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Location, Scheduling and Energy Optimization in Drone Delivery Systems with Recharge Stations

Carlos A. F. Teodoro [**Universidade Federal de Ouro Preto** | ***carlos.teodoro@aluno.ufop.edu.br***]
Fernanda S. H. de Souza [**Universidade Federal de Ouro Preto**| ***fsumika@ufop.edu.br***]

Departamento de Computação, Universidade Federal de Ouro Preto, Rua Quatro, Campus Universitário Morro do Cruzeiro, Ouro Preto - MG, 35402-136, Brazil.

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Abstract Recent advances in drone logistics have led to research on integrated planning models. These models combine infrastructure design, energy constraints, and temporal scheduling. This paper introduces the Drone Delivery Location and Scheduling Problem with Recharging Stations (DDLSP-R). DDLSP-R advances previous facility-location models by explicitly incorporating time-slot scheduling and delivery due dates. In this problem, each customer must be served within a set time window. Deliveries completed after the due date incur a disutility penalty in the objective function. The proposed model jointly determines the locations of facilities and recharging stations, as well as the allocation and sequencing of drone deliveries. The goal is to minimize total energy consumption and lateness costs, while maximizing coverage and service feasibility. To enable large-scale instances, the approach uses a heuristic decomposition to address strategic location decisions and operational scheduling, each solved via mixed-integer programming within bounded computational time. Experimental results in realistic urban scenarios demonstrate that including recharging stations and temporal scheduling enhances delivery flexibility and expands coverage. These findings highlight the importance of integrating spatial and temporal decision-making for sustainable drone-based logistics in smart cities.

Keywords: Drone delivery, Optimization, Heuristic, Facility location, Scheduling, Recharge station.

1 Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have transformed logistics and transportation by enabling faster, more cost-efficient solutions across sectors such as agriculture, emergency response, traffic monitoring, package delivery, and telecommunications [Otto *et al.*, 2018; Mohsan *et al.*, 2022]. Drones can operate autonomously or remotely, providing operational flexibility in both urban and rural environments. Compared to traditional ground vehicles, drones offer several advantages, such as reduced gas emissions, lower operating costs, and the ability to reach areas with limited access. Therefore, drone transportation becomes attractive in the context of smart cities, promoting greater sustainability, efficiency, and automation, which are essential requirements for the future of logistics [Macrina *et al.*, 2020; Shahzaad *et al.*, 2023].

Despite their great potential, the adoption of drones for deliveries presents several challenges [Huang and Savkin, 2022; Dukkanci *et al.*, 2024a]. From an operational standpoint, limitations in range due to battery autonomy and payload capacity must be highlighted. Geographically, facilities such as drone launch depots, recharging points, waiting areas, and vehicle packages transfer points, among others, need to be strategically located within the area of interest. Furthermore, environmental issues such as weather conditions, communication reliability, and safety regulations must be considered. [Sabino *et al.*, 2022].

Dukkanci *et al.* [2024a,b] identifies and categorizes fundamental facility location problems associated with drone delivery, focusing on drone and hybrid vehicle-drone systems with various facility types such as recharging stations and supply points. These studies highlight gaps in the existing literature, particularly regarding more realistic scenarios that address battery consumption, demand coverage, and drone routing and scheduling. Such restrictions have been studied in recent literature, through problems of coverage maximization [Chauhan *et al.*, 2019], deployment of recharging stations [Benarbia and Kyamakya, 2022], minimization of service time in humanitarian applications [Rabta *et al.*, 2018; Ackerman and Koziol, 2019], and scheduling of deliveries in applications with perishable products [Gentili *et al.*, 2022].

Most existing literature addresses only a subset of these constraints independently [Dukkanci *et al.*, 2024a], given the complexity of solving extended models with multiple constraints in an integrated manner. However, in practice, models are expected to incorporate many of these constraints to approximate real-world scenarios. To fill this gap, this work proposes the Drone Delivery Location and Scheduling Problem with Recharging Stations (DDLSP-R), which integrates infrastructure planning and scheduling under energy constraints. The proposed problem addresses (i) the location of storage facilities and recharging stations, (ii) the allocation of drones to facilities, and (iii) the scheduling of customer[1] deliveries. In this scenario, potential facilities should be located as depots or recharging stations to maximize coverage while minimizing energy consumption. Moreover, drones operate on a continuous time horizon discretized through time slots, and each customer is associated with a delivery time

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[1] Customers and demands are terms treated interchangeably in this work.

window defined by a due date. Deliveries made after the deadline incur a penalty proportional to the delay. The objective is to serve the maximum number of customers, minimizing energy consumption and delay costs, while ensuring operational viability.

Given the complexity resulting from combining spatial location, scheduling, and energy expenditure decisions to achieve a more realistic model, the problem becomes particularly challenging to solve using exact optimization techniques. Therefore, to solve real-world instances in a short computational time, a heuristic approach based on decomposing the problem into two stages is proposed. The first stage focuses on location decisions, determining which facilities and recharging stations to open while minimizing energy costs for customer service. The second stage focuses on operational scheduling, allocating drones to facilities and sequencing customers for service based on their service time requirements. Both stages are modeled using Integer Linear Programming (ILP) and solved using a commercial optimization solver under limited execution time. The proposal can provide efficient solutions with low computational time.

The contributions of this work are listed below:

- A spatiotemporal optimization model for drone delivery systems with delivery windows, extending classical facility location formulations;
- The integration of recharging station location into the delivery planning decision-making process, allowing for greater operational reach and energy efficiency;
- A solution with low computational time, allowing the integration of a large number of constraints to the problem under study while maintaining scalability.

