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DESIGNING THE CHARGING STATIONS NETWORK FOR FREIGHT DELIVERY BY DRONES USING SIMULATION-OPTIMIZATION

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ABSTRACT

Drones are a promising choice to the last-mile delivery in place of conventional vehicles that contribute to road congestion and air pollution. Despite the autonomy, flexibility, and agility of drones, their limited battery capacity and payload compromise their flight range. In this paper, this challenge is faced through the placement of charging stations where drone batteries are recharged to expand their flying span. This work relies on a simulation-optimization solution approach to determine the optimal number of the drone hubs to serve a given delivery order demand. The optimization aims at minimizing charging station installation costs, drone energy consumption, and operational costs. The simulation model is run to simulate the parcel delivery flights as well as the drone battery consumption and charging cycles. Moreover, allocating the customer demands to stations and dimensioning the drones fleet to deliver packages efficiently pinpoint the station locations and size.

1 INTRODUCTION

Technological advances have expanded the mobility capabilities of unmanned aerial vehicles (UAV), attracting the interest of researchers around the world. Even if the last-mile delivery of goods by drones is still considered to be at an experimental stage, drones represent one of the most promising technologies, with successful trials by international companies such as Amazon, which announced that its latest Prime Air drones will deliver to customers in three U.S. locations, as well as cities in Italy and the UK, by the end of 2024 (Amazon 2023). As Zou et al. (2023) highlight in their research, compared to traditional delivery vehicles, drone delivery offers higher delivery speeds by avoiding traffic congestion issues, flexible throughput capacity by adjusting fleet size, and lower operating costs than courier delivery systems. However, despite the positive benefits that drone delivery can bring to last-mile distribution, being one of them the reduction of the pollutant emission (Figliozzi et al. 2020), its main limitation cannot be ignored: its dependence on battery power for flight range. In addition, the payload is one of the key factors affecting the flight duration and should, therefore, be considered in drone planning as it affects battery endurance.

Thus, the motivation of this research is to address the flight range constraint by using one of the methods proposed in the literature, that is, by installing charging points for drones. With the aim of designing the most cost-effective network for a given demand disposition, an optimization problem is posed with the objective of minimizing all costs associated with the system: setup costs, flight or operational energy costs, and the costs of ignoring customer orders. Therefore, given the previous considerations, this work aims to design a model that finds the optimal number and size of drone hubs required to serve the customer orders assigned to each hub. The problem considers the following aspects of the drone delivery system: (*i*) limited battery and payload capacity of drones, (*ii*) limited flight range, and (*iii*) volatile delivery order scenarios. In particular, this model includes the effect of delivery weight, and it is used to account for the limitation of the maximum flight range of drones, constrained by the energy consumption and battery capacity of UAVs to select the optimal locations of charging stations (CS). Given the aforementioned ideas, the main contributions of this research are twofold: from the application side, the consideration of drone characteristics in modeling and, on the methodological side, in exploring the potential of integrating optimization and simulation techniques to address the posed problem. This work demonstrates the advantages of integrating Agent Based Modeling (ABM) and an Integer Programming (IP) optimization model to address drone-assisted delivery. Applications of ABM to logistic operations that consider electric vehicles, let alone those that include drones, are limited in the literature. Therefore, the novelty of this research, that differs from the previous work, is that the model considers battery energy consumption during UAV movement by incorporating System Dynamics Simulation into the ABS model.

2 LITERATURE REVIEW

The main challenge for UAVs is associated with battery limitations. There are at least three ways to mitigate this limitation: first, drone-truck collaboration Gonzalez-R et al. (2024) and second, dynamic landing zones that use public transport vehicles, such as the roofs of buses, for drone assistance (Moadab et al. 2022). For example, Deng et al. (2023) propose a novel routing and scheduling algorithm for drone delivery that takes into account the fixed schedules of public vehicles. The third one which is discussed in this paper is the establishment of charging stations or service hubs where drone batteries can be recharged.

2.1 Drone Infrastructure and Fleet Dimensioning Optimization Problems

With a large number of customers to serve over a large area, there is likely a need for battery recharging. Charging stations ensure longer flight times and are used as platforms where drones land and have their batteries changed or recharged (Raivi et al. 2023). Therefore, the implementation of freight transport by drones in urban and rural airspace will require an extensive infrastructure consisting of various types of service, operation or supply facilities. The problem of locating drone facilities has been investigated for numerous applications. That is the case of Ghelichi et al. (2022), who propose a novel stochastic optimization model to address demand location uncertainty in Facility Location Problems (FLP) and considers the critical aspects of a drone delivery system in humanitarian logistics. Furthermore, Chauhan et al. (2019) present the Maximum Coverage Facility Location Problem with Drones (MCFLPD), an Integer Linear Programming formalism with the objective of maximizing coverage while explicitly incorporating the drone energy consumption and range constraints. A case study on a Portland metropolitan area is presented to test the feasibility of using drones for deliveries. Likewise, Hadas and Figliozzi (2024) develop a novel optimization approach for drone fleet sizing, extending the news vendor model with stochastic demand in terms of two decision variables: firstly, the number of deliveries and, secondly, the deliveries weight or payload. As they pinpoint in their research, payload is important because for drones, unlike ground vehicles, payload is a major constraint that severely reduces drone range and impacts on its costs. In that research, the objective function is profit maximization and the costs associated with the drone size and unmet customer demands are considered, too.

