 2013; de Vries and Duijzer, 2017). As the actual discharge processes may depend on the weight of the package and other external conditions that are not known a priori (especially at the design stage of the network), we could consider the worst-case scenario where the ranges are at minimum to avoid the risk of drones depleting the battery charge before reaching the next station along the path.

Knowing the destination point, the path to the customer can be defined before the drone leaves the hub. Thus, the route and the intermediate stops can be defined as *a-priori*, knowing the departing hub and the final destination. This means that the drone must make no decision during the delivery task.

Each delivery point is served by one single hub. Even though it may be possible to define a path from many hubs to each delivery point, this paper focuses on the case in which each destination is *allocated* to a single hub, and thus one single path connecting each destination to a hub is required. The case with destination points allocated to more than one hub can be addressed under a network resiliency framework and is, therefore, out of the scope of the current study.

When a drone reaches a charging station, it can start the charging process immediately. The model does not consider congestion issues at the charging station, which is assumed to have enough space to accommodate a sufficiently large number of drones simultaneously. Since both the orders to be delivered and the paths between each hub-delivery point pairs is known a-priori, the scheduling of the arrival at the charging stations and the management of landing, charging, and departure from the charging stations can contribute to the potential congestion issue management. Indeed, the scheduling of the drones' missions can be done offline (i.e. with the complete knowledge of all the orders that should be delivered). The sizing of the recharging places requires a different study involving simulation and can be considered as a further step of the approach proposed in this paper.

Finally, we assume that the technology for rapidly charging/changing the batteries is available. For example, researchers at the Indian Institute of Science have designed charging ports for drones atop streetlights (Sandesh, 2019), similarly to an Amazon patent to recharge drones on streetlamps (Gentry et al., 2016), and Skycharge sells drone charging pads (https://skycharge.de/), to name a few. Therefore, this paper does not deal with the technology-related issues that technology may imply.

3.2. Problem's objectives

In designing the network of charging stations, different objectives are addressed. At the strategic level addressed in this study, it is possible to identify the following two as relevant. The first objective is related to the sum of the lengths of the paths connecting the hubs and the delivery points. It is possible to relate this objective to the minimization of the drones operating cost, under the assumption that (a portion of) the cost depends upon the travelled distances. The second objective is related to the minimization of the number of charging stations installed, under the constraint that all delivery points are covered and connected via a path to a hub. These two objectives can be combined in a multi-objective problem.

One of the simplest ways to deal with a multi-objective problem is *scalarization* (*global criterion method*) (Marler and Arora, 2004). Such a method implies the formulation of a single-objective optimization problem combining its multiple objectives into one scalar function:

$$\min_{\boldsymbol{x}\in\Omega} \sum_{w=1}^{W} \theta_w \bullet f_w(\boldsymbol{x}) \tag{1}$$

where W is the number of objectives, θ_w a parameter representing the "weight" (or a normalizing constant if the objectives are expressed on different scales) of the w-th objective function f_w and Ω the set of feasible solutions for the problem. This case considers two objective functions f_1 as the minimization of the sum of the lengths of the paths, and f_2 as the minimization of the number of active stations. These two objectives are then combined in a single objective function as

$$\min_{x\in\Omega} Z = \theta \bullet f_1 + (1-\theta) \bullet f_2 \tag{2}$$

4. Model formulation

In this section, a mathematical formulation of the problem described in Section 3 is provided. Let us consider a network $G = (\Gamma, E)$, where $\Gamma = S \cup I$ is a set of nodes (with S representing the set of hubs and I representing the set of candidate intermediate stations, as defined in Section 3, with $S \cap I = \varnothing$) and E is the set of feasible, directed edges connecting the nodes in Γ and defined as (being $d(i,j)$ a distance function)

$$E = \{(s,i) | s \in S, I \in I, d(s,i) \leq 2R\} \cup \{(i,j) | i \in I, j \in I, i \neq j, d(i,j) \leq 2R\}. \tag{3}$$

An edge is feasible if a drone can travel along it without an intermediate recharge, that is, if the edge is shorter than $2R$. Infeasible edges due to the presence of obstacles between the origin and destination points are excluded from E.

The formulation hereby provided aims at defining: *i*) which subset $K \subseteq I$ of candidate locations should be activated in order to cover all delivery points in the set N (we refer to K as the set of terminal stations), *ii*) which candidate locations in set I should be activated in order to guarantee the existence of a path from a hub $s \in S$ to stations in K (intermediate stations), and iii) which edges in E should be used to connect each station in K to a hub in S. In doing this, the goal is to minimize an objective function represented by a combination of the sum of the total lengths of the paths and the number of active stations.

