Economic Sustainability in Last-Mile Drone Delivery Problem with Fulfillment Centers: A Mathematical Formulation

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Abstract: This study is motivated by the increasing growth in the competitive e-commerce market where on-line *business-to-customer* retailers, seeking for cost-efficient and timely delivery services, are persuaded to adopt a drone-based delivery system against the traditional terrestrial one. Recently, the drone-aided delivery services have significantly been eased, thanks to the development of fulfilment centers, as aerial base stations monitoring and arranging back-and-forth drone trips between the fulfilment centers and customers' sites that also provide the retailers with services such as package handling, restocking, and drone recharge. Obviously, adopting a drone-based delivery system incurs various expenses: besides drone recharge, maintenance, and energy consumption costs, the usage cost for fulfillment centers, namely tariff, should be paid by the retailers to the FC manager. This study aims to address the economic sustainability of a drone-aided delivery system with fulfillment centers and to provide the retailer with an optimal delivery plan maximizing his profit. This could eventually provide a stable platform for new and small-sized business-to-customer retailers trying to survive in such a competitive market and to promote the use of drone fulfillment centers.

1 INTRODUCTION

The boom in e-commerce and the tremendous growth in on-line retail have created intense competition among new and small-sized *Business-to-Customer* (B2C) companies striving to meet customer expectations in terms of cost-efficient and timely delivery. This has provided potentials for the development of e-logistics services suggesting drone-based delivery solutions (Pani et al., 2020). The increasing interest towards drone-based delivery services, coming from the evident environmental impact, cost-inefficiency and long delivery time of terrestrial vehicles, has challenged logistics stakeholders to resort to more innovative and sustainable delivery solutions as Unmanned Aerial Vehicles (UAVs) or drones. The Amazon Prime Air project, Google Wing projects, Deutch Post DHL, and JingDong (Liu et al., 2021) are only a few examples of this successful and ambitious idea of introducing drone-aided delivery into the logistic sector.

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Recently, Amazon announced that by the end of 2024, the Amazon Prime Air will be expanded to Italy, UK, and other cities in the United States (Amazon, 2023), integrating in such a way, drone deliveries into Amazon's existing fulfillment center network.

Fulfillment Centers (FC) are specialized distribution centers that facilitate the drone integration into delivery systems. These drone base stations offer landing, takeoff, drone recharge, and package handling services to on-line retailers. Obviously, small B2C retailers cannot afford possessing such costly infrastructures. FC managers provide the service at a cost (also referred to as *tariff*) per drone, that might also be time-varying. Each delivery has an associated revenue, and a set of preferred time intervals. The variation in tariffs and revenues is related to the dynamic nature of the problem: tariffs reflect changes in workforce prices, whilst revenues vary depending on the type of shipping (standard, express) and by the customer's preferences. This suggests the use of a multi-period framework (instead of a static one) where the decisions can be adapted over time in order to capture such variations (Bakker and Nickel, 2024; Khodaparasti et al., 2018). In addition, the FC tariffs affect the economic sustainability of the drone-

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delivery system and the profitability of the retailer business. Recent researches showed the potentials for the establishment of new multi-level FCs to facilitate last-mile drone delivery services across European cities (Aurambout et al., 2022).

The appealing features of drone-based delivery solutions in terms of low environmental implications (CO_2 footprint and noise pollution) have somehow shifted the focus of practitioners and operational researchers to its green sustainability, ignoring or even downplaying the importance of addressing economic viability measures in delivery systems.

The present study aims to address the economic sustainability of drone-based delivery services with FCs through the design of an efficient delivery system operating on a daily basis, where drone-specific features, as energy consumption and recharge time, along with customers' preferences in terms of delivery time are properly incorporated. To design such a holistic delivery service, we adopt a multi-period framework that enables us to capture the inherent dynamicity of problem in terms of time-variant tariffs and delivery revenue.

We should highlight that the economic sustainability of system is highly affected by the retailer decisions on *how* (questioning the transport mode) and *when* the delivery plans are scheduled. With the aim of maximizing the retailer total profit over a short-term planning horizon of one working day, we present the optimal delivery plan specifying *i*) the transport mode and the delivery schedule for each customer; *ii*) the deployment schedule for each drone; *iii*) the set of FCs used to host the deployed drones. We also investigate the impact of different tariff setting policies on the system economic viability providing the logistics companies/the FC manager with managerial insights on how the appropriate share of FCs resources among different retailers could help to establish a stable platform for e-logistics businesses. In this way, we address the economic viability and sustainability of drone-deliveries with FCs in B2C logistics, investigating the effect of tariffs on both the retailer's revenue and the sustainability of delivery system.