This work is an extension of the article published at the 7th International Workshop on Urban Computing (UrbCom 2025). The main differences between the two works lie in the modeling of new constraints to the problem. The problem studied in [Teodoro *et al.*, 2025] considered the following functionalities in the model: facility location, facility capacity, multiple operating cycles, drone allocation between facilities and customers, limited drone load, and drone energy restored at each cycle. The objective was to minimize drone energy consumption while maximizing coverage. The new work explicitly models: facility location, recharging station location, facility capacity, limited drone load, drone allocation between facilities and customers, and scheduling/sequencing of deliveries with customer delivery windows. The objective is to minimize drone energy consumption, ensuring maximum coverage while minimizing delivery delays within service windows.

The remainder of this paper is organized as follows. Section II reviews the related literature for this study. Section III presents the mathematical formulation of the proposed DDLSP-R. In Section IV, the experimental setup and computational results are presented. Finally, Section V concludes with a discussion of the findings, limitations, and future research directions.

2 Related Work

Several studies have addressed the problem of drone deliveries, formulating it as a constrained optimization problem with different objectives. The following presents works from the literature that have advanced drone applications through new models and proposed solutions using optimization algorithms. Table 1 summarizes the characteristics of related literature.

Rabta *et al.* [2018] work models the optimization of last-mile deliveries of items to be distributed post-disaster in remote locations. The model aims to minimize the total drone travel distance, subject to load and energy constraints. Recharging stations are located to extend the drones' range, and priority levels can be associated with customers, altering the model to accommodate multiple service cycles; however, this is handled independently. The model assumes a single, fixed-location storage facility, limiting flexibility in potential installation sites. Temporal aspects are not considered in this model, unless they are handled independently for each priority class. Small-scale numerical examples are provided and solved using MILP in GAMS.

In [Shavarani *et al.*, 2018], a hierarchical model combining launch stations and recharging stations is proposed for drone deliveries, using the city of San Francisco as a case study. To overcome the complexity of solving the problem, a genetic algorithm is proposed, ensuring that demands are met while respecting the drones' autonomy limits and minimizing total transportation and installation costs. Although the article incorporates important decisions regarding recharge facilities, it is not possible to assess the continuous flow of operations over time or the definition of priorities or due dates.

Chauhan *et al.* [2019] proposes a model for the Maximum Coverage Capacitated Facility Location Problem with Range Constrained Drones (MCFLPD), which involves locating capacitated facilities and allocating drones with energy constraints to connect customers to those facilities. The problem is formulated as an integer linear program, and two heuristics are proposed to manage computational time. Computational experiments are run for a Portland City scenario with more than 100 customers and facilities. Although a large set of constraints is considered, some customers have their service limited by the drones' limited range, as recharging stations are not included. The installation of recharging stations emerges as a necessary extension in this work.

A heuristic approach is proposed by Huang and Savkin [2020] for deploying recharging stations at minimum cost while ensuring maximum customer coverage. The designed infrastructure must guarantee connectivity during drone flights and provide full or partial coverage of the demand area. The algorithm executes two stages: the first deposits an initial triangular grid, and the second performs iterative adjustments to remove redundancies and reposition remaining stations. Compared to baselines such as K-means or prior work, the proposed method guarantees near-optimal coverage with a significant reduction in the number of stations. This work develops an efficient spatial planning approach for recharging stations, but does not address other operational issues that characterize a realistic drone delivery system. There are no capacity, scalability, or logistical cost constraints for energy or maintenance beyond the fixed installation costs.

Table 1. Related work summary

Study	Approach	Objective	Facility location	RS location	Facility capacity	Drone battery	Time slots or cycles	Scheduling and Sequencing
Rabta *et al.* [2018]	Exact	Minimize total travel distance		✓		✓		
Shavarani *et al.* [2018]	Heuristic	Minimize total system cost	✓	✓		✓		
Chauhan *et al.* [2019]	Exact/Heuristic	Maximize coverage	✓		✓	✓		
Huang and Savkin [2020]	Heuristic	Minimize number of stations		✓		✓		
Ghelichi *et al.* [2021]	Exact	Minimize completion time		✓		✓	✓	✓
Gentili *et al.* [2022]	Exact	Minimize delay	✓			✓	✓	✓
Pinto and Lagorio [2022]	Exact/Heuristic	Minimize number of stations and distance		✓		✓		
Teodoro *et al.* [2025]	Exact	Minimize energy	✓		✓	✓	✓	
This work	Heuristic	Minimize energy and delay	✓	✓	✓	✓	✓	✓

Ghelichi *et al.* [2021] formulated a time-slot-based location-scheduling model to find an optimal set of trips for the drone fleet, to minimize the total completion time. The proposed model is designed to solve an integrated problem by simultaneously: i) determining the optimal locations for recharging stations, ii) scheduling and sequencing all deliveries, and iii) assigning a specific set of trips to each drone. The set of provider facilities is considered fixed in the work, and is not optimized with the recharging stations. A case study of Louisville, KY, is used in the computational experiments.

The model proposed by Gentili *et al.* [2022] solves the location of facilities (providers) and the scheduling of deliveries in discrete time windows. It adopts the concept of mobile facilities, which can be relocated to a second time period to serve customers who were not previously reachable. A single drone is assigned to each facility. The drone range cannot be extended through strategic recharging points in this case. Computational experiments consider a scenario in Central Florida with 100 customers and 25 potential facility locations over a 12-hour time horizon.