In the formulation, we represent the covering possibilities using a binary matrix $C = I \times N$ whose entries are defined as follows:

$$c_{in} = \begin{cases} 1, if \;\; d(i,n) \leq R \\ 0, otherwise \end{cases} \quad \forall i \in I, n \in N \tag{4}$$

Given the sets I and N, there may be delivery points $n \in N$ not close enough to any location in I. These cases can be easily detected as a delivery point $n \in N$ is not covered by any location in I if $\sum_{i \in I} c_{in} = 0$. In this case, it is required to extend the set I (i.e. including further candidate locations) until all delivery points in N can be covered by at least one candidate location in I.

The activation of a station in a candidate location $i \in I$ and the use of an edge $e \in E$ in a path between hub $s \in S$ and candidate location $i \in I$ is defined by the variables

$$x_i = \begin{cases} 1, if \;\; location \;\; i \;\; is \;\; active \\ 0, otherwise \end{cases} \quad \forall i \in I, \tag{5}$$

$$y_{esi} = \begin{cases} 1, if \;\; edge \;\; e \;\; is \;\; used \;\; in \;\; the \;\; path \;\; between \;\; s \;\; and \;\; i \\ 0, otherwise \end{cases} \quad \forall e \in E, s \in S, i \in I. \tag{6}$$

The following variables identify simultaneously which nodes are designated as terminal stations and the hub from which they are served:

$$u_{si} = \begin{cases} 1, if \;\; location \;\; i \;\; is \;\; terminal \;\; and \;\; connected \;\; to \;\; hub \;\; s \\ 0, otherwise \end{cases} \quad \forall s \in S, i \in I. \tag{7}$$

In other words, if $u_{si} = 1$ then there is a terminal station in i and a path connecting s to i. This variable is helpful in the formulation to control the existence of a path to a destination i.

For any edge $e = (i,j) \in E$ we represent with *source*(e) the starting node of the edge (i.e. i), and with *dest*(e) the arrival node of the edge (i.e. j). The model is formulated as a bi-objective problem with weight $\theta \in [0,1]$ as follows:

$$minZ = \frac{\theta}{\beta_1} \cdot \sum_{\substack{s \in S \\ i \in I \\ e \in E}} l_e \cdot y_{esi} \cdot u_{si} + \frac{(1-\theta)}{\beta_2} \cdot \sum_{i \in I} x_i \tag{8}$$

$$\sum_{e \in E: dest(e) = k} y_{esi} - \sum_{e \in E: source(e) = k} y_{esi} = \begin{cases} u_{si} if \;\; i = k \\ 0 otherwise \end{cases} \quad \forall s \in S, \forall i, k \in I \tag{9}$$

$$\sum_{e \in E: source(e) = s} y_{esi} \leq 1 \quad \forall s \in S, i \in I \tag{10}$$

$$y_{esi} \leq u_{si} \quad \forall e \in E, s \in S, i \in I \tag{11}$$

$$\sum_{s \in S} u_{si} \leq 1 \quad \forall i \in I \tag{12}$$

$$\sum_{\substack{s \in S \\ i \in I}} c_{in} \cdot u_{si} \geq 1 \quad \forall n \in N \tag{13}$$

$$\sum_{\substack{s \in S \\ e \in E}} y_{esi} \leq x_i \cdot M \quad \forall i \in I \tag{14}$$

$$x_i \in \{0,1\} \quad \forall i \in I \tag{15}$$

$$y_{esi} \in \{0,1\} \quad \forall s \in S, i \in I, e \in E \tag{16}$$

$$u_{si} \in \{0,1\} \quad \forall s \in S, i \in I \tag{17}$$

The constants β_1 and β_2 in the objective function (8) are normalizing parameters, whereas l_e is the length of edge e. For example, β_1 is set equal to the sum of the shortest paths between each pair hub-candidate locations, and β_2 is set equal to the cardinality of set I. The objective function minimizes a linear combination of the sum of the length of the selected edges composing the paths to the destinations in $K \subseteqq I$ selected to cover customers, and the number of stations activated. With $\theta = 0$, the objective is equivalent to the minimization of the number of active stations, whereas with $\theta = 1$ the objective is equivalent to the minimization of the sum of the lengths of the paths. The first term of the objective function is not linear as it involves the multiplication of two binary variables y and u; this case, however, can be easily linearized by introducing binary variables z_{esi} and the following constraints

$$z_{esi} \leq y_{esi} \quad \forall s \in S, i \in I, e \in E \tag{18}$$

$$z_{esi} \leq u_{si} \quad \forall s \in S, i \in I, e \in E \tag{19}$$

$$z_{esi} \geq y_{esi} + u_{si} - 1 \quad \forall s \in S, i \in I, e \in E. \tag{20}$$

In the light of these changes, the first summation in (8) becomes $\sum_{\substack{s \in S \\ i \in I \\ e \in E}} l_e \cdot z_{esi}$, and the overall model becomes linear. Constraint

