In-Flight Energy-Driven Composition of Drone Swarm Services

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Abstract—We propose a novel framework for swarm-based drone delivery services with in-flight energy recharging. The framework aims to enhance the delivery time of multiple packages by reducing the number of stops and recharging times at intermediate stations. The proposed framework considers various intrinsic and extrinsic delivery constraints. We propose to use support drones whose sole purpose is to recharge other drones in the swarm during their flight. In this respect, we compute the optimal set of optimal support drones to minimize the probability of delivery services and recharging time at the next stations. We also use two settings to position the support drones in a flight formation for comparative purposes. Two novel energy sharing methods are proposed, namely, Priority-based and Fairness-based methods. A re-ordering method of the delivery drones is presented to facilitate the in-flight energy composition process. An enhanced A* algorithm is implemented to compose the optimal services in terms of delivery time. Experimental results prove the efficiency of our proposed approach.

Index Terms—IoT services, drones swarm, in-flight energy recharging, service composition

1 INTRODUCTION

Combining unmanned aerial vehicle technologies with the service paradigm has given rise to the concept of Drone services [1]. It is defined as the use of drones to provide services [1]. A drone has the ability to sense the surrounding environment and carry payloads. DaaS are now routinely used in such domains as traffic monitoring [2], agriculture [3], and delivery [1]. Drone delivery services are the new technology that promises impactful and innovative solutions to the ever-expanding online shopping [4]. Drones provide a more cost-effective and environmentally friendly alternative when compared to terrestrial delivery services like trucks [5]. Examples of terrestrial services include FedEx and UPS. In addition, drones have been an enabling technology to mitigate the effect of pandemics such as COVID-19 by creating more resilient supply chains and socially distanced delivery services [6]. In that regard, the use of drones allows for the autonomous delivery of goods in a quicker, cheaper, and safer i.e., contactless manner. Major retailers are already integrating drones within their delivery options after governments around the world started relaxing regulations in response to the COVID-19 pandemic. For instance, Google’s Wing has expanded its drone delivery services by doubling its deployment rates in Australia.1

1. https://www.afr.com/technology/google-spreads-wings-as-drone-deliveries-up-500pc-20200929-p560bw

While single drone delivery provides a multitude of opportunities, there are instances where a swarm of drones may be required to fulfill the requirements of a delivery request. These include instances where a package is too heavy to be delivered by any one single drone or when multiple packages need to be delivered together. Federal aviation regulations dictate that payloads per drone not exceed 2.5kg.2,3 Hence, the swarm-based drone services are an effective alternative and solution to address these limitations [7]. The focus of this research is on the use of drone swarms for the delivery of packages as a service. More formally, a swarm is defined as a set of drones that move together within close proximity and arriving at any stop within a time window, thus acting as a single entity to achieve a certain goal. Swarms of drones have been used in various applications including military [8], airborne communication networks [9], sky shows [10], and delivery [11].

The limited battery capacity of drones presents a major challenge in swarm-based drone delivery services. Several solutions have been proposed to address this limitation. Intuitively, battery replacement would be the obvious solution. However, most automatic battery replacement approaches exhibit inadequate accuracy in outdoor environments [12]. Carrying additional batteries may be another solution. However, given the drones’ small size, this would severely limit their useful load. Solar energy is another option. However, its dependence on the weather conditions and slow charging process would make it hardly practical [13]. Moreover, the size of the solar panels would add to the payload [13]. Another suggested solution in the literature is

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2. Federal Aviation Administration (FAA) in USA- https://www.faa.gov/úaadvanced_operations/package_delivery_drone

3. Drone delivery company confident of taking flight in Queensland, Australia- https://www.brisbanetimes.com.au/national/queensland/drone-delivery-company-confident-of-taking-flight-in-queensland-20190731-p52ckx.html

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the use of laser beams fitted at rooftops. This would not be applicable in a delivery scenario as the range of the beam will vary when the drones move. Furthermore, the line-of-sight would be blocked by the urban environment [13]. A more realistic option is the use of recharging pads at delivery/recharging stations [7]. A major challenge is the limited number of recharging stations, thus limiting the number of parallel recharging of drones. This may result in extra waiting times until all drones in a swarm are recharged as they act as an atomic unit for delivery purposes. Consequently, delivery times would likely be negatively impacted. We propose the use of in-flight recharging drones to speed up swarm-based drone package delivery services. We introduce the concept of support drones that fly with a swarm to in-flight charge other drones.

In-flight charging refers to the technology that enables recharging drones’ batteries on the fly. For example, GET Air solution provides an in-flight wireless power charger which can give a maximum output power of 12kW. The drone only needs to hover over a recharging power station for six minutes. A new approach allows drones to deliver power wirelessly while in-flight [14]. The drone, in this case, transmits signals that can be harvested and rectified to DC voltage. We focus on energy sharing services, through the use of in-flight recharging, as an overlay to expedite swarm-based drone service delivery. Energy sharing services allow drone swarms to travel farther destinations reducing the number of stops needed to recharge. Energy sharing refers to the general process of sharing energy among IoT devices [15]. An IoT device (in our case, a drone) that shares energy is called an energy provider. In contrast, an IoT device that requires energy is called an energy consumer. In a swarm-based drone delivery services context, we view a drone that transmits energy as the provider. The consumer is the drone that received the energy.

Swarm-based drone delivery services lend themselves quite naturally to being modeled using the service paradigm because they map to the key ingredients of the services’ concept, i.e., functional and non-functional attributes [7]. The function of a swarm-based drone service is the delivery of packages from a source to a destination by a swarm. The non-functional properties include energy consumption, delivery time, etc. Likewise, we leverage the service paradigm to model energy sharing services, termed as Energy-as-a-Service (EaaS) [15], [16]. The function of EaaS is to share energy between a provider and a consumer. The non-functional properties include the amount of energy, sharing duration, etc. We propose a nested two-level service composition framework that consists of composing swarm-based drone services while achieving an Energy-as-a-Service composition (EaaS). In this respect, the first level composition of energy services acts as a non-functional (QoS) for the second level of composition of swarm-based services. Therefore, finding an optimal plan for swarm-based drone services for delivering goods from a source to a destination is a two-step service composition: 1. Finding the best energy service composition between each two directly connected node, and 2. Finding the best path using other criteria (e.g., time, cost, etc) between source and destination. The main contributions of this work are as follows:

- A novel in-flight energy sharing model in swarm-based drone delivery services.
- A Constraint-aware swarm-based drone services composition using a modified A* heuristic algorithm to compose the optimal delivery services.
- A two-level composition framework where the first level is the composition of energy services and second level is the composition of swarm-based services.