2.2 Agent Based Modeling and Simulation in Drone Delivery Systems

As Balaban et al. (2016) highlight, simulation-based research is used to provide initial insights into important factors that business stakeholders should consider. In the literature, a great range of works that tackles the last-mile delivery problem with drones address Vehicle Routing Problems (VRP) and, more specifically, focus on small fleet of drones assuming equal operating conditions (Benarbia and Kyamakya 2021). Nevertheless, in practice, delivery companies assemble fleets of drones considering heterogeneous configurations and characteristics (speed, endurance and energy supply technique) to satisfy various customer package demands (Wang et al. 2023). ABM has proven to be an alternative way to model complex problems. Over the last two decades, extensive work has been produced using ABM for many complex problems. As such, Wang, et al. (2022) utilize simulation to optimize the drone delivery system design in rural areas and consider the limited flight range of drones. They proposed a novel simulation-heuristic framework that considers three types of agents: customers, charging stations, and drone depots. Similarly, Chour et al. (2023) model the multi-UAV rendezvous recharging problem for surveillance purposes, which consists of energy-limited aerial vehicles that rendezvous with a mobile or fixed charging station. They discuss how the multi-UAV rendezvous recharging problem can be described as an agent-based model under a custom framework.

Finally, with the expansion of renewable energy towards a low carbon profile, alternative sustainable modes of transport have emerged as a potential solution to this environmental transition. The proliferation of electric vehicles in all their modes (road or air) poses a challenge for charging infrastructures, which will require an expansion to meet the future charging needs of these vehicles. The existing literature includes studies on ABM simulating the logistic operations of electric vehicles. As stated by Utomo et al. (2020), when such logistic systems are modeled, the use of a representative energy consumption model is also important. Their study presents the preliminary result for an ABM that analyzes an electrification strategy for the UK's long haul logistics operations and includes an an alternative approach to model the vehicle energy consumption. Likewise, Sing et al. (2022) present a hybrid model combining system dynamics and discrete event simulation for an electric vehicle charging system.

3 METHODOLOGY

3.1 The Simulation-Optimization Framework

As a novelty to previous contributions, a system dynamics simulation model has been integrated in the hybrid model to estimate battery energy consumption during UAV movement. Combining simulation and optimization approaches implies that the optimization model provides the initial simulation data: once the initial FLP is solved, the resulting station and demand assignment significantly influences the performance of the delivery system. While ABM and System Dynamics (SD) are popular in urban logistics, hybrid models combining these approaches, such as for electric vehicle charging systems, are novel in drone-assisted delivery scenarios, where the focus is on optimizing facility locations to maximize user participation and minimize setup costs. The estimation of energy consumption, total travelled distance, and delivery time are all considered within the hybrid approach. The model was realized using the commercial software AnyLogic, as it supports hybrid simulation by combining different simulation techniques, including system dynamics and discrete event simulation, and the development of ABM frameworks.

3.2 The Agent-based Simulation Model

For the simulation model, four types of agents are considered: customers, orders, charging stations, and drones. The locations of customers, charging stations, and drones are modeled on a Geographic Information System (GIS) map according to their latitude and longitude. As Sing et al. (2022) depict, using ABM to develop a model allows for different parameters to be set individually, enabling the exploration of different system and usage scenarios.

Drone performance is modelled through a statechart together with a SD model for the drone battery as depicted in Figure 1. Initially, drones stay in idle state, until an order arrives to the station where the drone is parked. When a drone is assigned to an order, it will pass to the *Go* state and move from the station to the assigned customer. In this state, the discharge variable is switched on activating the discharge flow and making the electric charge (in Wh) stock run out in the SD model. When the order is delivered, the drone will go back to its station to get recharged. At this moment, it will enter the charging state, switching off the discharge and switching on the charge variable in the SD model of the battery. Once the battery is fully charged, the drone will pass to the idle state, waiting for the next customer order to be served and switching off both charge and discharge flows in the SD model. Each drone in the system has its own attributes like speed, payload, and flight range. Drone speed is chosen from a triangular distribution $s_{go} = triangular(16, 30, 20)$, in m/s, when carrying a package and speeding up with a $s_{back} = triangular(16, 35, 25)$ when coming back empty to the station to recharge. Note that these triangular parameters are set according to the technical characteristics of the selected experimental drones.