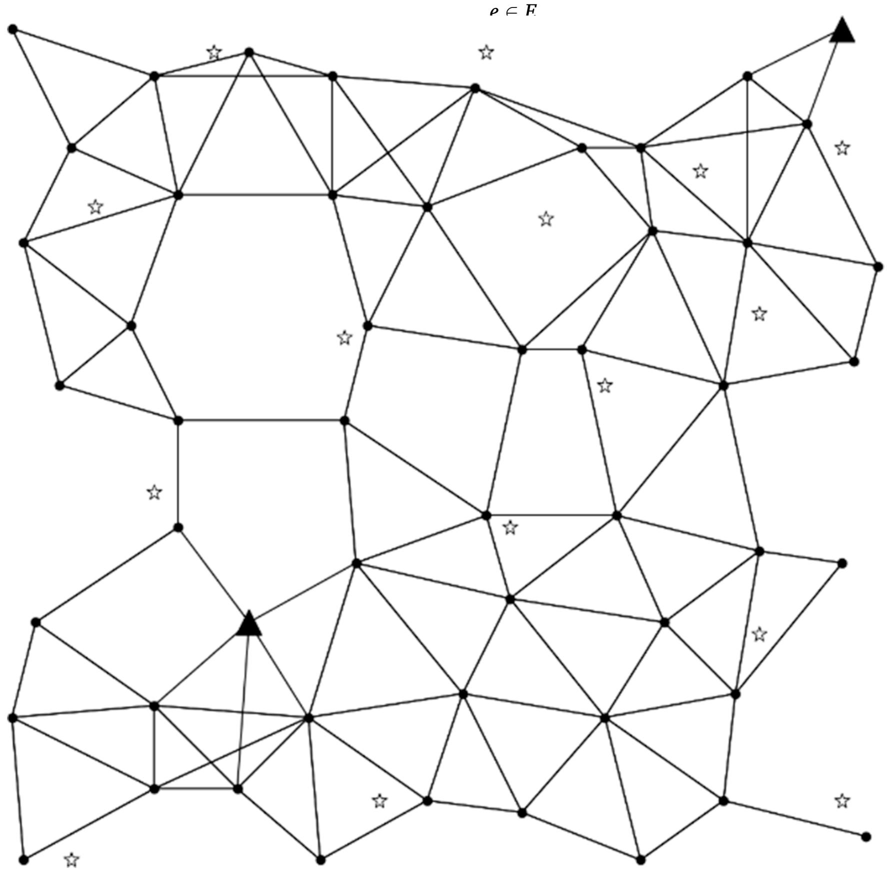

Fig. 3a. Hubs (▲), candidate locations (●), delivery points (☆), and connecting edges.

set (9) stipulates the balance of the nodes: terminal nodes (i.e. those $i \in I$ for which there is $s \in S$ such that $u_{si} = 1$) have only entering edges, whereas intermediate nodes have a balance of zero of incoming and outgoing edges. Notice that the balance is path-based: that is, a node i can be terminal in a path from s to i, and non-terminal (i.e. intermediate) in another path from s to another node j. Constraint set (10) forces at most one single edge originating in s for each path with origin in $s \in S$ and destination $i \in I$, while constraint set (11) prevents the activation of edges on a path from s to i if i is not selected as a terminal station served by s (hence $u_{si} = 0$). Constraint set (12) ensures at most one path to a node i, while constraint sets (13) and (14) enforce the coverage of the delivery points and link the activation of a node to the presence of one or more edges entering the node. The constant M in constraint set (14) can be set equal to the cardinality of the set I, that represents an upper bound to the number of stations that can be activated. Finally, constraint sets (15), (16), and (17) set the domains of the variables.

4.1. Numerical example

Let us consider an example with two hubs (H1 and H2) and 50 candidate locations randomly located in a square (Fig. 3a). With $\theta = 0$, the model minimizes the number of active stations, as illustrated in Fig. 3b. As no weight is given to the first term of the objective function (8), the resulting sum of paths lengths is not optimized, but the minimum number of nodes is activated to cover all delivery points in N. Conversely, with $\theta = 1$, the emphasis is on the minimization of the lengths of the paths, whereas the number of active stations is not optimized (Fig. 3d). For values of $\theta \in (0, 1)$, solutions that aims at minimizing a linear combination of the factors in equation (8) are obtained (Fig. 3c). As expected, shorter paths may require more active stations; conversely, fewer stations may lead to longer paths (Table 1). The choice of θ is in charge of the decision makers, that may test different alternatives and select the most appropriate one for the case on hand.

Solving some randomly generated problem instances, we have experienced a steep increase in the solution time when the size of the problem increases (see Table 3 in Section 5.1 for details), especially when solving the problem concerning the minimization of the number of stations (i.e. $\theta = 0.0$). For this reason, Section 5 presents an approximate solution procedure that aims at shortening the solving time, keeping a good quality of the solution.