2 Motivating Scenario

Consider the scenario of delivering medical supplies using a swarm of drones in a city. We consider a skyway network where the nodes represent buildings rooftops. Each rooftop may be a delivery destination, a recharging node with a number of stations or both (Fig. 1). Let us assume that a swarm is used to deliver multiple packages from supplier to a hospital. The requirement is that all packages must arrive as soon as possible and together within a predefined timeframe [17]. Such requirement stem from the inherent interdependencies of the supplied packages. For example, certain medical drugs need to be mixed at the hospital but compounds would need to be delivered separately and within a timeframe [18]. Hence, they need to arrive at the same time. Fig. 1 represents a skyway network. We assume that the packages requested are of different weights. An optimal composition of swarm-based drone services results in the optimal path from source to destination with the fastest delivery time operating under a set of constraints. The constraints include different intrinsic and extrinsic constraints. Intrinsic constraints include the different energy consumption rates in the swarm due to different payloads and the battery capacities. A drone carrying a heavier payload typically consumes more energy than a drone with lighter payload [7]. The extrinsic constraints include the limited recharging pads at a station, wind conditions, and the time-constrained arrival of packages. We assume that swarms are static: 1. the number of drones in a swarm are constant, and 2. drones in a swarm stay together spatially until they reach their destination [19]. We also assume that the optimal swarm formation is preset, i.e., has already been decided and selected, based on the averaged wind conditions and will not change until packages are delivered [20]. We adopt the five formations proposed in [20], including Column, Front, Echelon, Vee, and Diamond. These formations are popular formations inspired by bird flocks and military airforce for energy conservation purposes and protection [20]. An optimal formation is one that consumes the least amount of energy under certain
3R related work

3.1 Swarm-Based Drone Services

The use of drones for delivery is receiving increasing investment and interest from industry and research, respectively. Drones are used to deliver medicine [21], post [22], and pizza [22]. The benefit of using drones in delivery over traditional methods is time sensitivity [21]. Drones are fast and can deliver packages to areas that are hard-to-reach with vehicle-based services [23]. A natural progression of using single drones in different applications, including delivery, is the use of multiple drones cooperatively to achieve a common goal.

Tackling tasks as a collective unit adds to the benefits of a single drone. Drone swarms could cut down the time needed in target search [24], surveillance missions [2], site mapping [25], and agriculture applications [26]. In addition, it could achieve tasks that a single drone is not capable of doing. This includes fascinating sky shows [10] and the delivery of multiple packages to the same destination at the same time [27]. Swarm-based drone delivery is an emerging application that has been recently explored in the literature [7]. Multiple works in swarm-based deliveries refer to coordinating multiple individual operated drones as drone swarm [28], [29]. However, we refer to a swarm as a set of drones that act as a single entity and are bounded by a space window.

The large-scale adoption of drones in deliveries come with technical challenges to overcome. Power is considered the bottleneck of the drone industry [30]. This item is of particular interest when travelling long distances to deliver packages or medicine [21]. Solutions proposed include creating new types of batteries that live longer than the traditional Li-Po batteries [31]. Solar powered drones are also developed to extend the battery life [32]. CyPhy proposed a micro-filament solution to have an infinite flying time by connecting the drone with a micro-filament wire to batteries on ground [33]. Battery replacements throughout travel and the use of wireless charging stations midway is also proposed [1]. However, these solutions suffer of lack of mobility, weather condition reliance, human-power dependability, and added recharging times. In drone swarms, an alternative solution is proposed that utilizes drone flight formations to enhance the energy consumption during delivery missions [20].

The study of flight formations have been widely explored in the fields of military and birds migrations. A swarm in military takes different formations to allow for better protection, view, and aiming [34]. Birds take different formations for energy conservation purposes [35]. As a bird flies, a rotating vortex of air rolls of at each of its wingtips. This causes the air directly behind the bird to be pushed downwards (downwash). In contrast, the air to the side of the bird gets pushed upward (upwash). The upwash forces give a free lift to the birds at the back causing them to consume less energy on flapping. Hence, we see birds flying in Vee formations for instance [35]. The heart rate of birds flying in a vee formation were found to be less indicating less energy consumption [36]. This is specially important when birds travel for long distances during migration.

In swarm-based drone applications, the study of formation flying is still in its infancy. A swarm of UAV’s fly in different geometrical flight formations for 3d scene reconstruction purposes [37]. For energy conservation purposes, using a Vee formation in a fixed wing UAV swarm has proven to consume...
less energy and behave similar to birds [38]. In addition, the effect of different formation flying on energy consumption of quadcopters was studied under different wind conditions [20]. Flying in a formation proved to consume less energy for different wind conditions due to reduced drag and upwash/downwash forces. The study also presented that drones consume different amounts of energy based on their position in a formation [20]. However, to the best of our knowledge, the effect of reordering the drones in a formation was not explored previously. We propose to optimise the distribution of energy consumption between the drones in the swarm by re-ordering the drones within a formation. In addition, we propose to overcome the power limitation in swarm-based deliveries using in-flight energy sharing within a swarm.

3.2 Energy Sharing and Wireless Energy Transfer
There is a growing interest in wireless energy charging in the field of wireless sensor networks, internet of things, mobile social networks, vehicular ad hoc networks, and UAV networks [39]. A new paradigm of radio wave-based uncoupled wireless charging has enabled sharing and accessing harvested energy from IoT devices [40]. Multiple wireless charging methods were introduced in IoT and wireless sensor networks [39]. For example, a reliable energy supply method was proposed to charge low battery IoT devices using a mobile charger in the network [41].

Wireless energy sharing services have been introduced recently as an alternative ubiquitous solution to charge IoT devices [39], [42]. Energy service is defined as the wireless energy transfer among IoT devices [15]. Several methods were proposed to charge IoT devices using energy services [39], [43], [44]. A temporal composition algorithm was proposed to charge IoT devices in confined areas [15]. Another approach was proposed to charge IoT devices from highly fluctuating IoT energy providers [45]. Mobility pattern impact on IoT energy services was addressed in [46]. Other energy sharing compositions were proposed to address charging mobile IoT devices [46], [47], [48]. To the best of our knowledge, none of the previous work studied the use of drones as wireless chargers to reduce the delivery time in drone delivery services.

