Perpetual Flight for UAV Drone Swarms Using Continuous Energy Replenishment

Andrew Boggio-Dandry, *Student Member, IEEE*, Tolga Soyata, *Senior Member, IEEE*
Department of Electrical and Computer Engineering
University at Albany, State University of New York (SUNY), Albany, NY, USA
{aboggio-dandry, tsoyata}@albany.edu

***Abstract*—Today's off-the-shelf, inexpensive Unmanned Aerial Vehicles (UAVs) are an emerging breed of devices that promise to reshape tomorrow's search and rescue landscape. Multiple identical drones can be utilized to achieve more complex tasks when arranged in a swarm formation. In either the single-drone or swarm configuration, these Lithium Polymer (LiPo) battery-powered machines can only stay in the air for a brief period of time (usually between 10 and 30 minutes) due to the high power consumption of their motors. For example, drones weighing only 200 to 600 grams can consume between 100–600 Watts. Most search-and-rescue operations last for days, even weeks, rendering these inexpensive drones impractical.**

A novel charge replenishment mechanism is proposed in this paper that allows a swarm of drones to stay in the air perpetually. This is achieved by employing a fleet of drones much larger than the flying swarm in order to continuously replace and charge energy-depleted drones. The required fleet size for various drone models is calculated analytically and through a simulation. A rule-of-thumb formula is derived based on Queuing Theory and Energy Conversation to confirm the feasibility of this proposal with simulation results.

***Index Terms*—Unmanned Aerial Vehicles; Queuing Theory; Drone Swarms; Energy Replenishment, Drone Simulation, Energy Storage.**

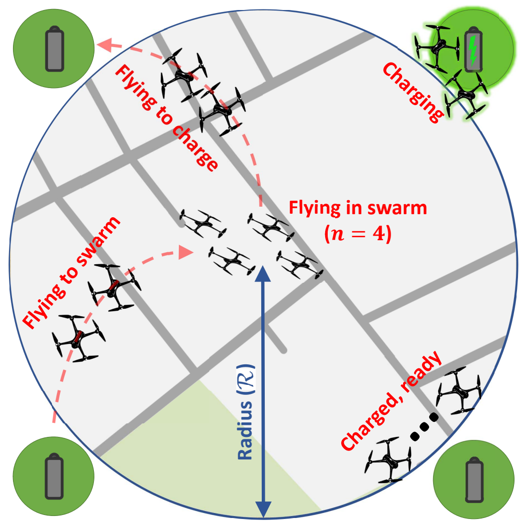

Fig. 1. Our proposed *continuous energy replenishment* method allows perpetual flight for a swarm size of n, however requires a much larger total fleet size of $\mathcal{N}$. As shown in our experimental study, a swarm size of $n=4$ can require a total of $\mathcal{N}=32$ drones. Energy replenishment stations are shown as the battery symbols on the sides.

I. Introduction

An unmanned aerial vehicle (UAV) can be described as a flying vehicle that does not need a human being on board to control/pilot it. Its flight, rather, is controlled autonomously or by a remote pilot. Myriad sensors can be installed on UAVs for data gathering, such as video recordings [1], analyzing the composition of atmospheric gases [2], [3], performing search and rescue operations [4], [5], and beyond. An interesting first step to realizing these goals is forming a swarm of identical drones, capable of perpetual flight, that can perform more complex tasks than an individual drone.

Perpetual flight can only be achieved if the drones flying in formation have sufficient energy to fly forever. Many techniques have been proposed to realize this vision, including wireless (in-air) charging [6]–[8], laser charging [9]–[11], and automated battery swapping [12]–[15]. While innovative, these approaches are drone-specific, require specialized and expensive equipment, and can even be dangerous [11], [16].