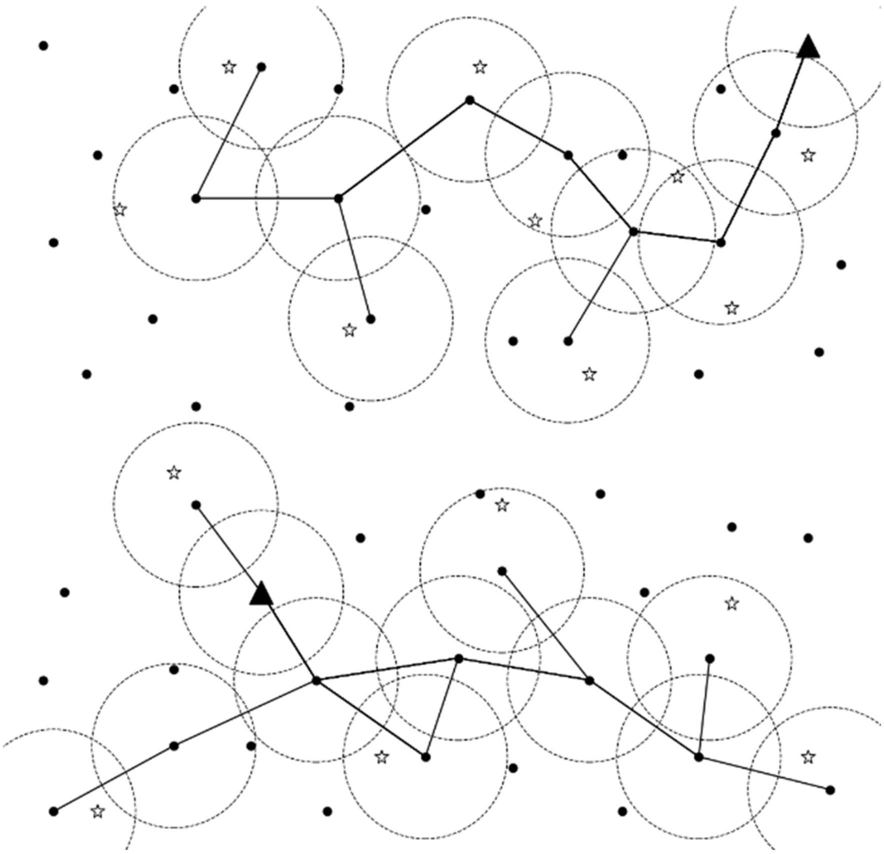

Fig. 3b. Solution with $\theta = 0$ (emphasis on minimizing the number of active stations). Dotted circles represent the area covered by each station.

5. An *m*-shortest path-based heuristic

Arguably, the main advantage of the optimization model is the identification of the best solution to a given problem setting. However, depending on the size of the problems, finding the optimal solution may become a daunting task requiring important computational resources and time. Therefore, this section proposes an alternative approach for the discussed problem based on the a-priori definition of paths between hubs and candidate locations. This alternative approach is a heuristic method (just heuristic for short in the remainder), aiming to obtain reasonable quality solutions in a shorter time compared with the model presented in Section 4. Although the main downside of heuristics in general is that they do not provide a proven optimal solution, a fast, good quality heuristic allows for exploring more alternatives in a relatively short time period. For this reason, we provide a comparison of the heuristic's performance against the optimal solutions obtained by the optimization model discussed in Section 4.

The heuristic is based on the pre-computation of m-shortest paths, an ordered list of m alternative paths of increasing length (if existing) available between a given source s and a destination i. Yen's algorithm (Yen, 1971) (and subsequent improvements by Lawler, 1972) allows finding these loopless paths (i.e., paths without repeated nodes) in pseudo-polynomial time.

Formally, we define $P_{si}^{(m)}(\lambda)$ as the set of at most m shortest paths between $s \in S$ and $i \in I$ with the length shorter than or equal to $\lambda \in \mathbb{R}_+ \cup \{+\infty\}$, where $m \in \mathbb{N}_+$ is a parameter defined by the decision-maker. With $m = 1$ and $\lambda = +\infty$ we refer to the shortest path between s and i. $P_{si}^{(m)}(\lambda)$ contains "at most" m paths because given λ, there may exist fewer than m paths shorter than or equal λ between any pair (s, i).

Once the paths in $P_{si}^{(m)}$ have been generated for all pairs $(s, i) \in S \times I$, the parameter δ_{pi} is then defined and computed as follows:

$$\delta_{pi} = \begin{cases} 1, if \;\; node \;\; i \in I \;\; is \;\; included \;\; in \;\; path \;\; p \in \bigcup_{s \in S} P_{si}^{(m)}(\lambda) \\ 0, otherwise \end{cases} . \tag{21}$$

The following variables represent the selection of a path and the coverage of the delivery points, respectively:

$$t_p = \begin{cases} 1, if \;\; path \;\; p \in \bigcup_{(s,i) \in S \times I} P_{si}^{(m)}(\lambda) \;\; is \;\; selected \\ 0, otherwise \end{cases} \tag{22}$$