The rest of the paper is organized as follows. Section 2 presents a review on pure-drone delivery problem in the literature pointing up the gaps. Section 3 describes the problem and presents the mathematical formulation. Section 4 is devoted to the computational experiments conducted on a real case study for the Portland city adapted from (Chauhan et al., 2019) and the discussion on managerial insights. Finally, Section 5 provides the concluding remarks and potential directions for future research.

2 LITERATURE REVIEW

Large part of the literature on UAV-based logistics systems is devoted to contributions on multi-modal delivery models where a fleet of drones and autonomous trucks cooperate to serve customers (Bruni et al., 2022; Dell'Amico et al., 2022; Moshref-Javadi and Winkenbach, 2021). However, the present contribution falls in the class of pure-play drone-based models where deliveries are handled just by drones.

The literature on pure drone delivery problem is categorized in two main streams depending on whether drones perform multi-visit or single visit tours. The multi-visit case involves routing decisions where drones can visit multiple customers per trip (Torabbeigi et al., 2020).This, of course, limits the applicability of proposed models to cases wherein the drone payload capacity and battery charge allow multiple deliveries per trip and requires to account for load-dependent energy consumption rates in drone battery. Following this stream, (Dorling et al., 2016) and (Cheng et al., 2020) presented multi-visit drone delivery models where the energy consumption in drone battery is explicitly modeled. (Bruni et al., 2023b) studied a routing problem for last-mile drone delivery with shared FCs and homogeneous parcel weight where the objective is to minimize the total travel cost (Bruni et al., 2023b). The authors model the energy consumption rates considering internal and external factors that affect energy consumption, including drone-specific features (such as the number of rotors, the drone frame and battery mass), the environmental factors (air density and gravitational force), and the mass of order(s) carried by drone. There are also other contributions on multi-visit drone delivery problem that account for energy consumption rates under the travel time uncertainty that is not the focus of present paper, and therefore, we refer the interested reader to (Bruni and Khodaparasti, 2022a; Bruni et al., 2023a; Bruni and Khodaparasti, 2022b).

As mentioned earlier, the limited drone flight endurance, payload and battery capacity makes the adoption of routing plans in many drone delivery applications impractical. On the other hand, the single visit drone delivery case where each drone performs multiple trips delivering the order of one single customer per trip is more realistic and practical, as supported by many contributions in the literature (Chauhan et al., 2019; Figliozzi, 2020; Pani et al., 2020; Dukkanci et al., 2021).

Following the single visit drone delivery context, we may recognize that some contributions model the energy consumption rates in drone battery as a linear function in terms of drone payload and travel time

(Chauhan et al., 2019; Chowdhury et al., 2017; Zhu et al., 2022), while some other studies do not account for energy consumption (Golabi et al., 2017; Pulver and Wei, 2018).

To the best of our knowledge, only (Dukkanci et al., 2021) introduced an explicit calculation of the energy consumption as a nonlinear function of the drone speed in a single visit drone delivery problem where drones are first transported by trucks to the proximity of customers and then perform multiple back-and-forth trips between the trucks and customers' locations to deliver orders.

Another important issue, mostly ignored in the drone-delivery context, is the battery recharge. In fact, most contributions do not account for it and for the charging time spent. For example in (Chauhan et al., 2019), the battery recharge is not taken into account and it is assumed that the drone batteries are recharged overnight or in-between planning periods.

In the present study, we bridge the gap in the literature by designing a multi-period drone-based delivery system with FCs, focusing on the economic sustainability and viability of the delivery system. We provide the retailer with optimal delivery schedules for a short-term planning horizon where the realistic assumptions on energy consumption in drone battery, the heterogeneity of fleet, the time required to recharge batteries after each depletion, the customer preferences in terms of delivery time, and the time-dependency of parameters are directly incorporated.