3.3 Services Selection and Composition
Service is the highest level in the computing chain where actions are built on knowledge [49]. A service consists of functional and non-functional (Quality of Service) aspects [50]. The key differentiator between services are the QoS measures. In this paper, we propose to leverage the service paradigm to model the functional and non-functional (QoS) properties to compose swarm-based drone delivery services and energy sharing services. Hence, we look at the work done in service composition.

The challenges in service computing can be grouped into four areas: service design, service composition, crowdsourcing-based reputation, and IoT [49]. The work proposed in this paper lies mainly under the two umbrellas of service composition and IoT. Drones play a role in IoT as they are dependent on sensors and embedded software to provide communication to achieve their goal [51]. In drone services specifically, a model for single drone-based services was proposed [1]. The single drone-based services model was defined by its functional and non-functional (QoS) properties including delivery time and cost. Each skyway segment is abstracted as a drone service which can be served by a single drone. Their work only focuses on the composition of single drone services. This concept was augmented to swarm-based drone service to compose the optimal path of drones swarm from a source to a destination under various constraints [7]. The concept of wireless energy sharing services between IoT devices has been previously defined as Energy-as-a-Service (EaaS) [15]. The existing work focused either on composing services in a confined area to fulfil the consumers queries [15], [45] or composing energy requests to maximize the utilization of spare energy [47], [52]. To the best of our knowledge, there is no previous work on composing swarm-based delivery services based on swarm formations, energy sharing, and re-ordering. Hence, this paper is the first attempt to model energy and time constrained delivery environment for swarm-based drone deliveries using in-flight energy sharing and formation re-ordering using a service-oriented approach.

4 SYSTEM ARCHITECTURE AND COMPOSITION MODEL
We present a high-level system architecture for swarm-based delivery services. As shown in the numbered Fig. 3, the architecture is premised on the delivery of multiple packages to a single destination in a line-of-sight skyway network with landing spots (LS) at each node (roofops) (1). The architecture is an adopted service-oriented architecture (SOA) with consumers, providers (warehouses), and registries. The provider registers their swarm-based delivery services in the registry for advertisement (2). Consumers would view, select, and invoke the desired services from the registry (3). When a customer invokes a swarm-based drone service, the delivery management system determines the set of drones needed, including the support drones and the path to be taken. The delivery management system shares the computations among the swarm, cloud, and edge nodes.

Simple computations including analysis of sensor data and battery information will be computed at the swarm level. More sophisticated and expensive computations will be performed at the edge level. These computations include swarm-based drone services and EaaS compositions. The edge nodes are distributed in strategic locations to aid delivery. It allows for lower latency and faster communication speed.
between the swarm and the edge. Computations requiring lots of data will be done on the cloud level. Such computations include navigation throughout the skyway network. As the swarm moves, the drones communicate their data, i.e., battery states and locations, to the cloud for storage purposes (4). The cloud advertises this data to the edge nodes at frequent intervals to help in decision making (5). The swarm receives multiple instructions such as picking up the packages, path to the destination, recharging, etc. These instructions are communicated with the swarm from the cloud through the edge server (6). On arrival of the swarm to the destination, the customer is notified.

We abstract each swarm traveling in a skyway segment as a swarm-based drone service, as explained earlier. Our goal is to select and compose the optimal set of swarm-based drone services from a source point to a destination point given the highly constrained environment due to different carried payloads, limited charging spots, and constrained delivery time window. We then aim to further optimize the swarm-based drone service composition by incorporating Energy-as-a-Service (EaaS). This paper considers the environment to be deterministic, i.e., the surrounding conditions do not change after compositions.

We formally define a Swarm-Based Drone Service. Then we define a swarm-based drone service customer request. Later, we formally define an Energy-as-a-Service (EaaS).

**Definition 1.** Swarm-based Drone Service. It is defined as a tuple of $\langle SDS, S, F \rangle$, where

- $SDS$ is a unique identifier.
- $S$ is the swarm traveling in a swarm-based drone service. $S$ consists of:
  - $D$ which is the set of delivery drones and support drones forming $S$, a tuple of $D$ is presented as $\langle D_1, D_2, \ldots, D_n \rangle$.
  - The battery levels of every $d$ in $D < h_1, h_2, \ldots, h_n$.
  - The payloads every $d$ in $D$ is carrying $\langle p_1, p_2, \ldots, p_n \rangle$.
- $F_{SDS}$ describes the delivery function of a swarm on a skyway segment between two nodes, $A$ and $B$. $F$ consists of the travel time $tt$, charging time $ct$, and waiting time $wt$ when recharging pads are not enough to serve $D$ simultaneously in node $B$. In many instances, the number of delivery drones $D$ would be larger than the number of available recharging pads at a node. Therefore, the drones will not be able to recharge simultaneously and will have to wait for each other.

**Definition 2.** Swarm-based Drone Service Request. A request is a tuple of $\langle \alpha, \beta, P \rangle$, $\alpha$ is the source node, $\beta$ is the destination node, and $P$ is the weights of the packages requested, where $P$ is $\langle p_1, p_2, \ldots, p_n \rangle$.

**Definition 3.** In-flight Energy-as-a-Service (EaaS). We adopt the definition of EaaS in [15]. An EaaS is defined as a tuple of $\langle id, F, Q \rangle$, where:

- $EaaS_{id}$ is a unique service identifier.
- $F_{EaaS}$ is the function of sharing energy by a support drone.
- $Q$ is a tuple $\langle ae, loc, st, et \rangle$, where each attribute donates a QoS property of EaaS as following: $ae$ is the amount of available energy that a support drone can share, $loc$ is the location of a support drone $\langle x, y \rangle$, $st$ is the start time of a support drone’s EaaS, and $et$ is the end time of a support drone’s EaaS.

**Definition 4.** In-flight Energy Service Request (ER). We adopt the definition of ER in [52]. An ER request is defined as a set of $\langle id, F, QR \rangle$, where:

- $ER_{id}$ is a unique energy service request identifier.
- $F_{ER}$ is the function of receiving energy by a delivery drone.
- $QR$ is a tuple $\langle re, loc, st, et \rangle$ where each attribute donates a requirement property of ER as following: $re$ is the amount of requested energy by a delivery drone, $st$ and $et$ are the start and end times of the delivery drone’s receiving duration, and $loc$ is the location of the delivery drone.