This paper proposes a *continuous energy replenishment* method, which enables a *swarm* of drones to attain perpetual flight by swapping freshly charged drones into the swarm to relieve their more energy-depleted counterparts. A conceptual depiction of the proposed method is shown in Fig. 1, which shows the drone swarm (in the middle) and the charge stations that the drones fly to/from for energy replenishment (battery symbols on the sides). Our proposed method eliminates the disadvantages of previously proposed methodologies for perpetual flight and creates a platform for utilizing inexpensive, disposable, and commercial off-the-shelf (COTS) drones. Despite its advantages, our proposed method introduces a challenge of its own: the size of the operational fleet (termed $\mathcal{N}$ throughout the paper) is large, when compared to a specified swarm size (termed n). For example, as we will comprehensively study in our experimental results in Section IV, the required fleet size can be $\mathcal{N}=32$ when the swarm size is $n=4$, although this disparity can be improved by using drones that have better battery capacities. Because our mechanism allows the usage of COTS drones, the challenge introduced by a large $\mathcal{N}$ is algorithmic, rather than financial; controlling a large number of drone take-off/landing/charge/flight patterns introduces algorithmic complexity, however, it makes the resulting fleet much less expensive and general-purpose. Our scheme not only allows the usage of COTS and disposable drones, but also drones with *heterogeneous* features (e.g., varying battery and flight characteristics), albeit at further increases in control algorithm complexity. This, in turn, permits newer and more efficient drone models to be brought into the system with minor (if any) updates to the control software.

The primary goal of this paper is to determine the required fleet size ($\mathcal{N}$) based on drone manufacturer specifications (such as battery capacity, flight speed, etc.) and user-specified parameters (such as the swarm size n). This paper approaches the problem both analytically and programmatically. For analytical formulation, equations are derived to model the fleet and swarm's expected behavior based on Queueing Theory and the conservation of energy. The goal of this analysis is to determine the required fleet size ($\mathcal{N}$), given the desired swarm size (n) and the manufacturer specifications of the drones (e.g., battery capacity, $\mathcal{B}$ and total charge time $\mathcal{C}$). For programmatical formulation, a software simulation is created to estimate values for various commercially available drone models. To this end, three drones of varying weight and power classes were flown to obtain experimental values. Additional drone models are examined based on the manufacturers' specifications. The simulation results are compared to the expected, computed theoretical best-case, confirming the viability of perpetual flight using the proposed continuous energy replenishment mechanism.

The rest of this paper is organized as follows: a review of related works and current literature is presented in Section II. The concept of continuous charge replenishment is explored in Section III, as well as the derivation of analytical formulae modeling the theoretical best-case scenario. Section IV details the creation and testing of simulation software to obtain values useful in drone fleet planning. Finally, a conclusion and remarks are offered in Section V.

II. Background

A. Related Work

Unmanned aerial vehicles have been the subject of increased research over the past decade. Remote building inspection and monitoring [17], UAV computer vision [18], UAVs in precision agriculture [19], UAVs for 3D mapping [20], simultaneous localization and mapping (SLAM) [21], and even surveying archaeological sites [22] are just a few examples of the wealth of research being performed. The literature is clear: better charging and energy replenishment techniques are necessary to increase the viability of UAV-based applications across disciplines.

The concept of wireless energy transmission to provide power to remote devices (modernly referred to as "far field power transmission") was first proposed by Nikola Tesla in the 19$^{\text{th}}$ century through his resonant inductive coupling technique [6], [23]. Two promising techniques for mid-air drone charging have emerged: laser charging and inductive charging. Laser charging involves transmitting energy to an in-flight drone via a beam of focused light, allowing it to recharge while in flight [9]–[11]. Inductive charging proposes a novel technique: charging UAVs by using the electromagnetic field produced by the power lines that already line city streets all over the world [24].

As an alternative to charging drone batteries in-air, there are numerous examples in the literature of swapping depleted drone batteries for freshly charged batteries rather than taking the drone out of commission for an entire charge cycle [25]. The batteries can then be charged while the drones remain in flight, and multiple sets of batteries can be available per drone to ensure continuous flight. The authors of [12] have developed an "endless flyer:" a UAV that never needs to charge. When the vehicle senses it is low on energy it flies to a designated battery exchange platform, where its battery is automatically exchanged for a fresh one. The automation of drone "refueling" (or, battery swapping) is also investigated in [26]. Their battery swapping system not only automatically swaps small UAV (helicopter) batteries, but also monitors their health with various algorithms.