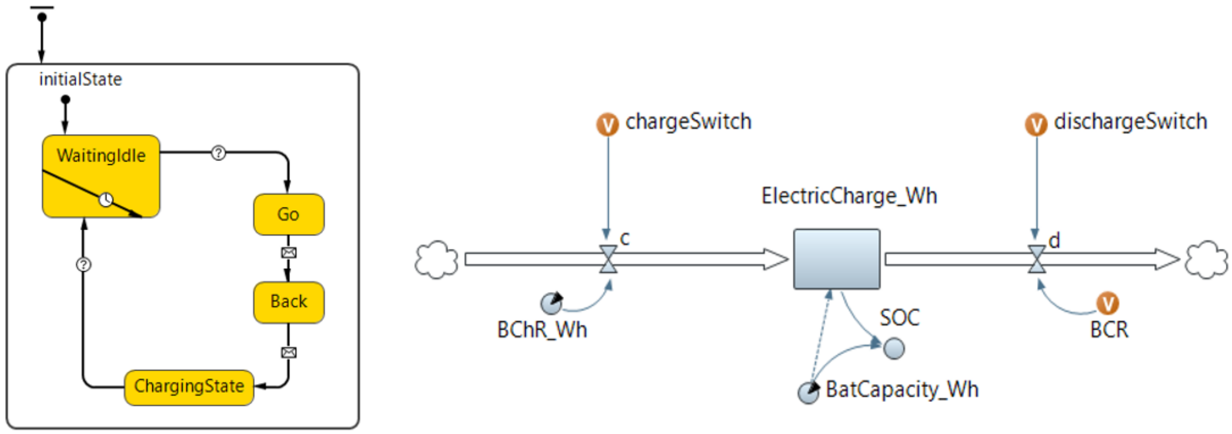

Figure 1: Drone agent statechart (left) and battery system dynamics model (right).

SD is combined with discrete event simulation, making the electric charge and discharge change continuous with respect to time while the drones fly or stay charging. The battery consumption rate (BCR) can be defined as the amount of charge consumption per minute. It is the rate at which battery charge decreases during the flight, and is measured in Watts (W). Thus, SD is used to represent power flows. As such, BCR is characterized for both package carrying and empty flying states in Equation 1 and Equation 2, where the relevant parameters are explained in Tables 2 and 3. The battery charging rate follows a $triangular(750, 1500, 1000)$ distribution in W to account for uncertainty.

$$\frac{d\ BCR_{go}}{dt} = \frac{(w_j + m_t) \cdot g}{ld \cdot \eta} \cdot s_{go} \tag{1}$$

$$\frac{d\ BCR_{back}}{dt} = \frac{m_t \cdot g}{ld \cdot \eta} \cdot s_{back} \tag{2}$$

Customer behavior is also modelled through a statechart, where initially a customer is in an idle state until an order is placed, following the order arrival schedule shown in Table 1. At that point, the customer can go to an unattended state or stay waiting for the order to be delivered according to the optimization problem solution. Once the order is delivered, the customer moves to a delivered state and its demand is satisfied. Simultaneously, the station agent models the action of order arrivals and drone assignment to those arrivals through a discrete event flowchart, where orders behave as entities and drones as resources. Station, customer, and drone agents are all connected through messages that announce a given event such as order arrival, concluded delivery, or a full charge taking place.

Table 1: Customer order arrival schedule.

Time			Order %
8:00	-	9:00	0.00112
9:00	-	10:00	0.01849
10:00	-	11:00	0.10970
11:00	-	12:00	0.23006
12:00	-	13:00	0.28125
13:00	-	14:00	0.23006
14:00	-	15:00	0.10970
15:00	-	16:00	0.01849

3.3 The Facility Location Model

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

Table 2: Model variables and model parameters.

Variable	Description
y_i	Binary variable valued 1 if CS $i \in \mathscr{I}$ is open, 0 otherwise
x_{ij}	Binary variable valued 1 if customer $j \in \mathscr{J}$ is assigned and served by CS $i \in \mathscr{I}$, 0 otherwise
u_{ij}	Binary variable valued 1 if customer $j \in \mathscr{J}$ is unattended and not assigned to CS $i \in \mathscr{I}$, 0 otherwise
Parameter	**Description**
sc_i	Setup costs of a CS $i \in \mathscr{I}$
M	Penalty costs for unattended demand
pe	Price of electricity in € per kwh
r_j	Flight range of drone for demand of customer $j \in \mathscr{J}$
w_j	Weight of demand of customer $j \in \mathscr{J}$ measured in kg
e_j	Specific energy consumption per km traveled measured in Wh/km
d_{ij}	Distance from customer $j \in \mathscr{J}$ to a CS $i \in \mathscr{I}$ in km
c_{ij}	1 if distance $d_{i,j}$ from customer node $j \in \mathscr{J}$ to a CS $i \in \mathscr{I}$ is smaller than r_j, and 0 otherwise
NC_i	Maximum number of customers that a CS node $i \in \mathscr{I}$ can host