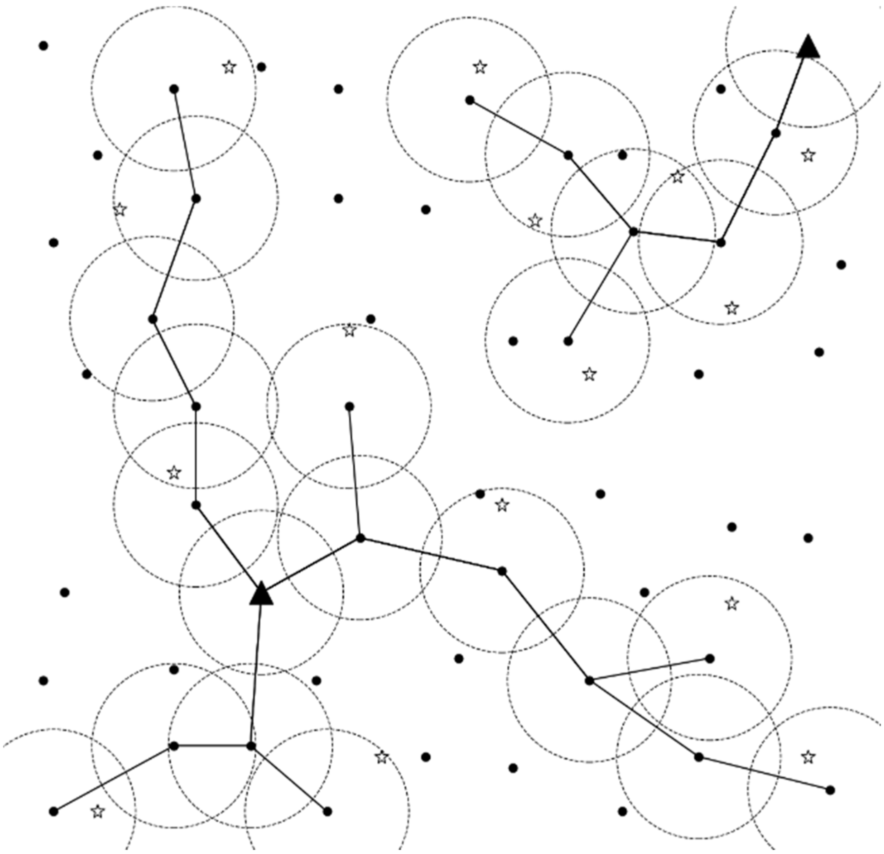

Fig. 3c. Solution with $\theta = 0.5$ (balanced emphasis on minimizing the sum of the lengths of the paths and minimizing the number of active stations).

$$q_i = \begin{cases} 1, if \ \ candidate \ \ station \ \ i \in I \ \ is \ \ activated \ \ as \ \ a \ \ terminal \ \ station \\ 0, otherwise \end{cases} . \tag{23}$$

Finally, parameter L_p represents the length of path p. With these variables and parameters, along with variables x representing the node activation introduced in Section 4, the problem can be formulated for given m and λ as

$$minZ(m,\lambda) = \frac{\theta}{\beta_1} \cdot \sum_{p \in P_{si}^{(m)}(\lambda)} L_p \cdot t_p + \frac{(1-\theta)}{\beta_2} \cdot \sum_{i \in I} x_i \tag{24}$$

$$\sum_{s \in S} \sum_{p \in P_{si}^{(m)}(\lambda)} t_p = q_i \quad \forall i \in I \tag{25}$$

$$\sum_{p \in P_{si}^{(m)}(\lambda)} \delta_{pi} \cdot t_p \le x_i \cdot M \quad \forall i \in I \tag{26}$$

$$\sum_{i \in I} c_{in} \cdot q_i \ge 1 \quad \forall n \in N \tag{27}$$

$$x_i \in \{0,1\}, q_i \in \{0,1\} \quad \forall i \in I \tag{28}$$

$$t_p \in \{0,1\} \quad \forall p \in P_{si}^{(m)}(\lambda) \tag{29}$$

The objective function (24) expresses the same objective of function (8). Constraint set (25) imposes that, for each candidate location i, a single path is selected among those in $P_{si}^{(m)}$ if i is activated as a terminal station (i.e. $q_i = 1$), and zero otherwise. Constraint set (26) allows binding the activation of a node $i \in I$ to the presence of such a node in the selected path between any pair $(s,i) \in S \times I$ (with M a large enough number, for example equal to the cardinality of set I, as discussed in Section 4). In fact, between any pair (s,i) at most one path p can be selected (because of constraint (25)); if node $i \in I$ appears in at least one selected path $p \in \bigcup_{(s,i) \in S \times I} P_{si}^{(m)}(\lambda)$, then