B. Energy Storage

The overwhelming majority of COTS drones available today employ rechargeable Lithium-ion Polymer (LiPo) batteries. Each LiPo battery cell has a nominal voltage of 2.4 V, which are typically connected in series to attain a higher voltage; for example, a 3S LiPo battery has 3 cells in series [27] with a nominal votage of 7.2 V. As they are lighter-weight and higher capacity (providing a higher specific energy) than their counterparts [28], they present the perfect solution for UAV power. Diagnostics can be performed on LiPo batteries [29] to monitor their health and longevity and to ensure that only healthy UAVs are flying. It is not recommended that the depth of discharge (DOD) exceeds 70% in order to maximize battery lifetime and efficiency [30]. To account for this phenomenon, we use the parameter λ to represent the maximum DOD throughout this paper.

III. Continuous Energy Replenishment

The goal of this study is to formulate a method of energy replenishment that will allow a swarm of homogeneous COTS UAVs to fly perpetually (in practice, as long as the swarm needs to be airborne to accomplish the task that a specific application may require). This section will investigate the queued charge replenishment finite state machine and work through the derivation of formulae to compute the theoretical best-case scenario.

A. Queued Charge Replenishment

To ensure that a swarm of size n can be in flight and operational at all times, charged drones need to standby to replace energy-depleted swarm drones when necessary. For ease of control and management, we propose that the drone fleet can be modeled as a finite state machine (as depicted in Figure 2). Every drone's current action(s) can be represented by a unique *state* and the drone will either stay in the same state or move to the next state depending on the situation. We assume that a central software makes decisions on individual drone states based on the status of the entire fleet.

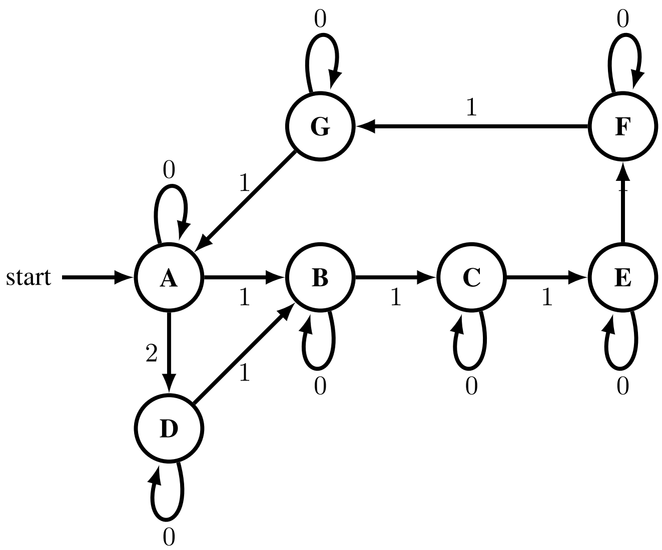

Fig. 2. A drone can be in one of the following finite states:
A: Ready, **B:** Flying in Swarm, **C:** In Swarm Awaiting Replacement,
D: Flying to the Swarm, **E:** Flying to the Charger,
F: In the Charge Queue, **G:** Charging.

TABLE I
TERMS USED TO MODEL DRONE OPERATIONAL CHARACTERISTICS.

Setting	Description
$\mathcal{N}$	Minimum number of drones required for perpetual flight
n	Swarm size (number of drones in the swarm)
λ	Percentage utilization ratio of the battery to prevent damage
$\mathcal{R}$	Radius (miles) of drone coverage area
$\mathcal{C}$	Charge time from 0–100% (min) required for Li-Po battery
$\mathcal{B}$	Battery 100% capacity (Wh)
$\mathcal{T}_h$	Time (min) drone can hover in place before battery depletion
$\mathcal{T}_f$	Time (min) drone can fly before battery depletion
τ	Total expected/actual operational flight time of the fleet (min)
$\mathcal{P}_h$	Power consumed (W) hovering
$\mathcal{P}_f$	Power consumed (W) during flight at maximum speed
$\mathcal{V}$	Maximum velocity (mph) allowed for the drone

Each drone in the fleet can be in any one of six states:

(A) Ready: when a drone is 100% charged and idle (not flying), it is in the Ready state. Every drone in the fleet begins in the Ready state at time 0. Drones will remain in the Ready state until they are dispatched (i) when a drone in flight requires a replacement or (ii) to form the initial flying swarm.