Table 1 serves as a reference for the meanings of the main symbols used in this paper.

| Symbol | Meaning |
|--------|---------|
| SDS | Swarm-based Drone Service |
| $S$ | Swarm |
| $D_d$ | Delivery drone |
| $D_s$ | Support drone |
| $dt$ | Total delivery time of the packages |
| $tt$ | Travel time within a segment |
| $nt$ | Node time (time spent at a node to recharge the swarm) |
| $ct$ | Charging time (time spent by a drone recharging, depends on the charging pad rate and required energy) |
| $wt$ | Waiting time (time spent by drones waiting for other drones to finish recharging due to limited number of pads) |
| $EaaS$ | Energy-as-a-Service |
| ER | Energy request |
| $st, et$ | Start and End times of a provisioned energy request |

### 4.1 Problem Formulation

Given a swarm-based drone service request from a consumer, the problem is formulated as composing the best SDS services from the source node $\alpha$ to the destination node $\beta$ using in-flight energy sharing. The composition is constrained by several challenges. First, the payload and battery limitations of the drones are intrinsic constraints. Second, the availability of the charging pads and the wind conditions are extrinsic constraints. Third, the rate of in-flight recharging might not be sufficient, in some instances, to cover the energy loss due to formation reordering and re-positioning the drones within a formation. As described earlier, drones consume different amounts of energy based on their positions within a formation. Moreover, there are a set of challenges when addressing SDS composition with in-flight energy sharing. First, the selection of which delivery drone to charge, when to charge, and for how long to charge affect the planning of the journey. Second, the composition of the next service, in addition to the aforementioned challenges, depends on the gain provided with in-flight energy sharing. Third, deciding the number of support drones $D_s$ to carry out the mission is an extra challenge that depends on various numbers of variables.
like the size of the swarm, the carried payloads and the wind conditions.

Given all the aforementioned constraints and challenges, our goal is to optimally compose two level services. First, composing SDS services from the source to the destination with the shortest delivery time \( \min(dt) \). Second, composing EaaS services within every SDS service. In the second level EaaS composition, the goal is to allocate the energy needing delivery drones to the support drones for an overall energy gain that will reduce the charging time at the next node. The EaaS provisioning is constrained by the start times \( st \) and end times \( et \) of energy requests \( ER \) by the delivery drones \( D_i \) and the \( st \) and \( et \) of the support drones EaaS service.

5 SWARM-BASED DRONE SERVICES COMPOSITION FRAMEWORK

The composition framework consists of two main modules namely, swarm-based drone services Pre-Composition, and swarm-based drone services Composition with in-flight charging. The second module is a nested two-level swarm-based drone service SDS and EaaS compositions. The result of these modules is an optimized composition of swarm-based drone services SDS. Fig. 4 depicts the steps involved in the proposed SDS composition framework.

5.1 Swarm-Based Drone Service Pre-Composition

Before composing the set of optimal services from a source to a destination we need to select the optimal swarm formation and support drones. In this section, we discuss how to select the optimal formation as proposed by [20], select the optimal number of support drones, and where to position the support drones in a formation.

5.1.1 Formation Selection

The selection of the swarm formation is essential for an energy-optimized composition of SDS services [20]. Drones in different swarm formations consume different amounts of energy due to two reasons. First, a drone in a formation experiences upwash and downwash forces from other drones in the swarm. These forces cause drones to consume different amounts of energy based on their position in the formation. Second, a drone in a formation experiences diverse drag forces based on its position and the external wind direction and speed. Hence, it is crucial to select an optimal formation to minimize the energy consumption of the SDS. For example, with a front wind, drones in a vee formation consume the least amount of energy compared to other formations. On the other hand, with a side wind, a diamond formation consumes less energy [20]. In this paper, we adopt a fixed formation for the swarm-based drone services [20]; once an optimal formation is selected initially, we assume that it will not change throughout the journey to destination. Five formations are identified, including Column, Front, Echelon, Vee, and Diamond. Fig. 5 shows the different formations. We adopt the study done in [20] to compute how much each drone consumes energy in different formations under different wind conditions.

5.1.2 Support Drones Selection

Redundancy is the duplication of critical components of a system to either increase the reliability of a system or to improve actual performance [53]. In this paper, we adopt the concept of redundancy to improve the performance in terms of energy consumption and delivery time by having support drones. We consider the inclusion of the support drones to be equivalent to redundancy. This is because we assume the support drones have similar specifications to the delivery drones. The only difference is the payload carried that comprises of extra batteries and the drones are equipped with energy transmitters. This is analogous to disk drives, which can be redundant for efficiency rather than just reliability [54]. In this step, we study the optimal number of support drones for a particular delivery request using the redundancy theory [53]. We then study the options for positioning the support drones in the formation before the SDS services composition.

There are different types of redundancies based on the needs of a system [53]. These include \( N + 1 \), \( N + 2 \), \( 2N \), and \( 2(N + 1) \) redundancies, where \( N \) is the number of components in the system. In our case, \( N \) is the number of the delivery drones in the swarm before adding the support drones. Each redundant component, i.e., support drone, added to the system decreases the probability of failures. In our scenario, a failure (i.e., unsuccessful delivery) occurs when a swarm cannot reach the destination due to the battery limits.
of drones. In this paper, we assume that the drones in the swarm are of the same size and specifications. For example, we use DJI Phantom 3 drone model for all the experiments in this paper. We also assume that the max payload a drone can carry is 1.4kg. The battery that the DJI Phantom 3 uses weighs 365g. Hence, in the case of this drone model, we assume a support drone can carry three additional batteries increasing its energy capacity. We also assume that all the drones are initially fully charged. We consider the following attributes that affect the delivery to compute the probability of failure and select the optimal number of redundant components, i.e., support drones, for a certain delivery request:

- The size of the swarm without the support drones $S_s$. This is based on the number of packages in an SDS request as explained in Section 4.
- The payload ratio for each drone $D_{pr}$. The payload directly affects the energy consumption in a drone. Hence, we compute the average payload ratio for all the drones in the swarm using the following equation:

$$D_{pr} = \frac{\sum_{i=1}^{n} \text{max payload capacity}}{\text{no. of drones}}$$

where $p_i$ is the payload drone $i$ is carrying, the max payload capacity is 5kg, and the no. of drones is the total number of drones in the swarm before adding any support drones.
- Distance between the source and the destination $d(\alpha, \beta)$. We use Dijkstra’s shortest path to compute the distance.
- Energy capacity of a support drone $E_s$. This is $3+1=4$ times of the delivery drone including the original battery as explained earlier.
- The averaged wind conditions $W$. As described earlier, wind highly affects the energy consumption of a swarm. Hence, the wind factor needs to be considered in support drones selection.