3 PROBLEM DESCRIPTION AND MATHEMATICAL FORMULATION

The last-mile drone delivery problem with FCs is described as follows. The FCs' owner manages a set of existing FCs as the distribution centers specialized for drone usage where drones are loaded with customer packages, launched and dispatched to the customers' locations, where the package is left at the doorstep, and are then retrieved back for the next delivery. The FCs offer different services such as restocking and package handling to the retail companies and are capacitated. The retail companies, considering the FCs' usage costs decide on how (by drone or traditional transport vehicles) and when to plan the customer deliveries. The retail company can consider an external delivery service as an alternative option to deliver some orders. The external service is usually performed by a terrestrial vehicle that is highly expensive, compared to the drone-delivery option, imposing a penalty cost to the retailer that loses the potential profit of that delivery request.

We should note that each customer has preferences in terms of delivery time, and thus, can be visited only during one of his preferred time periods. The retail company's main goal is to maximize the total profit (expressed in terms of total revenue minus total costs) gained from delivering orders within the preferred delivery times, specifying the transport mode for each single order (by drone or the terrestrial service) and the delivery schedules at each time slot. The total cost includes the FC's usage cost, the delivery cost, and the penalty cost for customers not being served by drones. The usage cost associated to a FC depends on both the time period at which the FC is used and its location, raising the issue of optimally select the FCs. The delivery cost includes the drone usage and maintenance costs plus the routing expenses monetized in terms of energy consumption in drone battery. The retail company owns a set of heterogeneous drones (denoted by U and indexed by u) and should deliver the orders of a set customers in I where the location of customer i and its parcel mass d_i (in kg) are already known. Each customer has preferred time interval(s) to receive the delivery. The set of preferred delivery time for customer i is denoted by $E(i) \subset H$ where H denotes the set of time slots (periods).

In fact, we consider a short-term planning horizon of one working day discretized into different time periods, with the same length (usually one hour), to capture the dynamicity of the problem in terms of time-varying FC tariffs, customer preferences for delivery time, and time-dependent delivery revenues. We should highlight that the hourly granularity is consistent with the average time required to recharge a typical drone battery (Leslie, 2024).

The representative retail company seeks maximizing the total profit expressed in terms of revenue minus the delivery costs. The retail company decides upon the selection of FCs over different time periods, the allocation of drones to used FCs, the delivery schedule for each drone meeting the customers preferences in terms of delivery time, and finally the choice of customers to be served by the alternative vehicle.

In summary, the problem's main assumptions are listed as follows:

- A set of capacitated FCs are available to host the drones
- A set of heterogeneous fully charged drones is available
- The planning horizon is divided into a set of discrete time slots

- Each drone can use only one FC throughout the entire planning horizon
- Each customer has preferences in terms of delivery time, limiting its visit to specific time periods
- At the beginning of a typical time period, each drone, if deployed, is loaded with a single customer's order and is launched from its host FC, delivers the order to the customer's location and is retrieved at the FC
- Drones are allowed to perform multiple single-visit trips within the same time period to serve multiple customers, as long as the drone battery is not depleted
- Battery recharge is allowed only at FCs and if the battery needs to be recharged, the drone spends the subsequent time period in the FC and therefore cannot be deployed

Figure 1 illustrates the delivery scheme for a typical drone-based delivery problem with FCs.

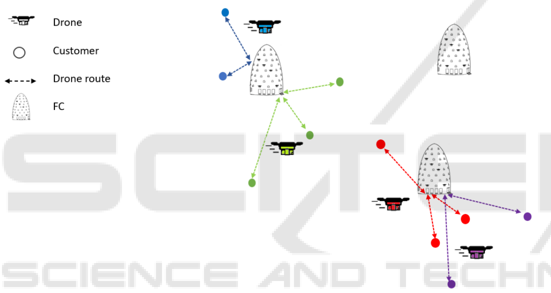

Figure 1: Scheme of the delivery system: A delivery example with 3 FCs, 4 drones, and 10 customers.

The problem notation is presented in Table 1.

Table 1: Notation for the mathematical model.