(B) Flying in Swarm: Drones part of the flying formation are in the Flying in Swarm state. Drones will continue to fly in the swarm until their battery level reaches a critical threshold (taking into consideration the energy needed to fly to the charging station). Only drones in the flying in the swarm state execute swarm tasks, such as capturing audio and video signals. A drone will remain in the Flying in Swarm state until it calls for its replacement.

(C) In Swarm Awaiting Replacement: When a drone flying in formation reaches a critical threshold (30% battery power remaining + energy to return to the charger), it calls for a replacement and enters the In Swarm Awaiting Replacement state. It will continue in formation in the In Swarm Awaiting Replacement state until it is relieved.

(D) Flying to the Swarm: When a replacement is needed to relieve a drone flying in the swarm, a Ready state drone is dispatched to rendezvous with the swarm. Once dispatched, the drone will remain in the Flying to the Swarm state until it joins the swarm.

(E) Flying to the Charger: Once a drone is relieved from the swarm, it must fly to a charging station and enter the Flying to the Charger state. It will remain in the Flying to the Charger state until it reaches a charging station and successfully lands.

(F) In the Charge Queue: Once a drone returning from the swarm lands on the charging station, it enters the In the Charge Queue state. If the charging station can accommodate it, it immediately moves to the Charging state. Otherwise, it remains in the In the Charge Queue state until charging is available.

(G) Charging: Once a charger is available, a drone enters the Charging state at the beginning of its charge cycle. It will remain in the Charging state until its battery level reaches 100%, and which point it will enter the Ready state and again be available for dispatch to the swarm.

B. *Computing Theoretical Best Case of $\mathcal{N}$*

A list of the parameters used in the derivation of formulae can be found in Table I. Assuming the goal of maintaining a swarm of n drones in flight at all times over total runtime τ, it is intuitive that a larger fleet of $\mathcal{N}$ drones will be necessary. The system will, however, reach a state of equilibrium where the number of drones returning to charge and being subsequently dispatched to relieve future energy-depleted drones in the swarm will be sufficient to achieve perpetual flight without the addition of any new drones.

Equation 1 gives the time (in minutes) of a round-trip from the charging station to the swarm, where $\mathcal{R}$ is the distance between the swarm and the charging station and $\mathcal{V}$ is the drone's maximum velocity. Total flying time is multiplied by 120% as flying drones will generally consume $\approx 20\%$ more power than hovering drones, by 2 to account for the round trip, and by 60 to convert from hours to minutes.

$$\mathcal{T}_{\text{flying}} = \left(2 \times 60 \times \frac{\mathcal{R}}{\mathcal{V}}\right) \times 1.2 \tag{1}$$

Equation 2 gives the time (in minutes) a drone can effectively hover in the swarm. The correction factor $\lambda = 0.7$ is used to ensure the drone's battery never falls below 30% (see Section II-B). Besides ensuring an optimal DOD, this 30% "buffer" is used to offset any unexpected operations the drone

Fig. 3. Three drones used to provide preliminary results in Table II.

may have to complete besides normal hovering and flying to/from charging stations and the swarm. $\mathcal{T}_h$ is the total amount of time (in minutes) a drone can hover until its battery is depleted from 100% to 0%.

$$\mathcal{T}_{\text{hovering}} = \lambda \times \mathcal{T}_h - \mathcal{T}_{\text{flying}} \tag{2}$$

Equation 3 gives the total number of swaps $\mathcal{S}$ that must occur to maintain a swarm of size n over total simulation time τ. $\mathcal{S}$, in other words, is the total number of instances that energy-depleted drones need to be replaced over τ. If no charged drones are reintroduced to the system, then $\mathcal{N} = \mathcal{S}$. This is the worst-case scenario, however, as most scenarios will allow energy-depleted drones to complete their charging cycle and return to the swarm.

$$\mathcal{S} = \left\lceil \frac{\tau}{\mathcal{T}_{\text{hovering}}} \times n \right\rceil \tag{3}$$