We use the aforementioned delivery affecting factors to compute how many redundant components, i.e., support drones, are needed. We do this by computing the probability of failure and matching the probability with the equivalent redundancy values in Table 2. We compute the probability of failure using the following equation:

$$P = \prod_{i=1}^{4} w_i \cdot \overline{p_i}$$

where $p_1 = d_{pr}$ is the drone payload ratio, $p_2 = d(\alpha, \beta)$ is the distance between the source and the destination, $p_3 = E_{sp}$ is the energy capacity of the support drones, and $p_4 = W$ is the averaged wind conditions. The weights $w_i$ in the equation are computed based on how much each factor consumes energy per unit time independently. For example, let us assume that a swarm consumes 3% of its total power to travel for 1 minute at a speed of 30 km/hr, hence, $w_2 = 0.03$. The distance between source and destination $d(\alpha, \beta)$ is 5km. Therefore, $P_{\alpha=2} = 0.03 \times ((5/30) \times 60) = 0.3$. The same is done to compute the rest of the weights $w_i$. Instead of taking the true value of each factor, we normalize them between 0 and 1 to unify the different ranges of the affecting factors $\overline{p_i}$. Once the probability of failure is computed, the number of redundant components (support drones) are decided according to Table 2.

### 5.1.3 Support Drones Positioning

Once the number of support drones in a swarm is decided, we need to study the optimal position to place the support drones in the swarm. The positioning is important for a couple of reasons. First, a support drone can charge other drones up to 1.2 meters distance [14]. Second, the position of the support drones in the swarm affects their energy consumption due to upwash/downwash and drag forces in different formations. The drones in different formations consume energy differently based on their positions in a formation and the wind direction. For example, a drone at the front of a Vee formation consumes the most energy if the wind is coming from the front [20]. In this paper, we propose to study the effect of two positioning settings. Fig. 6 describes the two settings. Note, in this step, we are only selecting the initial position of a support drone. Later, in Section 5.2.2, we will re-order them as needed.

- Location-aware Support Drone: Looking at the full swarm, i.e., the delivery drones and the support drones, we position the delivery drone carrying the maximum payload at the optimal position in the formation. Descendingly, we position the drones carrying the heavier payloads in the optimal positions and the least payload carrying in the worst positions. Lastly, we position the support drones in the worst positions. This setting would ensure that the delivery drones are consuming the least amount of energy due to the positioning. However, it comes with the cost of non-optimal support drones positioning. The support drones are aware of their location and give up their prime position for the sake of optimal positioning of the delivery drones.
- Energy-aware SD: Looking at the full swarm, i.e., the delivery drones and the support drones, we position the support drones at the optimal

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**TABLE 2**

| Redundancy Values for Different Failure Probabilities |
|------------------------------------------------------|
| Failure Probability $P$ | Redundancy Number |
|-------------------------|-------------------|
| 0-19                    | N+1               |
| 20-39                   | N+2               |
| 40-59                   | N+3               |
| 60-79                   | N+4               |
| 80-100                  | 2N                |

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**Fig. 6. Support drones positioning.**
position in the formation. Then descendingly, as the first setting, we position the delivery drones from the optimal positions to the worst positions based on their carried payloads. This approach would ensure that the support drones are consuming the least amount of energy due to their positions and would have more energy to share with the delivery drones. However, the delivery drones would be consuming more energy in this approach. The support drones are aware of their energy and are positioned in the least energy consuming positions.

As can be seen from the two settings, we need to compromise between the optimal positioning of the delivery drones and the optimal positioning of the support drones. Hence, in Section 6, we run experiments to test both approaches and reach a conclusion of which setting to be adopted.

5.2 Swarm-Based Drone Services Composition With In-Flight Energy Sharing

After pre-composition, we select and compose the optimal swarm-based drone services from the source to the destination using a modified A* algorithm. Optimality, in this paper, is a single objective of composing SDS services with the least delivery time. We assume the swarm is static, i.e., the members are decided at the source node and no additions or reduction of members occurs throughout the path to the destination [5]. Given a connected network, we compose the best available path from the source to the destination. The composition of the optimal services mainly depend on two components as shown in Fig. 4. The first is the intrinsic and extrinsic constraints surrounding the delivery environment. The second is the in-flight energy sharing process that will affect the composition of the services.

A swarm-based delivery environment is highly affected by multiple constraints. The intrinsic constraints include the different energy consumption rates between the drones due to payload and position in a formation. The extrinsic constraints include the wind conditions that highly affect the energy consumption of a swarm and the different number of recharging stations available at every node to serve the swarm. The proposed swarm-based drone services composition framework addresses the aforementioned constraints and optimizes the selection of the services through in-flight energy sharing.

Algorithm 1 describes the SDS services sequential composition with the in-flight energy sharing process. The swarm computes the shortest path in terms of distance only between the source and destination [55], at the source node. If all the drones $D = D_d + D_s$ in the swarm $S$ are able to reach the destination without the need to recharge at intermediate nodes, then the swarm will select this path and update the travel time $tt$ (lines 5-7). This capability is computed by considering the amount of consumed energy $E_c$ due to payload, formations, distance, and wind conditions. Otherwise, the swarm estimates the effect of in-flight energy sharing on the swarm to reach the destination directly (line 8). The in-flight energy sharing process consists of two main steps. Namely, composing EaaS services and re-ordering the drones in the formation when required to facilitate the energy sharing process. These two steps are described in Sections 5.2.1 and 5.2.2 respectively.

| Algorithm 1. Swarm-Based Drone Services Composition With In-Flight Energy Sharing Algorithm |
|----------------------------------------|
| **Input:** $S, R$ (Swarm $S$ and SDS Request $R$) |
| **Output:** $dt$ [Total delivery time from source to destination] |
| 1: $dt = 0$ |
| 2: while $S$ is not at destination do |
| 3: distance to destination = Dijkstra(current, destination) |
| 4: compute $E_c$ for every $D_d$ and $D_s$ in $S$ based on $R$ package weights, $S$ formation, wind condition, and distance to destination |
| 5: if all $D$ in $S$ can reach destination without intermediate nodes then |
| 6: $S$ travels to destination |
| 7: $dt += tt$ |
| 8: else if all $D$ in $S$ can reach destination without intermediate nodes using in-flight energy sharing then |
| 9: In-flight_Energy_Sharing_Composition() |
| 10: $dt += tt$ |
| 11: else |
| 12: find nearest neighbor nodes |
| 13: EaaS_Composition() |
| 14: select best neighboring node, min($tt + ct$) |
| 15: $S$ travels to neighboring node |
| 16: $dt += tt + ct + wt$ |
| 17: end if |
| 18: end while |
| 19: return $dt$ |

The proposed nested composition comes into play if the swarm cannot reach the destination directly, i.e., without stops at intermediate nodes, even with energy sharing (line 11). The path is composed sequentially based on our previously proposed approach [7] along with in-flight energy sharing at each line segment in the composed path. The swarm selects the nearest reachable node with the least travel time $tt$ and node time $nt$ (lines 12-14). The node time consists of the charging time and the drone’s waiting times to charge sequentially $nt = ct + wt$.