Sets and Indices	
I	set of customers indexed by i
D	set of FCs indexed by j
H	set of time slots indexed by h
U	set of drones indexed by u
$E(i) \subseteq H$	set of preferred delivery time slot for customer i
Parameters	
p_j^h	usage cost (tariff) for FC j at time slot h
λ	penalty cost for using external delivery service
ϕ_i^h	revenue for the order delivery of customer i at time slot h by a drone
e_{ji}^u	energy consumption of drone u across the path between FC j and customer i
e_{ij}^u	energy consumption of drone u across the path between customer i and FC j
E^u	battery capacity of drone u
K_j^h	capacity of FC j (in terms of total number of deliveries) at time slot h
c_{ij}^u	delivery cost of drone u to deliver order of customer i from FC j
Decision variables	
y_{uj}^h	binary variable takes 1 if drone u is deployed from FC j at time slot h; and 0 otherwise
x_{ij}^{uh}	binary variable takes 1 if order of customer i is delivered at time h by drone u from FC j; and 0 otherwise
w_i	binary variable takes 1 if customer i is served by express delivery service; and 0 otherwise
α_{uj}	binary variable takes 1 if drone u assigned to FC j is deployed at least in one time slot

The mathematical formulation is cast as follows:

$$\max : \sum_{i\in I}\sum_{j\in D}\sum_{u\in U}\sum_{h\in H}\phi_i^h x_{ij}^{uh} - \Big(\sum_{j\in D}\sum_{u\in U}\sum_{h\in H} p_j^h y_{uj}^h +$$

$$\sum_{i\in I}\sum_{j\in D}\sum_{u\in U}\sum_{h\in H} c_{ij}^u x_{ij}^{uh} + \sum_{i\in I}\lambda w_i\Big) \quad (1)$$

$$\sum_{i\in I}\sum_{u\in U} x_{ij}^{uh} \leq K_j^h \;\; j\in D, h\in H \quad (2)$$

$$y_{uj}^h \leq \alpha_{uj} \;\; u\in U,\ j\in D, h\in H \quad (3)$$

$$\sum_{j\in D}\alpha_{uj} \leq 1 \;\; u\in U \quad (4)$$

$$\sum_{i\in I}(e_{ji}^u + e_{ij}^u)x_{ij}^{uh} \leq E^u y_{uj}^h \;\; u\in U,\ j\in D,\ h\in H \quad (5)$$

$$y_{uj}^h + y_{uj}^{(h+1)} \leq 1 \;\; u\in U,\ j\in D,\ h\in H, h\neq |H| \quad (6)$$

$$\sum_{j\in D}\sum_{u\in U}\sum_{h\in H} x_{ij}^{uh} + w_i = 1 \;\; i\in I \quad (7)$$

$$\sum_{j\in D}\sum_{u\in U} x_{ij}^{uh} = 0 \;\; i\in I,\ h\in H\setminus E(i) \quad (8)$$

$$x_{ij}^{uh} \in \{0,1\} \;\; i\in I,\ u\in U,\ j\in D,\ h\in H \quad (9)$$

$$y_{uj}^h \in \{0,1\} \;\; u\in U,\ j\in D,\ h\in H \quad (10)$$

$$w_i \in \{0,1\} \;\; i\in I \quad (11)$$

The objective function (1) represents the total profit of the retail company expressed in terms of the revenue minus tariffs, delivery and penalty costs. Constraints (2) set an upper bound on the total number of deliveries performed from each FC during each time slot. Constraints (3) show the relation between variables α and y. Constraints (4) ensure that if a drone is deployed at least once from a FC, it should stay at that specific FC for the whole planning horizon, and thus, avoiding the unnecessary reallocation of drones between different FCs. Constraints (5) model the drone energy consumption over multiple trips, ensuring that, the total energy consumption over the back-and-forth trips of each time period is below the battery capacity. As said earlier, each drone could perform multiple back-and-forth trips between its host FC and different customers' sites within the same time period, if the battery is not depleted. Constraints (6) imply that each drone can be deployed only once during any two subsequent time slots, imposing one-time slot gap between consecutive drone deployments, as the time required for battery recharge.

Constraint (7) guarantee that each customer's order is delivered either by a drone or by the external service. Constraints (8) are related to the customer's delivery time preferences that prevent deliveries within undesirable time slots. Finally, constraints (9)-(11) represent the nature of variables.