The work of Pinto and Lagorio [2022] proposes a model that incorporates intermediate recharging stations to extend the operational range of drones. In this system, a drone can pass through a different number of recharging stations to reach its destination. The proposed biobjective model aims to minimize the number of stations installed and the total distance traveled. Conflicting objectives can be weighted through the parameter θ. An exact model and a heuristic approach are proposed to achieve scalability. As a significant limitation, only one facility is considered, and all routes depart from the same point. Temporal aspects are not considered in this work.

An optimization model for infrastructure planning and drone deliveries across multiple operational cycles is proposed in Teodoro *et al.* [2025]. The optimization problem aims to determine the locations of facilities and the allocation of customer demand to drones with payload and range capabilities over a set of periods. Each period represents an operational cycle for the drones, during which their batteries can be recharged. The objective is to minimize drone energy consumption while achieving maximum customer load coverage, subject to operational feasibility in an urban setting.

In summary, this work extends the literature from Chauhan *et al.* [2019]; Ghelichi *et al.* [2021]; Teodoro *et al.* [2025]. Specifically, a formulation that captures drone battery usage, payload limits, facility location, facility capacity, recharge station placement, and drone scheduling is presented. Two linear integer formulations are proposed in the next section, aiming to decompose the overall problem into smaller subproblems and thereby generate feasible solutions for the problem at hand.

3 Drone Delivery Location and Scheduling Problem with Recharging Stations (DDLSP-R)

The proposed problem, called the Drone Delivery Location and Scheduling Problem with Recharging Stations (DDLSP-R), integrates spatiotemporal decision-making that considers range constraints due to limited energy, along with delivery scheduling conditioned by customer delivery windows. The main objective is to determine the locations of facilities and recharging stations, and to schedule and sequence deliveries over a time horizon discretized into slots. Each customer delivery is associated with a deadline; if missed, it incurs a penalty for lateness.

The DDLSP-R is formulated as an integer linear optimization problem and solved using a two-stage heuristic decomposition approach that balances solution quality and computational efficiency. A key feature shared by both stages is a demand-coverage strategy, which enables the models to determine which customer demands to meet based on available resources, such as drone range and time availability. The uncovered demand points could alternatively be served using a traditional delivery method.

3.1 Stage I: Location of Facilities and Recharging Stations

Stage I addresses decisions on facility and recharging-station locations. Thus, from a set of potential candidates to host facilities and stations, a total of p facilities and q recharging stations are selected. The values of p and q are problem parameters. The objective is to make this decision while minimizing the drones' energy expenditure. Therefore, the objective function seeks to minimize energy consumption for customer service. A customer-facility allocation is also generated as a result. In this allocation, it is also noted that the facilities have a capacity limited to U, a parameter of the problem, and can serve demands who demand at most this total. Routes are not explicitly modeled in the proposed model. Deliveries are considered as a round trip between the facility and the customer in cases of direct service, and as a trip with a single stop at a charging station for serving unreachable customers. Considering the drone's limited transport capacity, and packages with loads close to that capacity, the use of explicit routes would not bring advantages to the system. If very light packages are considered, visiting multiple customers on the same route could bring energy and time savings, but this analysis is outside the scope of this work. One can note that drone assignment and scheduling decisions are not addressed in this stage, and are left for the next stage. Consider the following notation described in Table 2.

Table 2. Notation for Stage I

Sets and Indices	
I	Set of demand points, indexed by i.
J	Set of potential facility locations, indexed by j.
R	Set of potential recharging station locations, indexed by r.
Parameters	
b_{ij}	Total battery in the round-trip consumed from demand i to facility j.
b_{ri}	Total battery consumed in a round-trip from station r to demand point i.
b_{irj}	Battery consumed for a oneway-trip from facility j to station r carrying package from demand i.
w_i	Payload weight (kg) for demand i.
p	Maximum number of facilities to be opened.
U	Maximum payload capacity of a facility.
q	Maximum number of recharge stations.
B	Maximum drone battery capacity.
M	Penalty cost for not servicing a demand.
Decision Variables	
x_{ij}	1, if demand i is served by facility j and 0, otherwise.
u_{ijr}	1, if demand i is served by facility j through recharging station r and 0, otherwise.
a_i	1, if demand i is not served and 0, otherwise.
y_j	1, if facility j is active and 0, otherwise.
v_r	1, if recharging station r is active and 0, otherwise.

The Stage I of DDLSP-R can be modeled as:

$$\min \sum_{i\in I}\sum_{j\in J} b_{ij}x_{ij} + \sum_{i\in I}\sum_{j\in J}\sum_{r\in R} b_{irj}u_{ijr} + \sum_{i\in I} Ma_i \quad (1)$$

$$\sum_{j\in J} x_{ij} + \sum_{j\in J}\sum_{r\in R} u_{ijr} + a_i \geq 1 \quad \forall i \in I \quad (2)$$

$$\sum_{j\in J} y_j \leq p \quad (3)$$

$$\sum_{i\in I} x_{ij} + \sum_{i\in I}\sum_{r\in R} u_{ijr} \leq U y_j \quad \forall j \in J \quad (4)$$

$$\sum_{r\in R} v_r \leq q \quad (5)$$

$$u_{ijr} \leq v_r \quad \forall i \in I,\ j \in J,\ r \in R \quad (6)$$

$$u_{ijr} = 0 \quad \text{if}\, b_{ij} \leq B, \quad \forall i \in I,\ j \in J,\ r \in R \quad (7)$$

$$x_{ij} = 0 \quad \text{if}\, b_{ij} > B, \quad \forall i \in I,\ j \in J \quad (8)$$