This model is defined over the set of nodes $i \in \mathscr{I}$ and $j \in \mathscr{J}$ representing the potential locations for drone CS infrastructures and the potential customer demand points. Additionally, each demand point features a demand w_j (measured in kg). The notation, variables, and parameters are described in Table 2 whereas the mathematical model is contained in the Equations (3) – (8).

$$Min \quad \sum_{i \in \mathscr{I}} sc_i \cdot y_i + \sum_{\substack{i \in \mathscr{I} \\ j \in \mathscr{J}}} M \cdot u_{ij} + \sum_{\substack{i \in \mathscr{I} \\ j \in \mathscr{J}}} pe \cdot e_j \cdot d_{ij} \cdot x_{ij} \tag{3}$$

subject to

$$\sum_{i \in \mathscr{I}} (c_{ij} \cdot x_{ij} + u_{ij}) = 1 \qquad \forall j \in \mathscr{J} \tag{4}$$

$$c_{ij} \cdot x_{ij} \leq y_i, \qquad \forall i \in \mathscr{I}, \forall j \in \mathscr{J} \tag{5}$$

$$\sum_{j \in \mathscr{J}} c_{ij} \cdot x_{ij} \leq NC_i \cdot y_i \qquad \forall i \in \mathscr{I} \tag{6}$$

$$\sum_{i \in \mathscr{I}} w_j \cdot c_{ij} \cdot x_{ij} \leq p \qquad \forall j \in \mathscr{J} \tag{7}$$

$$x_{ij}, u_{ij}, y_i \in \{0,1\} \qquad \forall i \in \mathscr{I}, \forall j \in \mathscr{J} \tag{8}$$

The objective function (3) defines the minimization of installation and operational costs together with minimizing unattended demand, i.e., maximizing demand coverage. Restrictions considered in the optimization problem sum up to assignment constraints (4, 5), station capacity (6), and drone payload capacity (7). Finally, Equations (8) define the decision variable ranges.

The power consumed by a drone in a delivery action from CS $i \in \mathscr{I}$ to demand point $j \in \mathscr{J}$ is estimated with statistical methods as described in Equation (9), adapted from Figliozzi (2017), where the relevant parameters are explained in the Tables 2 and 3. The specific energy consumed by a drone is computed as

$$e_j = \frac{(w_j + m_t) \cdot g}{2 \cdot ld \cdot \eta} + \frac{m_t \cdot g}{2 \cdot ld \cdot \eta} \tag{9}$$

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

$$r_j = \frac{bc \cdot V}{e_j} \tag{10}$$

In order to avoid unfeasibilities, a penalty function is added to the objective function consisting of a penalty coefficient M with a sufficiently large number multiplied by an artificial variable $u_{i,j}$, that stands for the unattended deliveries. The travel distances of drones are considered Euclidean. This assumption is employed to estimate the energy consumption of each round trip done by a drone, which is used to calculate the last term of the objective function taking into account the electricity price pe. The price of electricity is fixed to a value obtained March 17$^{\text{th}}$ 2024 of €0.1228 per kWh consumed in Spain. The number of drones a station can host is limited to 75 for all the stations ($NC_i = 75$).

4 COMPUTATIONAL EXPERIMENTS

In this section, instances are generated to simulate drone-assisted delivery scenarios under different conditions of spatial demand distribution. The model is tested to create a framework that considers four potential locations for setting up the charging facilities and three demand scenarios. For each case, there are 100, 200, or 300 payloads to be delivered, which are randomly generated from a truncated normal distribution with mean 1 kg and standard deviation 0.4 kg (W $\sim \mathcal{N}(\mu = 1, \sigma = 0.4)$) and restricted to positive values. Similarly, the setup costs for each facility are also randomly generated, considering a uniform distribution $\mathcal{U}[500, 1000]$. Computational experiments are run for multi-rotor-type drones, which are predominant for delivery purposes. The parameters characterizing the drones are shown in the Table 3. Gravity is taken as $g = 9.81\ m/s^2$.

Table 3: Drone parameters considered for experiments.

Parameter	Description	Value
ld	Lift to drag ratio	3.5
η	Power transfer efficency	0.67
m_t	Tare weight of a drone without load in kg	4 kg
bc	Battery capacity from datasheet in mAh	10000 mAh
V	Voltage of battery from datasheet in V	37 V
p	Maximum payload of a drone in kg	2.3 kg

The distribution of orders arriving during an eight-hour workday is modeled through a schedule following a discretized continuous beta distribution. Starting with the beta distribution parameters α and β, as well as lower and upper limits l and u (Hadas and Figliozzi 2024), equidistant values are generated along the cumulative distribution function of the beta distribution and obtain the discrete values representing the number of orders arriving in each hour (Table 1). Before the simulation, all the agents are initialized with their longitude and latitude, and the rest of their parameters.