The charging time $ct$ is the required time to charge the drone to 100%. As the energy consumption is different among the swarm members, we take the longest charging time $ct$ to be the $wt$ of parallel recharging drones. The waiting time $wt$ highly depends on the number of available recharging pads. When the number of pads is less than the number of drones, an optimization problem takes place to find the best set of drones to charge together to minimize the node time $nt$. Since the number of pads is finite, we use a brute force approach to compute the node time $nt$. For example, if there are 5 drones with charging times $ct < 60, 50, 40, 30, 20 >$ minutes. Then the node time will be computed as follows:

- 1 pad available: node time = $60 + 50 + 40 + 30 + 20 = 200$ minutes.
- 3 pads available: pad 1: $60 = 60$, pad 2: $50 + 20 = 70$, pad 3: $40 + 30 = 70$, node time = $\max(60, 70, 70) = 70$ minutes.
- 5 pads or more available: node time = $\max(60, 50, 40, 30, 20) = 60$ minutes.

The node time $nt$ is highly affected by the in-flight energy sharing process before it reaches the node. The drones will reach the node with higher battery capacity as it would be without the energy sharing process. Once the swarm is fully
recharged, it tries to find if the destination is directly reachable and repeats the steps mentioned above until it reaches the destination. The total delivery time \( dt \) comprises the total travel time \( tt \) and the total node times \( nt \) (line 16).

### 5.2.1 In-Flight Energy Sharing Composition

The in-flight energy sharing composition will be invoked in the path composition. The support drones will share energy with the neighboring drones in the swarm. In the case of multiple support drones, we assume that each support drone will be responsible for charging a subset of the delivery drones. We also assume that a support drone can share its energy to one delivery drone at a time [15], [45]. The energy sharing time window is the travel time between the current node and the next destination node, i.e., a line segment in the composed SDS services path. The delivery drones will trigger an energy sharing request. Each drone has a different energy consumption model depending on several factors. The factors include the distance travelled, carried payload, wind condition, and the drones position within a formation. If any of these factors change during the composition, the energy consumption for each drone is recomputed. Once the drone’s battery capacity decreases to a predefined threshold \( \gamma \), an in-flight energy sharing request is launched. The in-flight energy sharing composition aims to select and compose the energy requests \( ER \) that will maximize the utilization of support drones’ energy. Maximizing the energy utilization will reduce the required time to wait and charge at charging pads in an intermediate node. In this paper, we propose to compose \( ER \) using two approaches and study their impact on the travel time. The first approach, i.e., Priority-based (PB) energy sharing, is inspired by the first come first served scheduling algorithm [56]. In PB approach, the support drone charges drones based on the start time of their request. Moreover, the support drone fully charge each selected drone based on their requests. The second approach, i.e., Fairness-based (FB) energy sharing, charges each drone partially in a round robin manner.

**Priority-Based (PB) Energy Sharing** This approach is a modified version of the first come first served scheduling algorithm [56]. Thus, the priority in selecting \( ER \) will be defined by the requests’ starting times \( st \). In this approach, selected \( ER \) will be charged fully according to their requested amount. Each delivery drone requesting energy defines the starting time \( st \) and the requested amount \( re \) for their request. If the support drone has enough spare energy to provide and multiple requests overlaps, the earlier request will be selected. If multiple requests start simultaneously, then the request with the highest requested energy will be selected. For instance, using this approach on the given requests in Fig. 7, ER1 is selected since it is the earliest request.

**Algorithm 2. In-Flight PB Energy Sharing Composition**

| Line | Code |
|------|------|
| 1    | \( ER = \text{Generate}_\text{ER}(\text{battery}[D]) \) |
| 2    | \( \text{SortedER} = \text{sort}(ER, st : \text{ascending}, re : \text{descending}) \) |
| 3    | \( st = tt \).st |
| 4    | \( et = tt \).et |
| 5    | for \( er \in \text{SortedER} \) do |
| 6    | if \( er, st \geq SD.st \text{ and er}.re \leq SD.ae \) then |
| 7    | \( st = er, et \) |
| 8    | \( SD.ae = SD.ae - er, re \) |
| 9    | \( \text{ER}_\text{composition}.add(\text{er}) \) |
| 10   | \( \text{battery}[D] = \text{battery}[D] + \text{er}.re \) |
| 11   | \( \text{SortedER}.\text{remove}(\text{er}) \) |
| 12   | \( \text{battery}[D] = \text{Reorder(Fixed/Flexible)} \) |
| 13   | \( \text{newER} = \text{Generate}_\text{newER}(\text{battery}[D]) \) |
| 14   | if \( \text{newER} = \emptyset \) then |
| 15   | \( \text{SortedER} = \text{SortedER} \cup \text{newER} \) |
| 16   | \( \text{SortedER} = \text{sort}(\text{SortedER}, st : \text{ascending}, re : \text{ascending}) \) |
| 17   | end if |
| 18   | end if |
| 19   | end for |
| 20   | \( \text{updated}_{\text{battery}}[D] = \text{battery}[D] \) |
| 21   | return \( \text{updated}_{\text{battery}}[D] \) |

**Algorithm 2.** In-Flight PB Energy Sharing Composition. In this approach, a fixed amount of energy will be provided to each drone in a
round robin fashion based on the drone’s id until the end time of the segment. The amount of energy may vary from small to large amount. Algorithm 3 describes the Fairness-based in-flight energy sharing composition. The amount of provided energy is fixed based on a user-defined value λ (Line 3). Lines 4, computes the charging time based on the charging rate of the support drone. The algorithm then goes through drones in order of ID to provide a fixed amount of energy (Lines 5 -16). Note that the energy will be provided by the support drone in rotation between the delivery drones as long as: (1) the support drone battery is greater than a threshold δ, the threshold δ is used to keep enough spare energy for the support drone’s own energy consumption. (2) there is enough time to charge a delivery drone. Similar to the Priority-Based energy sharing approach, once a drone is selected (Lines 5 - 11), the battery of all drones will be updated (Lines 9 - 11) and a formation re-order function will be called (Line 12). The re-order function checks if a re-positioning of the drones is required to deliver the requested energy. As previously mentioned, the positions of the drones affect their energy consumption which needs to be updated in the current in-flight energy sharing composition. The formation re-ordering approach is discussed in detail in Section 5.2.2.