$$b_{ri}u_{ijr} \leq B \quad \forall i \in I,\ j \in J,\ r \in R \quad (9)$$

$$b_{irj}u_{ijr} \leq B \quad \forall i \in I,\ j \in J,\ r \in R \quad (10)$$

The objective function (1) aims to minimize the total energy, composed of the consumed energy for direct delivery routes and the consumed energy for routes that use a recharging station. A high penalty is added for any demand that cannot be served to guarantee maximum attendance. Constraints (2) are the demand coverage requirement, ensuring that every demand i is either served directly, served via a station, or is explicitly acknowledged as unserved and thus incurs the penalty M. Constraint (3) defines that the total number of facilities opened cannot exceed a maximum of p. Constraints (4) ensure that the total demand assigned to any facility j does not exceed its operational capacity U. Similarly, Constraint (5) restricts the total number of active recharging stations to a maximum of q. Constraints (6) ensure that only active recharging stations are used. Constraints (7) and (8) enforce service exclusivity based on the drone's battery range B: a demand within direct range cannot be served via a station, and a demand outside direct range cannot be served directly. Finally, Constraints (9) and (10) are the battery constraints, which ensure that for any route using a station, both the flight from the facility to the station and the subsequent round-trip flight from the station to the demand are within the drone's battery limit B.

3.2 Stage II: Scheduling and Drone Allocation

The Stage II leverages the outputs of the first stage to determine an optimal delivery schedule over a finite time horizon, which is discretized into time slots (t). This optimization involves assigning each drone to a specific facility, allocating a set of demands for it to serve, and defining the precise delivery sequence. As this is a coverage-based strategy, the objective is to find the best operational configuration within the given constraints. In this work, the total time horizon is 75 minutes, corresponding to 5 time slots (T = 5), each with a duration of 15 minutes, according to other literature works [Gentili *et al.*, 2022].

3.2.1 Score Function

Following [Gentili *et al.*, 2022], a scoring function, denoted by f_{it}, is defined to quantify the timeliness of demand fulfillment. For each demand, a due date d_i (an integer value defining the slot of time to the delivery to be made) is generated randomly based on its transit time, p_i (explained further). This approach allows the evaluation of heterogeneous delivery urgency across the demand set, avoiding bias from any particular demand pattern. The score associated with a given demand decreases progressively after its due date. Consequently, the model is driven to allocate drones to demands to maximize the aggregate score across all demands. A decay value of 0.92 was selected to represent a gradual loss of delivery value as delay increases. A sensitivity analysis using alternative values showed that the decay value has a negligible impact on structural model decisions, primarily affecting the absolute value of the score, not the operational results. The score function is determined as follows:

$$f_{it} = \begin{cases} 0 & \text{if demand } i \text{ is unassigned} \\ g_{it} & \text{if demand } i \text{ is assigned} \end{cases} \tag{11}$$

where the score g_{it} for an assigned demand is defined as:

$$g_{it} = \begin{cases} 1000 & \text{if } 0 \leq t \leq d_i - \frac{p_i}{2} \\ (g_{i,t-1} \cdot 0.92) & \text{otherwise} \end{cases} \tag{12}$$

Note that if a delivery has a transit time of p_i for the entire trip, the package is considered delivered approximately $p_i/2$ of the way through. This means that after this time, the delivery is already late, and the penalty begins to incur.

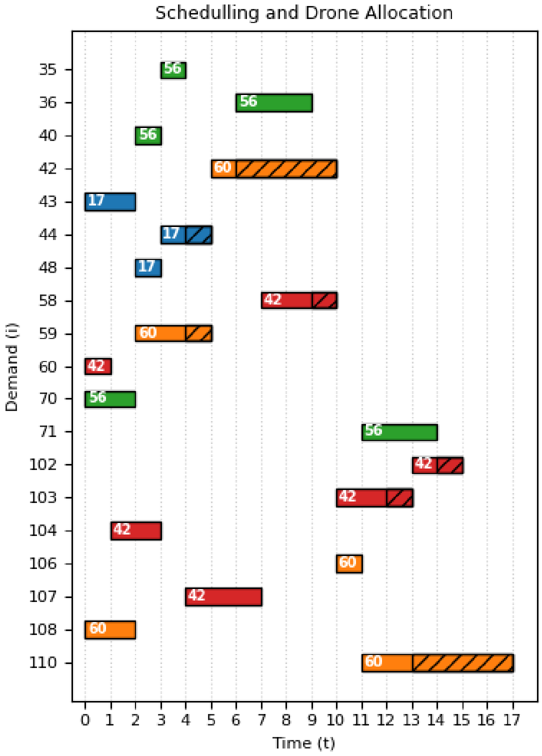


Figure 1. Scheduling and drone allocation example.

Figure 1 illustrates an example of the scheduling and sequencing performed in Stage II. There are four drones allocated among four different facilities: 17, 42, 56, and 60. Each horizontal bar represents a drone allocation to fulfill a specific demand. For example, the first bar from top to bottom corresponds to demand 35. A drone is allocated to this delivery starting at $t = 3$ at facility 56. This demand has a processing time $p_{35} = 1$, meaning the drone was busy for one time slot, finishing at $t = 4$. After completing this task, the same drone (represented by green) is later assigned to demand 36, which starts at $t = 6$ and takes three slots to complete. The hatched pattern on a bar represents when the delivery is due. For instance, consider demand 110. This delivery starts at $t = 11$ and has a processing time of $p_{110} = 6$, finishing at $t = 17$. The hatching on the bar begins at $t = 13$, so the delivery is due after this point. Because the demand is actually delivered at $t - p_i/2$, which corresponds to $17 - 3 = 14$, the score function for this demand goes from 1000 to 920, a penalty is for being one slot late.