5 RESULTS AND DISCUSSION

All experiments are conducted on a Windows 11 desktop with Intel Core i7-10750H CPU 2.60GHz, and 16 GB of RAM and are solved using IBM®ILOG CPLEX 12.6.2 API for the Java Environment solver in the Anylogic simulation software. Results show the optimal configuration of drone charging stations and the optimal assignment of customers to stations for a given demand of orders.

5.1 Facility Location Problem Results

In all the scenarios of demand posed, four potential charging station locations are considered. While in the case of 100 customers only three stations are opened, in the other two cases all stations are used. The GIS map in Figure 2 shows the location of opened facilities and demand nodes (in red unattended and blue attended). Demand coverage values lie around 96 % and 99 %, being the least populated scenario the one with the highest coverage with a single customer unattended. The demand coverage corresponds to the percentage of attended customers. Depending on the instance, the amount of customers to be attended is different and can be either 100, 200, or 300. In most cases the reason to leave a client unattended has to do with the payload limitation. When it comes to computed costs of the delivery system, it can be seen that the higher the population and concentration of demand, the higher the cost. These results are in line with the number of facilities selected after solving the FLP and collected in Table 4. The actual cost of the framework are computed from subtracting the unattended penalty costs from the objective function.

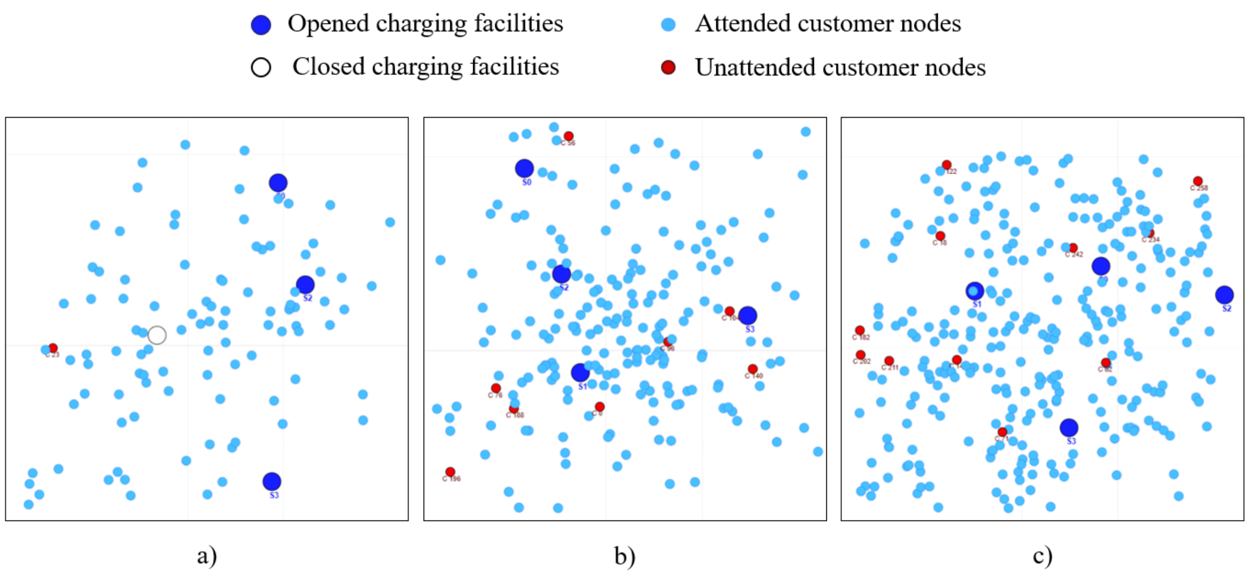

Figure 2: Drone charging station configuration and demand nodes obtained from solving the FLP for a) 100 customers, b) 200 customers and c) 300 customers.

Table 4: Average values of results obtained from solving the FLP in each demand scenario.

Instance	Total costs (€)	Coverage (%)	Avg. range (km)	Avg. e_j (Wh/km)
100 customers	4,910.16	99.00	18.94	19.54
200 customers	6,562.92	96.00	18.98	19.50
300 customers	10,251.65	96.33	19.00	19.48

5.2 Drone Performance in Simulation Results

This section gathers the results retrieved from the simulation model, which represent drone operation performance. The key performance indicators are summariced in Figure 3 for the travel distance and in Table 5 for coverages, average distances flown from stations to customers, and flight times. Simulated values of drone flight time and distances can be compared with the results obtained from the optimization problem. On the one hand, the average travel distance of drones flying from Station 0 in the 100-customer instance (20.05 km) can be seen to be slightly longer than the calculated average range (18.94 km). The same comparison can be done with all the stations in each scenario, and it can be seen that in some cases the average travelled distance exceeds the calculated average flight range. This implies that the energy consumption per km travelled lacks the effect that speed has in energy consumption, which is actually included in the simulation model. Besides, if focusing on the travel distance for each scenario as displayed in Figure 3, drones in the model are able to perform flights ranging from 5 km up to 30 km. Despite the assumption that station assignment minimizes travel distance, some stations end up covering longer distances to serve their customers.