Algorithm 3. In-Flight FB Energy Sharing Composition

**Input:** battery[D], S
**Output:** updated_battery[D]

1: et = tt.st
2: et = tt.et
3: amountE = λ
4: chargingt = amountE/chargingRate
5: while et < et and SD.ac > δ do
6:   for d_i in battery[D] do
7:     if et < et and SD.ac > δ then
8:       et = et + chargingt
9:       SD.ac = SD.ac - amountE
10:      if battery[D] is not full then
11:         battery[D] = battery[D] + amountE
12:        battery[D] = Reorder(Fixed/Flexible)
13:     end if
14:   end if
15: end for
16: end while
17: updated_battery[D] = battery[D]
18: return updated_battery[D]

5.2.2 Formulation Re-Ordering

Once the in-flight energy sharing process gets initiated, the swarm may need to re-order itself to facilitate the process. The support drones, as described earlier, could share their energy to up to 1.2 meters [14]. Hence, the support drones should neighbor the energy requesting delivery drone. Therefore, the drones in the swap swap positions to facilitate the process. For simplicity, we assume that there is no overhead time and energy during re-ordering. However, the energy consumption rate of the drones will change due to their position change in the formation. We recompute the new energy consumption model whenever re-ordering occurs. In this paper, we investigate a fixed approach for swarm re-ordering.

In a fixed approach, the support drones do not change their positions. Once the energy sharing is initiated and the distance between the support drone and the energy requesting delivery drone is more than 1.2m, the delivery drones swap their places to neighbor the support drones. Otherwise, the support drone directly shares its energy without re-ordering. In this method, we ensure that the energy consumed by the support drone does not change. If the support drone is placed in the optimal position initially, it will be consuming the least amount of energy due to its position. On the other hand, the delivery drones swapped may be placed in a non-optimal position during the energy sharing process. Once the energy sharing process ends, the drones re-order themselves again to their initial positions.

6 Experiments and Results

We evaluate the proposed swarm-based drone services composition framework with in-flight energy sharing. We assess the proposed framework against three composition algorithms, baseline [7], Dijkstra’s [55], and Floyd-Warshall’s [57]. We first conduct a set of experiments to evaluate the effectiveness and feasibility of the system under the different controlling attributes, including the initial positioning and energy sharing methods. We assume the amount of energy shared per round for the Fairness-based energy sharing method is 2240mA. We first compare the number of fulfilled requests under the different energy sharing methods. Second, we compare the delivery times of the proposed requests under different settings. Finally, we compare the runtime efficiency of the composition methods.

6.1 Dataset and Experiments Setup

To the best of our knowledge, there is no publicly available data of drone trajectories in skyway networks. Therefore, the dataset used for the experiments is an urban road network dataset from London city to mimic a skyway arrangement. The nodes are the intersections in the city, and the edges represent the distances between the nodes [58]. We took a sub-network of connected nodes with the size of 195 nodes to mimic how a skyway network may look like for our experiments. We then synthesize 10000 requests with random source and destination nodes. We also synthesize different wind speeds and directions for the skyway segments. We only consider wind speeds under 13.8m/s that drones are safe to fly in [20]. We have incorporated a real drone trajectory dataset [59] used in the energy model calculations. The dataset however has limitations of being only for single drones. Hence, it does not reflect the formations effect on the energy consumption due to drag and upwash/downwash forces. Therefore, we used the payload and flight range effect on the energy consumption from the dataset. We then augmented the real dataset with the computational fluid dynamics study proposed in [20] to learn the behaviour in terms of swarm formation and the wind effect on the energy consumption. The maximum weight of a package is assumed to be 1.4 kg following the payload capacity of DJI Phantom 3 used in the experiments. The real-drone dataset uses the CrazyFLie 2.1\(^5\) drone which is a small drone with 240mAH and

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5. https://www.bitcraze.io/products/old-products/crazyflie-2-0/
3.7 V battery compared to the DJI Phantom 3 with 4480mAh and 15.2 V battery. Therefore we multiply the consumption rate by the increasing factor, i.e., 4.1. Table 3 summarizes the experimental variables. The variables are used to compute the energy consumption.

We compare the proposed composition algorithm against a baseline approach [7], Dijkstra’s algorithm [55] and Floyd-Warshall’s algorithm [57]. The baseline approach considers all aspects of composition without the in-flight energy sharing. Formations, intrinsic constraints, and extrinsic constraints are all considered in the baseline approach. Hence, we evaluate across the two levels. The blue parts of Fig. 4 represent the baseline approach. For Dijkstra’s and Floyd-Warshall’s methods, we consider the cost of every edge to be the travel time $t$ of the edge and the node time $nt$ (charging + waiting times). The proposed framework is evaluated under the two different positioning settings of the support drones. The first setting positions the support drones at the worst positions (location-aware). The second setting positions the support drones in the best positions (energy-aware). In addition, the proposed framework is evaluated using the different energy sharing methods proposed, i.e., Priority-based (PB) and Fairness-based (FB) sharing.

| Variable                          | Value       |
|----------------------------------|-------------|
| No. of nodes in the network subset | 276         |
| No. of nodes in the largest connected network | 195       |
| No. of generated requests        | 10000       |
| Max weight of a package          | 1.4 Kg      |
| Drone model                      | DJI Phantom 3 |
| Speed of the drone               | 30 km/h     |
| Battery capacity                 | 4480 mAh    |
| Voltage                          | 15.2 V      |
| Rate of in-flight energy sharing | 5.88 mAh/min|

Fig. 8. Number of successful requests using in-flight energy sharing.