3.2.2 Transit Time

The transit time (p_i) represents the travel duration for each trip in discrete time units. It is calculated by first determining the continuous travel time using the distance (d_i) between the demand and its corresponding facility from stage I and an average drone speed of $v = 12$m/s, as studied in Tamke and Buscher [2023]. This duration is then divided by the model's time interval size Δt and rounded up to the nearest integer. Equation 13 presents the calculation of p_i.

$$p_i = \left\lceil \frac{d_i}{v \cdot \Delta t} \right\rceil \tag{13}$$

Table 3. Notation for Stage II

Sets and Indices	
I	Set of demand points, indexed by i.
K	Set of drones, indexed by k.
T	Set of time slots, indexed by t.
Parameters	
f_{it}	Score value for demand i being served at instant t.
p_i	Total slots necessary for delivery of demand i.
l_{ij}	Binary indicator that demand i can be served exclusively from facility j (output of Stage I).
Decision Variables	
x_{itk}	1, if demand i served in instant t by drone k and 0, otherwise.
z_{jk}	1, if drone k is allocated to facility j and 0, otherwise.

Consider the notation from Table 3 regarding Stage II. The Stage II of DDLSP-R can be modeled as:

$$\max \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} f_{it} \left(t - \frac{p_i}{2} \right) x_{itk} \tag{14}$$

$$\sum_{i \in I} \sum_{\tau = t - p_i + 1}^{t} x_{i,\tau,k} \leq 1 \quad \forall t \in T, \forall k \in K \tag{15}$$

$$\sum_{j \in J} z_{jk} = 1 \quad \forall k \in K \tag{16}$$

$$x_{itk} \leq \sum_{j \in J} l_{ij} z_{jk} \quad \forall\, i \in I,\ t \in T,\ k \in K \tag{17}$$

$$\sum_{k \in K} \sum_{t \in T} x_{itk} \leq 1 \quad \forall\, i \in I \tag{18}$$

The objective function (14) aims to maximize the total score derived from attending demand i at time t. The time of service at demand point i is calculated as $t - \frac{p_i}{2}$, where t is the time the drone returns to its facility and $\frac{p_i}{2}$ represents the halfway transit time. Constraints (15) ensure that a drone can perform only one delivery at a time. While it's flying to a location and back, it is considered occupied and cannot be assigned to any other demand. Constraints (16) determine that each drone is associated with a single facility (already opened by Stage I). Constraints (17) ensure that a drone k can only service demand i if its assigned facility j. Finally, Constraints (18) state that each demand i can be serviced at most once throughout the entire time horizon.

In the current formulation, it is assumed battery swapping rather than conventional recharging. Under this operational assumption, the time required for battery replacement is significantly shorter than the duration of the discretized time slots adopted in the scheduling model. Therefore, the swapping process is considered negligible within the temporal resolution of the problem and does not alter the scheduling feasibility conditions. Incorporating explicit recharging times would introduce an additional temporal parameter, but would not fundamentally modify the structural properties of the model. Because the swapping operation is assumed to be fast, a limit on the number of drones that can be served simultaneously at a station was not imposed. Furthermore, additional landing and takeoff times were not incorporated into the time calculation because they are constant and affect all deliveries equally, which are made individually, and would not generate changes in the system's behavior if disregarded.

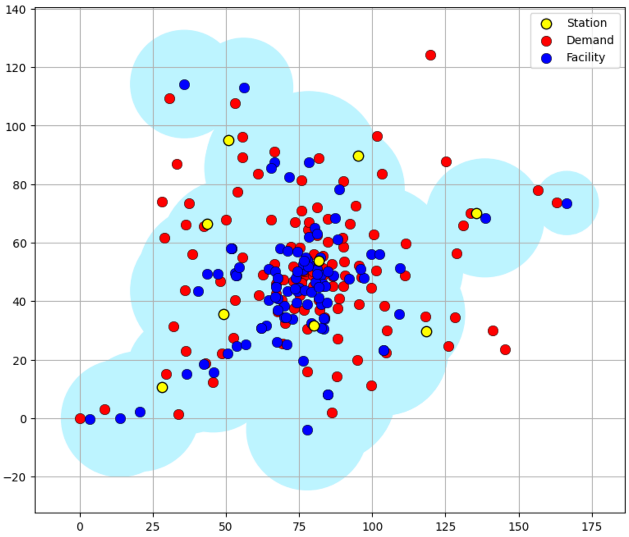


Figure 2. Demand, facilities and recharging stations.

4 Experimental Setup

All experiments were run on a system equipped with an AMD Ryzen 5 1600 six-core processor, 32 GB of RAM, and running Debian GNU/Linux 12. The Gurobi Optimizer version 12.0.2 was used, with a time limit of 60s per run.

The instances evaluated in this study are based on those proposed by Chauhan *et al.* [2019], with points generated for the Portland Metropolitan Area. The dataset includes 122 customer demand points and 104 candidate locations for the facility. Due to the drone's operational range limitations, six demand points in the dataset are unreachable from any facility, even with a minimum payload. This is shown by the light blue coverage area in **Figure 2**. The red dots represent the demand points, and the blue dots represent potential facility locations. The yellow dots represent potential locations for the recharging stations (generated by running the k-means algorithm on the set of facility candidates with $k = 9$).

The parameters considered in the experiments are listed in Table 4.