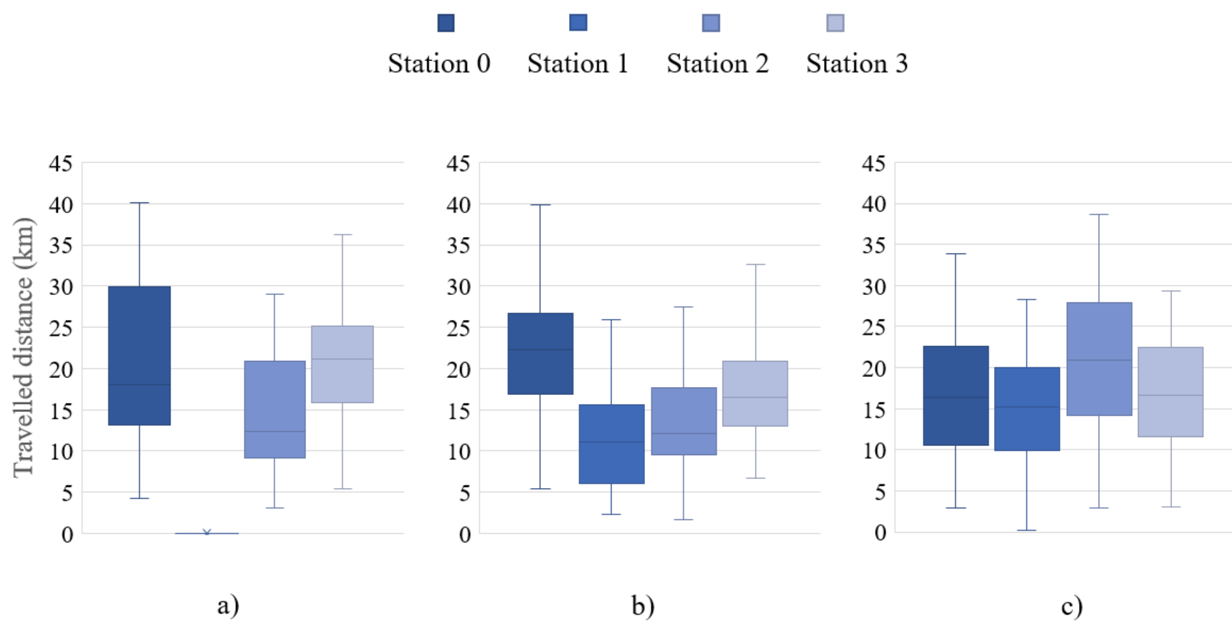

Figure 3: Travelled distance per drone from its station to its assigned customer for cases a) 100 customers, b) 200 customers, and c) 300 customers.

On the other hand, as presented in Table 5, flight time and delivery time also change depending on the scenario and the analyzed station. The mean delivery time, which corresponds to the flight time from the station to the customer (t_c in the table), lies between 8.75 and 21.63 min considering all scenarios and stations. Meanwhile, the total travel time average lies between 16.69 and 31.85 min. Thus, from running the proposed experiments it is obtained that the average flight times are in line with the specifications from commercial drone models such as AmazonAir MK27-2 (Amazon 2023) or Wing drones (Wing 2022), claimed to be able to sustainably deliver a vast selection of items in under an hour, and possibly within 30 minutes. This results also coincide with those of Figliozzi (2018), reporting that most available commercial UAVs flying times are in the range of 20 to 30 minutes. Note that these average values have been computed with the times recorded during simulation from all the drone flights from departing to arrival at a given station.

Table 5: Summary of stations results.

	100			200			300		
	d_t (km)	t_c (min)	t_s (min)	d (km)	t_c (min)	t_s (min)	d (km)	t_c (min)	t_s (min)
Station 0	20.05	15.46	14.16	21.81	16.86	14.99	17.25	13.15	11.65
Station 1	-	-	-	11.58	8.75	7.94	15.05	11.28	10.35
Station 2	14.45	11.70	9.49	13.55	10.47	9.43	21.10	16.31	14.55
Station 3	20.50	15.40	13.99	17.26	13.51	11.75	16.73	12.32	11.69

In Table 5, d_t is defined as the average distance from a station to a customer travelled by a drone, which is calculated for each station. The variable t_c is the average flight time to a customer from a station, and t_s is the flight time back to this station from the customer node, calculated on average for a given station.