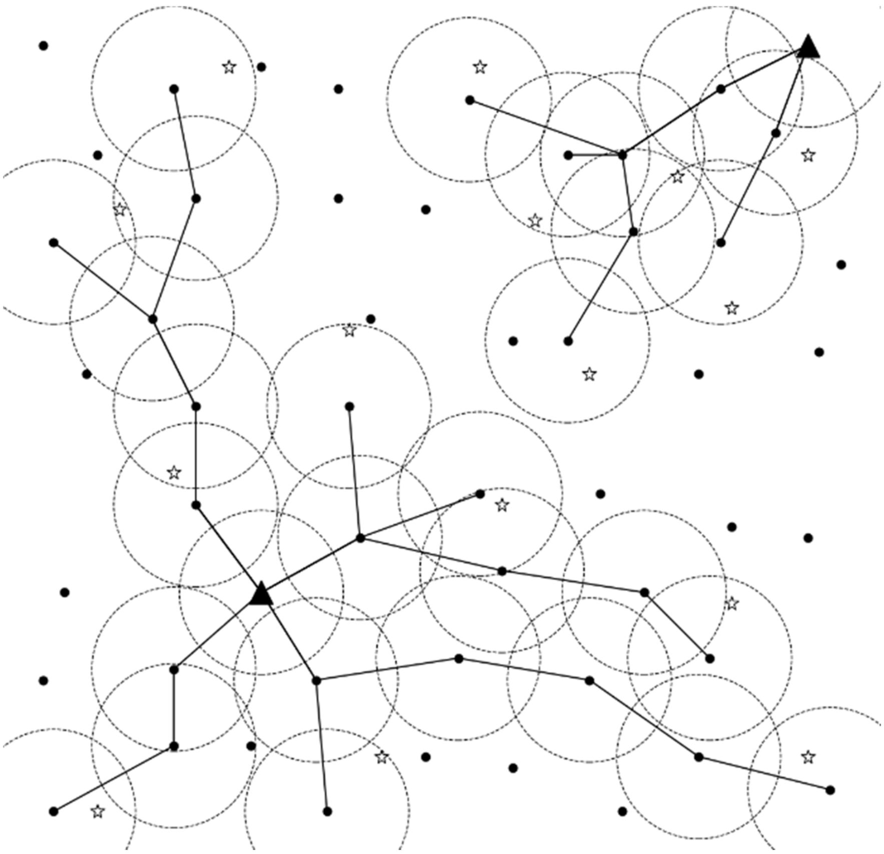

Fig. 3d. Solution with $\theta = 1$ (emphasis on minimizing the sum of the lengths of the paths).

Table 1
Summary of the example results (solve with ILOG CPLEX 20).

	$\theta = 0.0$	$\theta = 0.5$	$\theta = 1.0$
Total length	709,83	462,95	425,92
Number of active stations	21	22	50
Solution time (seconds, rounded)	14,1	13,4	11

$\delta_{pi} = 1$, $t_p = 1$, and x_i is forced to one. Conversely, if node $i \in I$ does not appear in any path, the left-hand side of equation (25) is equal to zero, and equation (26) is satisfied with $x_i = 0$. Constraint set (27) enforces the coverage of the delivery points, and constraint sets (28) and (29) defines the domains of the variables.

5.1. Numerical experiments

This section reports the results of numerical experiments carried out to assess the performance – in terms of optimality gap and solution times – of the optimization models and the relative advantage of the proposed heuristic. Given the characteristics of the problem and the number of dimensions to be addressed, it is not possible to be in any sense exhaustive; however, some indications emerge from the reported results concerning a variety of problem setups.

Different scenarios with 2, 3 and 4 hubs and with a number of candidate locations in the set $\Omega = \{50, 75, 100\}$ have been tested. The set Ω has been defined as follows: considering a radius R, it is possible to define a hexagonal tessellation (with hexagon sides equal to R) that perfectly covers an area (Fig. 4): for the sake of illustration, with a radius $R = 5$ km, about 26 stations are enough to cover a city as large as Rome, Italy (1.285 km2), Los Angeles, US (1.302 km2), and London, UK (1.572 km2), to name a few. Therefore, 100 intermediate candidate stations would allow for the consideration of many alternative locations.

The candidates' locations and hubs have been drawn randomly in a square of size 100. Although in a real setting the radius R would depend on the real autonomy of the drones, for the sake of generating random instances of various sizes, we defined the radius R in each instance as the minimum integer value that generates a connected graph (i.e. for each instance, after generating the positions of the candidate locations and the hubs in the square of size 100, R has been selected in such a way that, considering only edges shorter than or equal to $2R$, generates a connected graph) to avoid unreachable nodes in the network. In these tests, we set $\lambda = +\infty$ not to limit the number of paths considered in the heuristic. For each combination of the number of hubs and number of candidate locations, five instances have been generated and solved for $\theta \in \{0, 0.5, 1\}$ and $m \in \{1, 50, 100, 200\}$. The problem instances have been solved using the ILOG CPLEX solver version 20.1, setting a time limit of 14.400 s (4 h). This limit has been arbitrarily chosen to define a common reference point for measuring the optimality gap as $\frac{optimal\ \ value - lowerbound}{lowerbound}$.