Table 4. Parameters used in instance configuration

Notation	Description	Value
I	Set of demands	$\lvert I\rvert = 116$
J	Set of potential facilities	$\lvert J\rvert = 104$
R	Set of potential recharge stations	$\lvert R\rvert = 9$
K	Set of drones	$\lvert K\rvert \in [25, 100]$
p	Number of facilities	$[5 - 60]$
q	Number of stations	9
T	Number of time slots	$\lvert T\rvert = 5$
Δt	Duration of a time slot	15min
η	Power transfer efficiency	0.66
θ_s	Lift to drag ratio	3.5
B	Battery capacity	$777Wh * 0.8$
$m_b + m_t$	UAV battery mass + UAV mass tare	10.1
w_i	Demand load	$[0.5 - 5.0]$
U	Facility capacity (# of customers)	$[10, 40]$

Energy consumption for each drone trip is calculated based on the distance between demands and facilities, the drone's mass, the mass of the battery and package, efficiency, the lift-to-drag ratio, and gravity. Equation (19) defines the round-trip calculation between the facility and the demand, as presented in Chauhan *et al.* [2019]. A one-way trip can be calculated similarly, assuming outbound trips include the package's weight while return trips do not.

$$b_{ij} = \frac{2 * (m_t + m_b) + w_i}{\theta_s * \eta} * g * d_{ij} \tag{19}$$

The following metrics are used to evaluate the performance of the models:

- **Coverage (%)**: ratio between the sum of the load served and the sum of the total load of demands.
- **Covered customers**: number of customers served.
- **Energy consumption (Wh)**: sum of the energy consumed by all drones to cover the customers served.
- **Energy ratio**: ratio between the number of customers served via recharge stations and total customers.
- **Drone rate (%)**: average drone utilization rate.
- **Time (s)**: algorithm execution time in seconds.
- **Late deliveries**: Number of deliveries after the due date.

- **Score (f_{it})**: objective function to measure the timeliness of demand fulfillment.

5 Computational Results

5.1 Stage I Analysis

Table 5 summarizes the results of Stage I for different numbers of facilities (p). The number of recharging stations to be installed was fixed at $q = 9$, allowing any point obtained by clustering to be used. The facility capacity is fixed at $U = 10$. The metrics reported in Table 5 are those described in section 4. Optimal results were obtained within a few seconds.

It can be observed that coverage increases as more facilities are installed, reaching a maximum of 97% with 14 facilities. A 100% coverage is never achieved, even with recharging stations, because a specific demand point remains unreachable due to its distance from the closest facility and its payload weight. The model optimizes the use of recharging stations, activating only those strictly necessary to guarantee coverage. The number of stations varies between 4 and 7, with the maximum occurring at intermediate values of p. This behavior reflects the role of recharging stations as a complementary mechanism, proving indispensable when the number of facilities is not dense enough to provide adequate coverage.

Energy consumption increases with p, while maximum coverage is not reached. From this point, lower energy consumption becomes possible since distances can be shortened with the increase in the number of facilities. The energy ratio confirms this pattern, peaking at $p = 12$ when 40% of the energy is consumed through indirect routes, and declining as the role of recharging becomes less relevant with increasing facility infrastructure density.

Figure 3 shows the graphical results for the instances with 14 and 40 facilities. Red dots indicate demand points, blue dots represent facilities, and green dots represent active recharging stations. Black lines indicate direct deliveries from facilities to demand points. Green lines represent indirect deliveries; dashed lines show connections between facilities and recharging stations, and solid lines show connections between stations and demand points. In both scenarios, a coverage of 97% of the demand is achieved. It is possible to observe that recharging stations play a crucial role when the number of stations is smaller (Figure 3a), whereas greater facility availability distributed throughout the space reduces the need for stations (Figure 3b).

5.2 Stage II Analysis

Table 6 shows the results of stage II, which schedules and sequences deliveries using the available drone fleet, based on the locations of facilities and customer allocations from stage I. In stage II, the number of drones (k) is varied to assess its influence on coverage, delivery delays, and drone utilization.

It is evident that the size of the drone fleet directly affects whether the coverage obtained in stage I will be achieved during the scheduling phase. When the number of drones is reduced, coverage suffers a significant operational loss. For example, for $p = 5$ and $k = 5$, only 21% of demands are met, despite the 39% coverage in stage I. With an increase in k, this difference is mitigated. With intermediate fleets (e.g., $p = 15$ and $k = 25$ or $p = 10$ and $k = 30$), coverage increases to over 70%. For $k \geq 45$, 97% coverage is achieved for most scenarios.

Drone availability impacts the number of delayed deliveries. Reduced fleets cause queues in the scheduling process, and delays as drones need to return and make the next delivery. Late deliveries are observed when there is high coverage in stage II ($\geq 70\%$) and a fleet averaging 1-2 drones per facility. Scenarios without late deliveries occurred only for a higher number of available facilities ($p \geq 30$), which led to greater load balancing and fewer deliveries per drone.

The above behavior is confirmed by analyzing the score function, which improves as more drones are made available to open facilities. The drone utilization rate also reflects this pattern, since smaller fleets result in a stressed system ($\geq 80\%$) across fewer facilities (between 5 and 15). With the increase in drone numbers, the load is reduced, reducing bottlenecks and avoiding delays.