Following (Dorling et al., 2016), the energy consumption (in Watt-hours, Wh) is expressed as a nonlinear function in terms of drone payload capacity, frame and battery mass, and the travel time. The energy consumption for drone u flying from FC j to location of customer i with travel time t_{ji}^u (in hour) while carrying the order of customer i with mass of d_i (in kg) is expressed as:

$$e_{ji}^u = \sqrt{\frac{g^3}{2\rho\xi^u s^u}}(W^u + M^u + d_i)^{3/2} t_{ji}^u \qquad (12)$$

where g is the gravity constant (in N/kg), ρ represents the fluid density of air (in kg/m^3), ξ^u is the area of spinning blade disc (in m^2), s^u is the number of rotors of drone u, and W^u and M^u indicate, respectively, the drone frame and battery mass (in kg). The energy consumption of drone u that travels back empty is expressed as

$$e_{ij}^u = \sqrt{\frac{g^3}{2\rho\xi^u s^u}}(W^u + M^u)^{3/2} t_{ij}^u \qquad (13)$$

4 COMPUTATIONAL EXPERIMENTS

In this Section, we test the efficiency and the validity of the proposed model. In particular, we report the results of a real case study for drone-based last-mile delivery in Portland city (Chauhan et al., 2019). The input data and the problem size were slightly modified to fit the characteristics of drone delivery with FCs. To be more precise, we first solved a maximum covering model, considering the original case study with 122 customer locations and 104 potential FCs, to determine ten potential FCs and the largest set of customers that can be served by a fleet of ten Alta 8 drones and the following features: battery capacity of $E = 0.355$ kWh, the frame and battery mass of, respectively, $W = 6.2$ kg and $M = 2.8$ kg, the payload capacity of 9.1 kg, with $s = 8$ rotors and $\xi = 1.204$ m^2. Also, the fluid density of air is set to $\rho = 0.1256$ kg/m^3 and $g = 9.81$ N/kg. This reduced the set of customers to 61, for which we set the same order mass values as reported in the original case study (Chauhan et al., 2019). We assume a short-term planning horizon of a typical working day from 8 AM to 4 PM, split into eight time periods, each with one-hour length. This granularity level is also consistent with the average recharge time for an Alta 8 drone.

The preferred delivery times of each customer were generated randomly considering that each customer can be served during 3 to 6 different time slots. We also set the upper bound $K_j^h = 5$ for the maximum number of back-and-forth trips operated from FCs during each period. The delivery revenues (in dollars) were generated randomly following the uniform distribution $U(8, 20)$. All the data about the drone delivery costs and external delivery costs were taken from (French, 2017). Finally, for the FC tariffs, we considered a general pricing rule where the forth and fifth time slots (from 11 AM to 1 PM) have the highest tariffs, followed by the third, second and first periods. The sixth, seventh and eighth time slots have, respectively, the same tariffs as the third, second and first ones.Under this general rule, we generated three different scenarios; in the first two scenarios, tariffs are time-dependent and the third scenario is a time-invariant case. In Scenarios I and II, the FCs manager sets, respectively, low and high tariff rates randomly generated from $[0.3, 0.8]$ and $[0.5, 0.9]$ rounded to one decimal digit. In Scenario III, the FCs manager set time-invariant tariffs that are the same for each FC throughout the planning horizon. Such tariffs for each FC are calculated as the maximum value over the average of the tariffs under Scenarios I and II.

Figures 2-4 display the tariffs under each scenario.

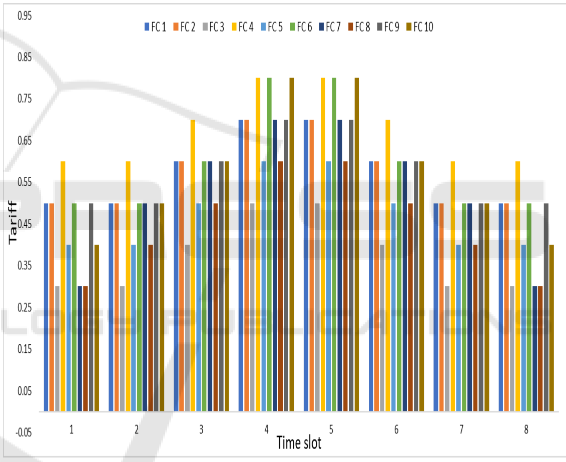

Figure 2: Time-dependent tariffs: Scenario I.