Regarding the summary results reported in Table 2 and Table 3, where the header OPTIMAL refers to the results of the model (8)–(20), and the header HEURISTIC refers to the results of the model (24)–(29), it is possible to draw the following, general indications:

- Both models (OPTIMAL and HEURISTIC) solve the problems to optimality with $\theta = 1$ (minimization of the sum of the paths lengths). In fact, the corresponding gaps in Table 2 are always zero. However, the heuristic method performs significantly faster than the optimal model (Table 3). The fact that the value of m in the heuristic is not relevant (the heuristic method solves at optimality even with $m = 1$) is because minimizing the sum of the paths lengths is similar to choosing the shortest path for each pair *hub-candidate location*. By generating the (single) shortest path between each pair, it is required to select at most one path from each source to each destination. However, this simple enumerative procedure does not automatically consider the covering of the delivery points in set N. The heuristic proposed efficiently combines the enumeration of the paths with the evaluation of demand covering.
- The OPTIMAL model solves the problem at optimality also for $\theta = 0.5$, whereas the HEURISTIC model presents a small gap (though relatively low in most cases), which depends on the value of m: the gap of the heuristic method decreases significantly as m increases (Table 2, only the extreme cases $m = 1$ and $m = 200$ are shown). In fact, with few alternative paths (i.e. small values of m), the probability of finding many nodes in common among the paths is low, resulting in a higher number of stations; conversely, with many alternative paths (large values of m), such a probability is higher. Although the same values of m have been tested for all problems sizes, it should be tuned to the size of the instance since the number of possible paths increases with the increment in the number of nodes. However, due to the short time required to run the heuristic, it is possible to test different alternatives. Indeed, the solution time of the HEURISTIC increases slowly with m (Table 3) and is consistently smaller than the time required by the OPTIMAL model.
- In the case $\theta = 0.0$ (i.e. minimization of the number of active stations), the optimal model does not always solve the problems at optimality when the instance is relatively large. The gap for the OPTIMAL model is greater than zero when there are 100 candidate locations. Further tests on large instances reported an average gap of about 8% after about 20 h of solver time. This result supports the necessity of a fast and reliable heuristic method.
- The average time required to solve the OPTIMAL problems increases steeply with the network size. Indeed, the number of involved variables increases significantly with the number of nodes considered. Comparatively, the time required by the HEURISTIC method is less sensitive to the network size. This result would support the use of the HEURISTIC for larger instances to test different alternatives in a relatively short time.

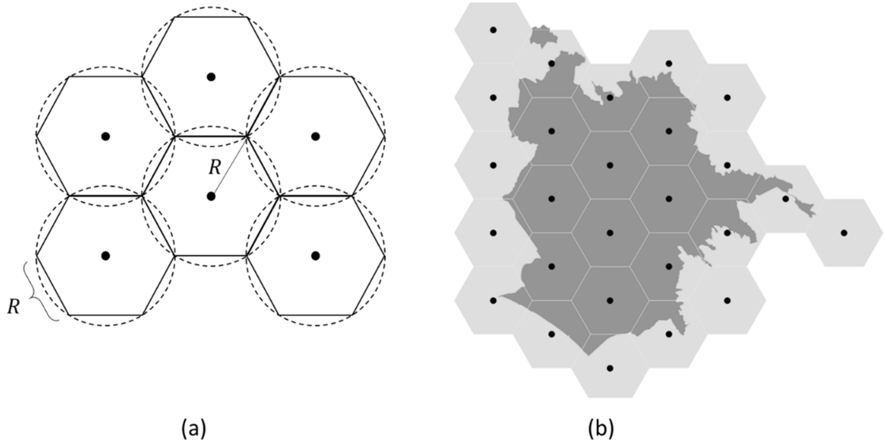

Fig. 4. (a) Hexagonal tessellation and circular covering areas. The dots in the middle of the hexagon represent the candidate locations. (b) Application to the city of Rome, Italy (the dark grey area).

Table 2
Average optimality gaps.

		OPTIMAL			HEURISTIC ($m = 1$)			HEURISTIC ($m = 200$)		
HUBS	CANDIDATE LOCATIONS	θ = 0.0	θ = 0.5	θ = 1.0	θ = 0.0	θ = 0.5	θ = 1.0	θ = 0.0	θ = 0.5	θ = 1.0
2	50	0,000	0,000	0,000	0,086	0,032	0,000	0,020	0,001	0,000
	75	0,000	0,000	0,000	0,305	0,177	0,000	0,120	0,041	0,000
	100	0,027	0,000	0,000	0,371	0,213	0,000	0,112	0,020	0,000
3	50	0,000	0,000	0,000	0,139	0,047	0,000	0,000	0,000	0,000
	75	0,000	0,000	0,000	0,253	0,157	0,000	0,089	0,047	0,000
	100	0,030	0,000	0,000	0,335	0,106	0,000	0,088	0,002	0,000
4	50	0,000	0,000	0,000	0,149	0,147	0,000	0,000	0,000	0,000
	75	0,000	0,000	0,000	0,135	0,121	0,000	0,013	0,008	0,000
	100	0,158	0,009	0,000	0,254	0,092	0,000	0,154	0,014	0,000

Table 3
Average solution times. (*) means that at least one instance did not solve to optimality within the time limit of four hours.