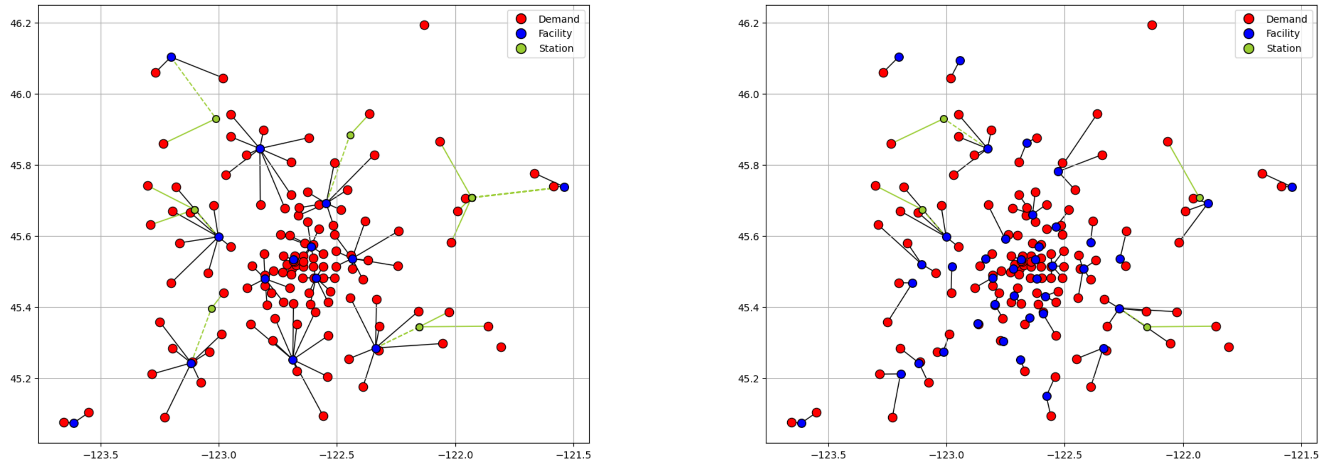
While decomposition into two stages improves the scalability of the problem, it can introduce some loss compared to an integrated model. This is because stage I optimizes energy-aware spatial coverage, but without considering temporal interactions that are only addressed in stage II. Therefore, lower accuracy is expected in scenarios where infrastructure and scheduling decisions are highly coupled, such as when the number of drones is very small, time windows are tight, or many customers are concentrated near few facilities. On the other hand, when the drone fleet is larger and the facility layout is denser, the temporal feasibility of stage I decisions can be met by stage II, reducing the potential loss of optimality.

Computational time indicates the model's efficiency and demonstrates scalability across different scenarios. Instances that achieved the time limit of 60s presented a gap to the linear relaxation bound below 1%. In summary, the results indicate that fleet size is crucial in maintaining the coverage achieved for a stage I facility and station configuration. Stage II analysis suggests that the threshold is between 30 and 45 drones, depending on the spatial configuration of the stations. An even larger number ensures the complete elimination of late deliveries.

5.3 Recharge Station Impact Analysis

To better understand the structural role of recharging stations in drone delivery systems, further analysis was conducted using facilities with higher service capacity ($U = 40$). Previous experiments adopted a conservative approach, with facilities limited to fewer services ($U = 10$). Since in real-world scenarios facilities can handle higher volumes, the role of recharging stations is analyzed in a context where the need to open many facilities is reduced. Thus, Stage I is evaluated with and without recharging stations to determine whether increasing facility capacity alone is sufficient to achieve maximum coverage or whether recharging stations remain relevant for reaching distant areas.

According to Table 7, for all tested p values, the use of recharging stations provides greater coverage, with more significant improvements ranging from 8-16% for lower p values



(a) Stage I for $p = 14$. When fewer facilities are available, the model relies on recharging stations to extend the range of facilities and reach demand points that would otherwise be inaccessible.

(b) Stage I for $p = 40$. In scenarios with more facilities available, the optimal configuration tends to distribute them more evenly, reducing the overall energy consumption.

Figure 3. Comparison of facility location and recharge stations

Table 5. Stage I Results

p	q	time (s)	coverage (%)	covered customers	SD	DD	energy consumption (Wh)	energy ratio (%)
2	0	2	17	20	0	20	1806	-
4	0	1	32	40	0	40	4875	-
5	0	2	39	50	0	50	6560	-
6	0	2	48	60	0	60	8720	-
8	1	4	67	80	2	78	15727	0.09
10	4	4	82	100	5	95	24451	0.15
12	7	2	96	118	17	101	43453	0.40
14	6	3	97	120	11	109	37235	0.29
15	5	14	97	120	9	111	33960	0.26
16	5	3	97	120	6	114	30753	0.16
18	4	1	97	120	4	116	28484	0.12
20	4	1	97	120	4	116	27154	0.12
25	4	1	97	120	4	116	24884	0.14
30	4	1	97	120	4	116	23406	0.14
35	4	1	97	120	4	116	22433	0.15
40	4	1	97	120	4	116	21695	0.16
50	4	1	97	120	4	116	20782	0.16
55	4	1	97	120	4	116	20465	0.17
60	4	1	97	120	4	116	20216	0.17

p - number of facilities, q - number of recharge stations, DD - demands allocated directly to facility, SD - demands allocated to a facility via a recharge station

and stabilizing at 3% for $p \geq 14$. Using recharging stations, the system achieves 97% coverage with few facilities (from $p \geq 6$), whereas this coverage is not achieved by the approach without stations, even for higher p values. Thus, it is clear that recharging stations are necessary to reach customers farther away.

The energy consumption analysis indicates higher costs when stations are available, due to greater customer coverage. However, as p increases, energy consumption decreases because more customers can be served directly. This reinforces the complementary role of the stations, which proves essential for serving four customers unreachable by the model without stations.

5.4 Time Slot Discretization Impact Analysis

To evaluate the impact of temporal discretization applied to the scheduling of stage II, experiments with with finer time-slot granularity were conducted. While the original configuration divides the planning horizon into 6 slots of 15 minutes each, the alternative configuration uses 18 slots of 5 minutes each. According to Table 8, it is possible to observe that the alternative configuration reduces the impact of rounding in mapping the continuous travel time to a discrete value. The impact on the average delivery delay is reduced from approximately 6.5 minutes to 2.5 minutes, increasing coverage by approximately 6%.