6.2 Effectiveness

In the first experiment, we compare the number of successful requests between the different settings proposed. A successful request is a request that was able to be served by the swarm without getting stuck in intermediate nodes due to lack of power. We compare the 4 different combination of settings against the Baseline, Dijkstra’s, and Floyd-Warshall’s algorithms. This includes the initial positioning, and energy sharing approaches. As shown in Fig. 8, the trend shows that positioning the support drones in the optimal position (energy-aware) generally results in less number of successful requests (18,050 successful requests out of 20,000 compared to 19,271 in location-aware setting). This is because positioning the support drones in the optimal position means the rest of delivery drones will be shifted to worst positions. The number of delivery drones is usually higher than the support drones and hence more energy consumption occurs during the travel. Although in this setting the support drones consume the least amount of energy and is able to share more of its excess energy with the delivery drones, the number of energy requests generated by the delivery drones is more than what the support drones can serve at a time. Hence, more failures occur. Last, we can note that the PB energy sharing approach performs better in all settings. All requests are successfully delivered compared to the Fairness-based energy sharing. This finding is explained in the second experiment. In comparison with the baseline, Dijkstra’s, and Floyd-Warshall, our proposed energy sharing approach performed much better. In baseline, only 8839 requests are successful out of 10,000 which is less than any of the 4 combinations. This is because a swarm in the baseline approach solely depends on the delivery drones batteries and in many cases are stuck at a node due to the battery limitations. Floyd-Warshall’s performed worse than the baseline but slightly better than Dijkstra’s (6,691 successful out of 10,000). Dijkstra’s performed worse in terms of successful requests (6,646 successful out of 10,000). This is because our modified A* sequential composition algorithm can detour its path, in the baseline and in the energy sharing methods, if the swarm would get stuck at a node. In contrast, Dijkstra’s and Floyd-Warshall’s composition of the path is solely based on the cost of each segment only. Hence, the composed path may have segments that a swarm can’t travel in due to its battery limitations.

In the second experiment, we focus on studying the behavior of the two proposed energy sharing methods, i.e., Priority-based (PB) and Fairness-based (FB). Figs. 9a and 9b present the delivery times of the successful requests in PB and FB sharing under the different positioning settings. The $x$-axis presents the distance in kilometers and the $y$-axis is the delivery time in hours. The successful requests are grouped by the distance between the source and the destination at 0.5km intervals. The average delivery time of requests in every interval is presented on the graphs. As shown in the figures, the PB sharing is steadily performing the best in the different settings. This is because the energy sharing requests by the delivery drone are generated dynamically after every served request (refer to Algorithm 2). This ensures proactive dynamic generation of energy requests. Hence, most needy drones are served first which ensures better distribution of energy. Better distribution of energy means less time spent at intermediate nodes to charge and may also mean the ability of skipping nodes if the swarm can reach the destination directly without stopping. Hence, a better delivery time. With FB, the delivery drones are equally served at every $i$ interval. This means that there is no priority in charging. Most needy delivery drones may be served later or might not get the chance to be charged if the skyway segment is short. As explained earlier, the energy sharing process is constrained by the travel time of an edge. The better performance of PB sharing is more visible in the energy-aware setting where the support
drones are positioned in the optimal positions and the delivery drones are losing more energy due to their positions. This means that the delivery drones are generating more energy requests in this positioning approach and the difference between the energy sharing methods is more evident.

In the third experiment, we study the initial positioning settings and their effect on the delivery times. As shown in Fig. 9a, positioning the support drones in the worst position (location-aware) results in worst delivery times compared to the baseline at longer distances although it had the most number of successful requests (Fig. 8). When the swarm lands on a recharging station, all the drones charge fully. If the support drones are in the worst positions they consume the most energy (in addition to given energy in the sharing process). Since the support drones have bigger battery capacities than delivery drones, the time taken to recharge fully will be higher when landing as the rest of the swarm is waiting for it. This is especially significant at longer distances as shown in Fig. 9a. This behaviour is reflected in Fig. 11a that represent the nodes time with the location-aware setting. The time spent at the node is higher than the baseline due to the charging of the support drones which are placed in the worst position consuming the most amount of energy. With longer distances, the support drone consumes more energy and shares more energy, hence, spends more time charging. Whereas in an energy-aware setting, the time taken for charging will be lower as the drone is located optimally.

6.3 Runtime Efficiency

We measure the execution times of the proposed methods. Figs. 12a and 12b depict the execution times of different positioning and energy sharing approaches. As shown in the graphs, the positioning does not affect the execution times. However, in both positioning settings, the execution time of the PB energy sharing method outperforms the FB energy sharing methods. This is because PB sharing only gives energy on request. The FB is pre-emptive and keeps charging the drone iteratively by switching between them, increasing the algorithm’s execution time. In addition, with the FB energy sharing, the shared amount per round is determined. If the goal is to serve as many requests as possible, the support drones would be placed in the worst positions. Otherwise, if the goal is to serve requests as fast as possible, the support drones would be placed in the best positions. For example, in emergency cases the delivery time would be the most critical objective. If the delivery is successful then the energy-aware setting should be adopted, otherwise the location-aware setting would be adopted to ensure the success of the delivery. Moreover, the in-flight energy sharing composition outperforms the baseline under the best positioning setting (Fig. 9b). This reflects the usefulness of implementing in-flight energy sharing to overcome a swarm’s battery limitation and increase its flight range. Figs. 11a and 11b represent the node times of the delivery requests without the travel times. The figures prove that the improvement in delivery times is due to the reduction of node times because of in-flight recharging. The behaviour of the lines are similar to Figs. 9a and 9b but with lower times demonstrating the reduction in node times mainly.
parameterized. This means the amount of shared energy per round is input by the user. The smaller the amount is, the more rounds there are which would make the execution time longer. For this experiment, we assume the support drones share 2240 mA per round. If the amount is smaller, less time would be needed to share the energy and therefore more rounds in the FB execution. The baseline’s execution time is less than any proposed method because it does not have any in-flight energy sharing processes.

7 Conclusion

We propose a novel Swarm-based Drone-as-a-Service framework for delivery with in-flight energy sharing. We formulate the composition problem as a single objective to optimize a consumer’s request delivery time. We then introduce the use of support drones that share their extra available energy with the delivery drones. We propose a redundancy-based method to estimate the number of support drones and reduce the failure probability. Two settings are presented to position the support drones in a flight formation initially. Two novel energy sharing methods are proposed which are based on FCFS and Round Robin approaches. A formation re-ordering method is presented to facilitate the energy sharing process. A modified A* algorithm is implemented to compose the best and optimal services from the source to the destination. Experimental results show the efficiency of our proposed approaches compared to Dijkstra’s, Floyd-Warshall’s, and baseline approaches. We will expand this problem to a multi-objective problem in future work to include the cost and the overall energy utilization. We will also consider uncertainties and changes in the environment and their effects on the in-flight recharging.

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