Equation 4 gives the time (in minutes) it takes to charge a drone from 30% to 100%. $\mathcal{C}$ is the time (in minutes) it takes to charge a drone from 0% to 100% (as reported by the drone manufacturer). A linear charging cycle is assumed, and for the purposes of this study drone batteries will never fall below 30%.

$$\mathcal{T}_{\text{charging}} = \lambda \times \mathcal{C} \tag{4}$$

Equation 5 gives the total number of drones that will *both* fly in the swarm *and* recharge in time to re-enter the swarm to relieve other drones. In other words, n_c is the number of completed charge cycles over time τ. As previously mentioned, without n_c the fleet size $\mathcal{N}$ would have to equal $\mathcal{S}$ as a new drone would be required for every necessary swap. Also, the condition of summation $\mathcal{T}_{\text{hovering}} \mid i$ (read $\mathcal{T}_{\text{hovering}}$ divides i) ensures that the summation index only increments by multiples of $\mathcal{T}_{\text{hovering}}$ (swarm drones will require replacement every $\mathcal{T}_{\text{hovering}}$ minutes). It should be noted that for the purposes of this study, the initial set of swarm drones is assumed to immediately be flying in formation at time 0.

$$n_c = n \times \sum_{\substack{i=\mathcal{T}_{\text{hovering}} \\ \mathcal{T}_{\text{hovering}} \mid i}}^{\tau} \begin{cases} 1, & \tau - (i + \mathcal{T}_{\text{hovering}} + \frac{\mathcal{T}_{\text{flying}}}{2} + \mathcal{T}_{\text{charging}}) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Given the total number of necessary swaps and the total number of charged drones introduced back into the swarm, the total fleet size $\mathcal{N}$ necessary to maintain a swarm of n drones over time τ can be computed with Equation 6.

$$\boxed{\mathcal{N} = \mathcal{S} - n_c} \tag{6}$$

The energy consumption of the fleet can now be investigated. Equation 7 gives the total initial energy of the fleet, assuming that each drone begins with a full charge, while Equation 8 gives the total energy added to the system from charging drones over τ. The total energy in, therefore, is given by Equation 9.

$$\mathcal{E}_{\text{initial}} = \lambda \times \mathcal{B} \times \mathcal{N} \tag{7}$$

$$\mathcal{E}_{\text{charging}} = \lambda \times \mathcal{B} \times n_c \tag{8}$$

$$\mathcal{E}_{\text{in}} = \mathcal{E}_{\text{initial}} + \mathcal{E}_{\text{charging}} \tag{9}$$

The total energy consumed by the fleet's operations can be broken into two parts: total energy consumed while flying, given by Equation 10, and total energy consumed while hovering, given by Equation 11.

$$\mathcal{E}_{\text{flying}} = \mathcal{S} \times \mathcal{T}_{\text{flying}} \times \mathcal{P}_f \tag{10}$$

$$\mathcal{E}_{\text{hovering}} = \tau \times n \times \mathcal{P}_h \tag{11}$$

By conservation of energy, the total energy consumed by the fleet must be less than or equal to the amount of energy introduced to the system, as shown in Equation 12.

$$\mathcal{E}_{\text{in}} \geq \mathcal{E}_{\text{flying}} + \mathcal{E}_{\text{hovering}} \tag{12}$$

$\mathcal{E}_{\text{in}}$ must be *greater than or* equal to the energy consumed, as the fleet may require more energy in than it actually consumes.

TABLE II
EXPERIMENTALLY OBTAINED INDIVIDUAL DRONE PARAMETERS. *PARAMETERS BASED ON MANUFACTURER SPECIFICATIONS.

Parameter $\Rightarrow$		$\mathcal{B}$	$\mathcal{C}$		$\mathcal{T}_h$	$\mathcal{P}_h$	$\mathcal{T}_f$	$\mathcal{P}_f$	$\mathcal{V}$
Drone Model	**Cost ($)**	**Battery (Watt-hours)**	**Charge Time (minutes)**	**Weight (grams)**	**Hover Time (minutes)**	**Hover Power (Watts)**	**Flight Time (minutes)**	**Flight Power (Watts)**	**Speed (mph)**
Skyracer-901H	30	0.81	36	24.9	11	4.42	8.8	5.52	10
X5SW-V3	99	1.85	55	119	10	11.1	8	13.88	15
Contixo-F18	299	15.5	92	454	8	116.25	6.4	145.31	20
DJI Phantom 4*	999	81.3	120	1380	28	174.21	22.4	217.77	25
DJI S900*	3198	278	150	3300	40	417	32	521.25	30