5.3 Battery System Dynamics Model Results

This section displays an example of the results obtained with the system dynamics simulation model of the drone battery state of charge (SOC). One operative drone is selected for this aim from the instance where 100 customers are considered, in order to show the evolution of the battery state during operation. The results of the electric energy are shown in Figure 4, accounting for a single delivery and an entire charging cycle. As visible in the figure, the drone is assigned an order around 10:00 (120 minutes of simulation), and begins its fly towards the customer to be served decreasing its battery with a given BCR. This implies that the SD discharge flow will be switched on and the battery charge will be consumed. The order is delivered in approximately 10 minutes, and afterwards the drone goes back to its station to get recharged (depicted in green in Figure 4). It takes around seven minutes to get back to the station, with 45 % of its battery consumed for delivery purposes. The BCR decreases in the return trip, as the mass decreases significantly once the payload is put down. When arrived at the station, the SOC increases from 55 % to fully charged in twelve minutes, on a constant battery charging rate, as depicted in yellow.

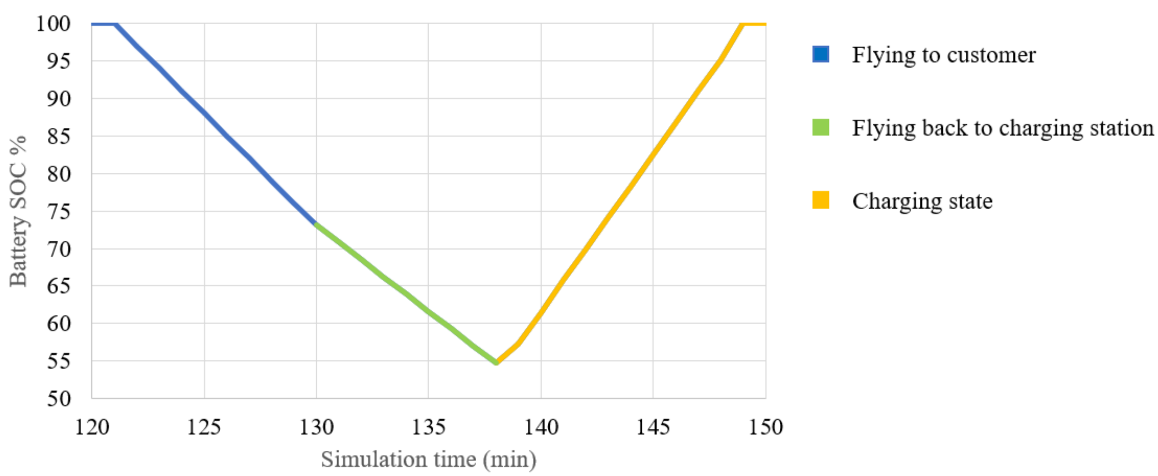

Figure 4: Drone battery evolution during delivery operation.

6 CONCLUSIONS

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

Therefore, there are two major conclusions derived from this work. Concerning the results, it has been demonstrated that considering the weight of parcels and the flight distance significantly impact the performance of drone distribution to stations, as they have a direct effect on the battery consumption dynamics and the flight range. These findings highlight the importance of adjusting operational parameters based on drone payload and range to optimize the delivery system. Second, this research highlights the convenience of hybrid methodologies for addressing real-world complex problems. The authors explored the integration of optimization and simulation techniques and demonstrated the advantages of combining Agent-Based Modeling and Integer Programming optimization to tackle drone-assisted delivery, a novel approach in logistics literature. This hybrid approach provides greater flexibility and capacity to capture the inherent complexity of modern distribution systems, making it a valuable tool for strategic decision-making in the last-mile logistics domain. Additionally, by incorporating System Dynamics Simulation into the ABM model, this study addressed the energy consumption dynamics during UAV movement, enhancing the realism of the simulations. The advancements in Operations Research demonstrated in this work pave the way for refining similar models applicable to autonomous vehicles, robotic-assisted deliveries, and other innovative solutions for last-mile delivery.

While this hybrid model has proven effective in optimizing last-mile logistics, certain limitations must be acknowledged. Data limitations, potential inaccuracies, and omitted factors like climate impact and traffic circumstances may have affected the analysis. Future research should focus on overcoming these limitations by acquiring primary data sources and conducting in-field surveys to enhance the accuracy and reliability of models. Parameter values selected for the experiments could be easily adjusted according to other scenarios that could be posed in future works. As highlighted by Dukkanci et al. (2023), substantial uncertainties surround the costs associated with drone-assisted delivery operations, facility expenses, and battery charging costs and times due to the relatively new and developing technology. This underscores the need for ongoing research and adaptation as technology progresses. Future work should address these uncertainties, considering the dynamic nature of demand and optimizing drone hub locations accordingly. Moreover, alternative methods should be also considered in future contributions to analyze cost savings, efficiency improvements, and other key metrics in the delivery system.