However, this improvement increases the computational cost of stage II, since a higher number of time slots implies a significant increase in the number of variables in the model

Table 6. Stage II Results

p	k	time (s)	S-I cov. (%)	S-II cov.(%)	covered customers	late deliveries	Score (f_{it})	drone rate (%)
5	5	0	39	21	25	0	25000	92
	15	1	39	39	50	1	49920	83
	25	0	39	39	50	0	50000	57
	35	0	39	39	50	0	50000	45
10	10	1	82	35	45	3	44760	82
	20	7	82	62	75	12	73966	81
	30	5	82	79	97	15	94070	78
	40	6	82	82	100	5	99526	70
15	15	1	97	51	62	5	61458	83
	25	10	97	73	89	12	87478	82
	35	14	97	88	109	15	106534	79
	45	21	97	97	120	14	117608	68
20	20	15	97	62	76	7	75298	79
	30	20	97	83	102	15	99960	77
	40	60	97	97	119	17	116368	74
	50	60	97	97	120	7	119366	66
25	25	18	97	74	90	11	88564	79
	35	47	97	90	110	14	108250	75
	45	60	97	97	119	11	117824	69
	55	23	97	97	120	1	119920	61
30	30	17	97	83	101	13	99262	73
	40	61	97	93	115	14	113108	68
	50	60	97	97	120	8	119212	60
	60	1	97	97	120	0	120000	57
35	35	9	97	89	109	13	107262	71
	45	60	97	97	120	14	118108	65
	55	60	97	97	120	3	119760	56
	65	1	97	97	120	0	120000	51
40	40	29	97	90	111	12	109410	70
	50	18	97	97	120	11	118824	60
	60	3	97	97	120	0	120000	53
	70	2	97	97	120	0	120000	49

p - number of facilities, k - number of drones, S-I cov. - Stage I coverage, S-II cov. - Stage II coverage, DD - demands allocated directly to facility, SD - demands allocated to a facility via a recharge station

Table 7. Impact of recharge stations for $U = 40$

		Without stations				With stations					
p	Δ cov. (%)	time (s)	energy	coverage (%)	DD	q	time (s)	energy	coverage (%)	DD+SD	SD
2	8	2	28770	59	73	3	12	31530	67	80	11
4	16	2	35553	77	93	8	6	59085	93	114	28
6	13	2	33497	84	102	7	6	58704	97	119	27
8	8	3	36036	89	109	7	15	50638	97	120	22
10	5	2	36708	92	113	5	17	42570	97	120	10
12	4	2	33083	93	115	5	12	36325	97	120	7
14	3	3	29983	94	116	5	4	32225	97	120	6
16	3	1	26639	94	116	4	2	29925	97	120	5
18	3	1	24910	94	116	4	3	28296	97	120	4
20	3	1	23575	94	116	4	1	26961	97	120	4

p - number of facilities, q - number of recharge stations, DD - demands allocated directly to facility, SD - demands allocated to a facility via a recharge station

and consequently longer execution times. The results with 18 time slots were limited to one hour of execution. Thus, a tradeoff between temporal precision and computational time is observed. The 15-minute discretization adopted in the main experiments is able to capture the main system behavior while keepingthe model computationally manageable.

Table 8. Sensitivity analysis with respect to time-slot discretization

Slots: 6 – Interval: 15 min – Horizon: 1h30m									
p	k	gap	time (s)	coverage(%)	cov. customers	late deliveries	drone rate (%)	RI (min)	Score (f_{it})
20	20	0.00%	15	62	76	7	79%	6.56	75298
30	30	0.00%	17	83	101	13	73%	7.12	99262
40	40	0.00%	29	90	111	12	70%	6.61	109410
Slots: 18 – Interval: 5 min – Horizon: 1h30m									
p	k	gap	time (s)	coverage(%)	cov. customers	late deliveries	drone rate (%)	RI (min)	Score (f_{it})
20	20	1.79%	3600	70	89	18	67%	2.49	83241
30	30	2.52%	3600	91	111	27	54%	2.49	103072
40	40	11.33%	3600	92	114	22	51%	2.49	107785

p - number of facilities, k - number of drones, gap - to optimality, cov. customers - covered customers, RI (min) - rounding impact in the delays in minutes

6 Conclusion

This paper introduces a two-stage optimization model for drone delivery logistics that addresses both strategic infrastructure placement and operational scheduling. The first stage extended the work from Chauhan *et al.* [2019] by incorporating recharging stations to enhance service range. The second stage integrated the formulation from Gentili *et al.* [2022] to schedule drone assignments and deliveries over a discretized time horizon, maximizing a score-based objective function that prioritizes timely service.

This study contributes a comprehensive framework that highlights the critical interplay between fixed infrastructure and mobile assets in drone logistics. The findings offer valuable insights for decision-makers on balancing investments in facilities, recharging stations, and the drone fleet to achieve cost-effective, efficient operations.

However, the proposed approach has some limitations, such as not explicitly modeling routes, which prevents multiple stops at customers or recharging stations. This point also restricts the flexibility of long-range missions. Future research could explore an integrated model that simultaneously solves the location and scheduling problems to find a global optimum considering a known demand and addresses routing to extend attendance. Global optimum in dynamic scenarios cannot be calculated without knowing future demands, working only as a lower or upper bound on quality. Further extensions could incorporate stochastic demand, variable weather conditions, and heterogeneous drone fleets to better reflect real-world complexities. Finally, expanding the model to consider hybrid vehicle-drone delivery systems remains a promising field for investigation.

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Authors' Contributions

CAFT contributed to the conception of this study, developed the methodology, performed the experiments, and wrote the manuscript. FSHS contributed to the conception of this study, developed the methodology, and reviewed the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

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