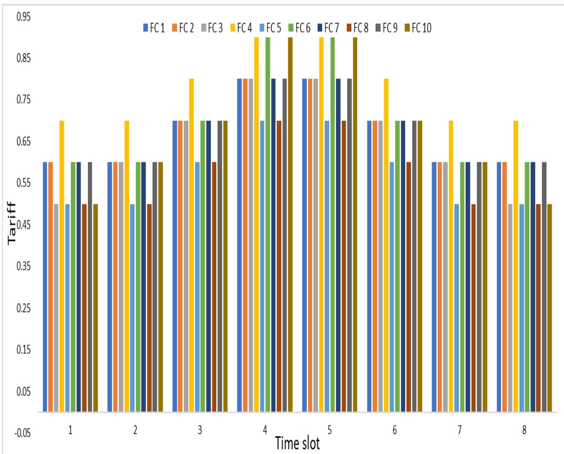

Figure 3: Time-dependent tariffs: Scenario II.

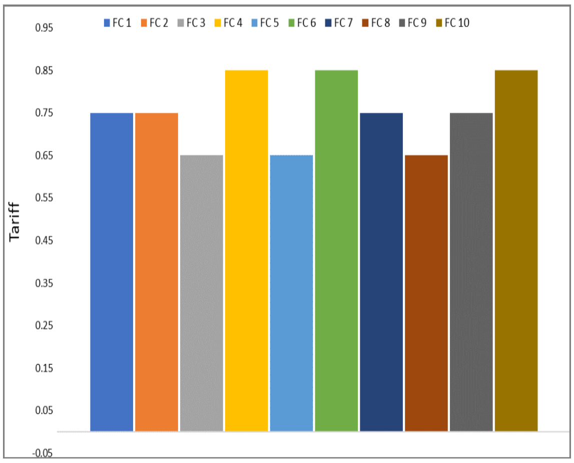

Figure 4: Time-invariant tariffs: Scenario III.

All the experiments were run on an Intel Core i7-10750H, with 2.60 GHz CPU and 16 GB RAM working under Windows 11. The model was implemented in the algebraic modeling language AIMMS 4.79.2.5 The solution times for Scenario I and Scenario II, are 10 and 14 minutes, respectively, followed by 15 minutes under Scenario III. First, we comment on the results for Scenario I, considered as the baseline. Figure 5 displays the optimal delivery plans. All deliveries performed during the same time period are depicted by the same color. The selected FCs are displayed in red and the non-selected FCs are shown in black. As we can see, all the orders are delivered by the drones and no external service is used. We also observe quite promising results where the retailer expenses, in terms of FC tariffs and total drone related and delivery costs, represent only 8% of the total revenue. If the drone-based delivery service with FCs is not available and all the orders are delivered by the external service, assuming the same delivery cost of 2.5 $ per order as mentioned in (French, 2017), the retailer business completely fails. This managerial insight shows the importance of adopting an efficient delivery system to ensure the economic sustainability of business. As for the fleet workload, the results show that each drone is deployed at least within 3 and at most 4 time slots. Reminding the gap imposed between two consecutive drone deployments, we deduce that the workload between drones is appropriately balanced. In total, drones are deployed 35 times within different slots, performing from 1 to 4 deliveries per time period in order to complete 61 delivery trips (on average in each drone deployment, 1.7 customers are served).

A percentage of 58% of customers preferred to receive their orders within 11 AM and 1 PM, and therefore, many deliveries had to be scheduled within the forth and the fifth time slots when the tariffs are the highest. However, the total tariff cost is only 4% of the total revenue showing that the designed delivery system not only meets the customers' expectations but also is sustainable with respect to economic criteria.

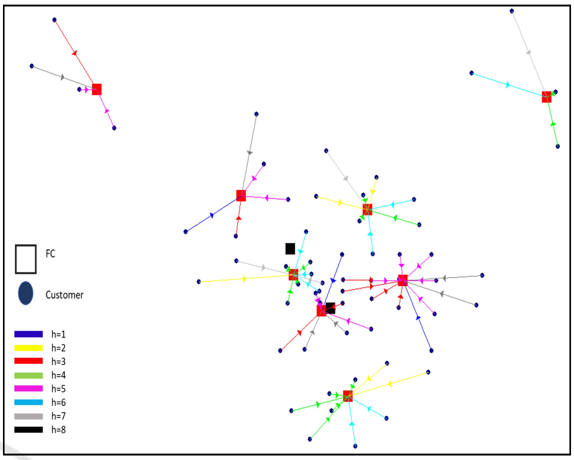

Figure 5: Optimal solution under scenario I.