ACKNOWLEDGMENTS

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REFERENCES

Amazon 2023. "Amazon is Launching Ultra-Fast Drone Deliveries in Italy, the UK, and a Third Location in the U.S.". https://www.aboutamazon.com/news/operations/amazon-prime-air-drone-delivery-updates. Accessed on February 22, 2024.

Balaban, M. A., T. W. Mastaglio, and C. J. Lynch. 2016. "Analysis of Future UAS-Based Delivery". In *2016 Winter Simulation Conference (WSC)*, 1595–1606. IEEE.

Benarbia, T. and K. Kyamakya. 2021. "A Literature Review of Drone-Based Package Delivery Logistics Systems and Their Implementation Feasibility". *Sustainability* 14(1):360.

Chauhan, D., A. Unnikrishnan, and M. Figliozzi. 2019. "Maximum Coverage Capacitated Facility Location Problem with Range Constrained Drones". *Transportation Research Part C: Emerging Technologies* 99:1–18.

Chour, K., J.-P. Reddinger, J. Dotterweich, M. Childers, J. Humann, S. Rathinam *et al*. 2023. "An Agent-Based Modeling Framework for the Multi-UAV Rendezvous Recharging Problem". *Robotics and Autonomous Systems* 166:104442.

Deng, T., X. Xu, Z. Zou, W. Liu, D. Wang and M. Hu. 2023. "Multi-Drone Parcel Delivery via Public Vehicles: A Joint Optimization Approach". *IEEE IoT Journal* 11(6):9312–9323.

Dukkanci, O., J. F. Campbell, and B. Y. Kara. 2023. "Facility Location Decisions for Drone Delivery: A Literature Review". *European Journal of Operational Research* 316(2):397–418.

Figliozzi, M., J. Saenz, and J. Faulin. 2020. "Minimization of Urban Freight Distribution Lifecycle CO_{2e} Emissions: Results From an Optimization Model and a Real-world Case Study". *Transport Policy* 86:60–68.

Figliozzi, M. A. 2017. “Lifecycle Modeling and Assessment of Unmanned Aerial Vehicles (Drones) CO_{2e} Emissions”. *Transportation Research Part D: Transport and Environment* 57:251–261.
Figliozzi, M. A. 2018. “Modeling the Sustainability of Small Unmanned Aerial Vehicles Technologies: Final Report”. *Civil and Environmental Engineering Faculty Publications. FMRI Reports.*:1–65.
Ghelichi, Z., M. Gentili, and P. B. Mirchandani. 2022. “Drone Logistics for Uncertain Demand of Disaster-Impacted Populations”. *Transportation Research Part C: Emerging Technologies* 141:103735.
Gonzalez-R, P. L., D. Sanchez-Wells, and J. L. Andrade-Pineda. 2024. “A Bi-Criteria Approach to the Truck-Multidrone Routing Problem”. *Expert Systems with Applications* 243:122809.
Hadas, Y. and M. A. Figliozzi. 2024. “Modeling Optimal Drone Fleet Size Considering Stochastic Demand”. *EURO Journal on Transportation and Logistics* 13:100127.
Moadab, A., F. Farajzadeh, and O. Fatahi Valilai. 2022. “Drone Routing Problem Model for Last-Mile Delivery Using the Public Transportation Capacity as Moving Charging Stations”. *Scientific Reports* 12(1):6361.
Raivi, A. M., S. A. Huda, M. M. Alam, and S. Moh. 2023. “Drone Routing for Drone-Based Delivery Systems: A Review of Trajectory Planning, Charging, and Security”. *Sensors* 23(3):1463.
Sing, K., P. Mertiny, and M. Pruckner. 2022. “Modeling and Simulation to Improve Real Electric Vehicles Charging Processes by Integration of Renewable Energies and Buffer Storage”. In *2022 Winter Simulation Conference (WSC)*, 867–878. IEEE.
Utomo, D. S., A. Gripton, and P. Greening. 2020. “Long Haul Logistics Using Electric Trailers by Incorporating an Energy Consumption Meta-Model into Agent-Based Model”. In *2020 Winter Simulation Conference (WSC)*, 147–158. IEEE.
Wang, X., Z. Liu, and X. Li. 2023. “Optimal Delivery Route Planning for a Fleet of Heterogeneous Drones: A Rescheduling-Based Genetic Algorithm Approach”. *Computers & Industrial Engineering* 179:109179.
Wang, X., K. Swanson, Z. Liu, G. Jones, and X. Li 2022. “A Simulation-Heuristic Approach to Optimally Design Drone Delivery Systems in Rural Areas”. In *2022 Winter Simulation Conference (WSC)*, 1581–1592. IEEE.
Wing 2022. “Wing Aviation LLC”. https://wing.com/how-it-works/. Accessed on February 22, 2024.
Zou, B., S. Wu, Y. Gong, Z. Yuan, and Y. Shi 2023. “Delivery Network Design of a Locker-Drone Delivery System”. *International Journal of Production Research* 62(11):4097–4121.

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