		OPTIMAL			HEURISTIC ($m = 1$)				HEURISTIC ($m = 200$)			
HUBS	CANDIDATE LOCATIONS	θ = 0.0	θ = 0.5	θ = 1.0	θ = 0.0	θ = 0.5	θ = 1.0	AVG PATHS GEN. TIME	θ = 0.0	θ = 0.5	θ = 1.0	AVG PATHS GEN. TIME
2	50	13,5	13,7	11,7	0,1	0,1	0,0	0,01	1,6	1,7	1,3	22,3
	75	836,8	804,2	72,3	0,1	0,1	0,1	0,03	3,4	3,3	3,0	45,5
	100	5821,0 (*)	1015,7	167,9	0,2	0,2	0,1	0,06	5,6	6,0	5,2	69,7
3	50	22,9	25,7	20,2	0,2	0,2	0,1	0,03	2,3	2,3	2,1	26,1
	75	1280,2	651,3	88,9	0,2	0,2	0,1	0,06	4,9	5,0	4,6	76,2
	100	9087,4 (*)	2775,8	340,4	0,2	0,3	0,1	0,07	8,7	9,1	8,2	117,4
4	50	690,1	1702,9	94,7	0,2	0,2	0,1	0,04	3,0	3,2	2,7	37,5
	75	1620,4	1542,8	278,8	0,2	0,2	0,1	0,07	6,2	6,6	5,8	110,1
	100	13709,2 (*)	6936,6 (*)	951,6	0,3	0,3	0,1	0,20	11,1	11,3	10,7	172,3

- A significant portion of the overall time of the HEURISTIC (about 92% on average across all instances with $m = 200$) was spent in generating the alternative paths (see columns AVG PATHS GEN. TIME in Table 3), which is still a quite efficient procedure that can be further optimized. For example, parallelizing the paths generation can drastically reduce the required times. In contrast, the minimization of the number of active stations with the OPTIMAL model (case with $\theta = 0.0$) usually requires the most significant amount of time (hours rather than seconds). The time effectiveness of the heuristic approach, along with the good results in terms of solution gap, would allow for the application on even larger problem instances and test several alternatives for preliminary considerations about the network structure.

6. Conclusion

As transport inefficiencies and other negative externalities raise economic, social, and environmental costs for both businesses and citizens, it is important to advance the knowledge and expertise on distribution processes alternative to road transport. Appropriate planning methods and models are required to support policy-makers in making decisions, especially at the strategic level where the availability of data and information is crucial in participatory planning process where different stakeholders cooperate to create environmentally sustainable and economically feasible innovative solutions. This paper discussed the drone-based delivery network design problem, presenting a model to design a charging station network for drones to reach all the potential delivery points served by a parcel company. A two-objective model has been developed to address this goal, encompassing the trade-off between the minimization of the number of charging stations and the minimization of the sum of the lengths of the paths. A model and a heuristic method that allows for the fast evaluation of a large number of alternatives have been proposed and discussed.

The goal of this study was to define a high-level problem and related solution methods coherently with the strategic perspective adopted in the research. With respect to the implications for practitioners, decision-makers can use the proposed models in their analysis to obtain more information (that, at the strategic level, may be scarce) to drive the planning processes, opting for either the OPTIMAL or the HEURISTIC model according to the size of the problem, the time available, and the goal of the decision-making process. It is up to decision-makers to define the appropriate parameters to be used in relation to the specific problems addressed.

The paper explores a speculative scenario that can open new perspectives in last mile delivery process, although not imminent due to technology and regulatory constraints. Therefore, the paper may suffer from limitations due to the current lack of real implementations. With respect to the implications from the research point of view, a relevant direction for future development results from relaxing the assumption that only one hub can serve each terminal station. Indeed, this would induce more flexibility at the operational level to decide from which hub a specific delivery point should be served. Conversely, this would increase the complexity of the models.

However, the interest in the broad subject of drone-based delivery networks and the examples of pilot implementations imply the possibility of their extensive adoption in the future, supporting the relevance of research addressing the problem under different perspectives. Further extensions of the research proposed in this paper may address the minimization of the deviation of the drones' determined routes from their theoretical shortest paths (that is, the shortest path that could be theoretically travelled in a network where all the intermediate candidate stations are activated), the initial locations of hubs with respect to a two-tier distribution system, and the robustness of the network, exploring the consequences of any intermediate station going out of service.

CRediT authorship contribution statement

Roberto Pinto: Conceptualization, Methodology, Supervision, Writing – review & editing. **Alexandra Lagorio:** Software, Validation, Investigation, Writing – original draft.

Declaration of Competing Interest

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

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