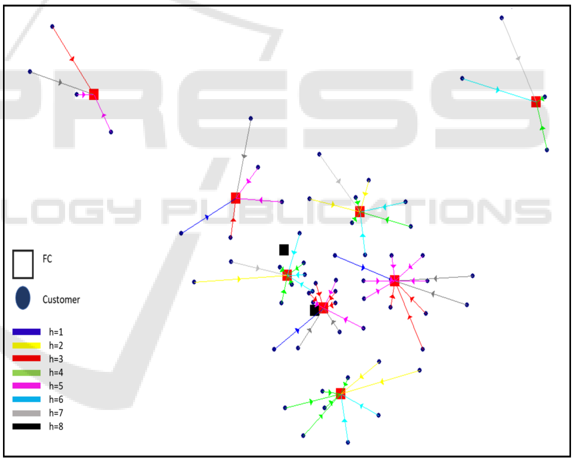

Figure 6: Optimal solution under scenario II.

We obtained similar results under scenario II where the FCs manager increases the tariffs on average by 27% (at least 20% and at most 100%). Of course, the delivery plans are different and the set of used FCs is different as shown in Figure 6. The increase in the tariffs increases the total cost for FC usage up to 20%. However, the results show that it is still beneficial to use the FC services and to perform all the deliveries by using drones. This is also an interesting insight for the FC manager showing that the retail companies can tolerate on average 30% increase in the tariff rates and still prefer to handle all deliveries using FC services. Of course such tolerance exists only in a monopoly situation where all the FCs belong to the same owner.

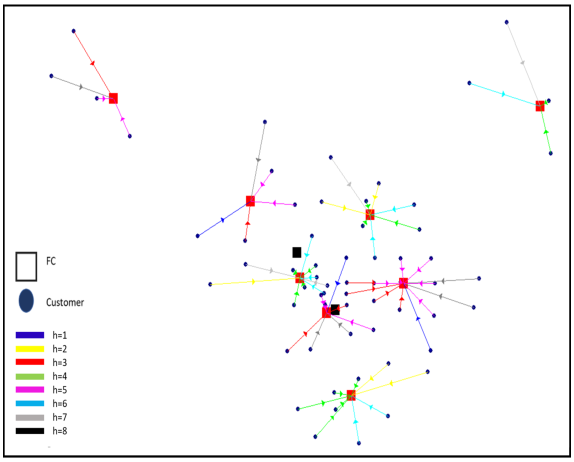

Figure 7: Optimal solution under scenario III.

Clearly, in a competitive market, the situation can be more complicated requiring an in-depth investigation.

The optimal delivery plans under Scenario III are illustrated in Figure 7. As we can see, even when the FCs manager imposes time-invariant tariffs, we can still serve all the customers by drones, showing the reliability of the designed delivery system. As expected, under Scenario III, the FC usage costs increase by about 8% and 27%, respectively, compared to Scenario I and Scenario II. To have an idea on the computational efficiency of the proposed model for larger instances, we tested the model on a set of cases with 100, 200, and 500 customers. All the input parameters for such instances were randomly generated using the uniform distribution and the minimum and maximum values reported in the case study. For instance, in the case study the orders' mass varies from 1.25 to 5 kg, so we set $d_i \sim U(1.25, 5), i \in I$. The same general rule was followed to generate other input parameters. Under a time limit of 1500 seconds, only instance with 500 customers were not solved to optimality where the gap is below 0.68%.

5 CONCLUSIONS

In this study, we addressed the economic sustainability and the efficiency of a drone delivery system to handle the daily last-mile deliveries for small B2C retailers. The delivery system encompasses a set of fulfillment centers, as specialized drone stations that facilitate drone deliveries, and a heterogeneous fleet of drones where each drone performs multiple back-and-forth single-visit trips between the FCs and customers' locations to deliver the orders. We formulated the problem as a mixed integer program incorporating realistic problem features, like energy consumption in drone battery, customer preferences with respect to delivery time, and the recharging time for drone batteries. The experiments carried out on a real case study showed informative insights on the economic sustainability of the designed drone-based delivery system, under different tariff setting policies. Future research should focus on the interplay and interaction between the FCs manager and retailer, to better frame the impact of tariff setting policies on the delivery service.

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