TABLE III
SIMULATION RESULTS INDICATING THE MINIMUM NUMBER OF DRONES ($\mathcal{N}$) NECESSARY TO ENSURE CONTINUOUS FLIGHT. *Theoretical* REFERS TO THE THEORETICAL BEST-CASE AS COMPUTED FROM FORMULAE DERIVED IN SECTION III-B. *Simulation* INDICATES SOFTWARE SIMULATION RESULTS.

Drone Model	**2-Drone Swarm**		**4-Drone Swarm**		**8-Drone Swarm**	
	Theoretical	*Simulation*	*Theoretical*	*Simulation*	*Theoretical*	*Simulation*
Skyracer-901H	16	16	32	32	64	64
X5SW-V3	20	22	40	44	80	88
Contixo-F18	26	38	52	76	104	152

For example, some drone batteries may charge towards the end of time τ that do not discharge before the fleet ceases operation.

IV. SIMULATION RESULTS

Three small, commercially available drones were purchased and flown to determine their actual *hover* and *flight* times. These results were used in both analytical and computer simulation calculations to determine the minimum fleet size ($\mathcal{N}$) to ensure perpetual flight.

A. Drone Selection

Various specifications were considered when choosing test drones, including their cost, battery capacity, weight, and recharge time. Table II lists this information, along with experimentally determined values (such as hover time and power, flight power, and speed). Hover power was calculated using Eq. 13. As the drones that were purchased for this study did not perform well enough, two additional, professional drone models are included in Table II –the **DJI Phantom 4** and the **DJI S900**. The 3 swarm candidate drones tested in this study (the **Skyracer-901H**, **X5SW-V3**, and **Contixo-F18**) are shown in Figure 3.

$$\mathcal{P}_h = \frac{60 \times B}{\mathcal{T}_h} \tag{13}$$

B. Test Case Computation

To gain intuition into Eq. 6, let us calculate the necessary fleet size ($\mathcal{N}$) for a swarm of $n = 8$ using the **X5SW-V3** drone. From Table II, we derive the following drone parameters:

- $n = 8$
- $\lambda = 0.7$
- $\mathcal{V} = 15$ mph
- $\mathcal{T}_h = 10$ minutes
- $\mathcal{R} = 0.5$ miles
- $\mathcal{C} = 55$ minutes
- $\mathcal{P}_h = 7.8$ Watts
- $\mathcal{B} = 1.85$ Watt-hours
- $\tau = 120$ minutes

Substituting these parameters into Eqs. 3–6:

$$\mathcal{S} = \left\lceil \frac{120}{0.7 \times 10 - 144 \times \frac{0.25}{15}} \times 8 \right\rceil \quad \Rightarrow \quad \boxed{\mathcal{S} = 209}$$

$$n_c = 8 \times \sum_{\substack{i=\mathcal{T}_{\text{hovering}} \\ \mathcal{T}_{\text{hovering}} \mid i}}^{120} \begin{cases} 1, & 120 - \left(i + \mathcal{T}_{\text{hovering}} + \frac{\mathcal{T}_{\text{flying}}}{2} + \mathcal{T}_{\text{charging}}\right) > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$n_c = 8 \times 16 \quad \Rightarrow \quad \boxed{n_c = 128}$$

$$\therefore \mathcal{N} = 209 - 128 \quad \Rightarrow \quad \boxed{\mathcal{N} = 81}$$

This result shows the theoretical minimum $\mathcal{N}$ of 81 for a swarm of size $n = 8$ using the **X5SW-V3** drone. Values have been calculated for various drones and swarm sizes, and are shown in Table III.

C. Simulation Software

Simulation software was developed in order to determine the minimum number of drones necessary, $\mathcal{N}$, to ensure a drone swarm's perpetual flight over varying conditions. The simulation accepts parameters from the user, such as the drone model, length of simulation (τ), and desired drone swarm size (n). The simulation then offers the user a choice:

i Calculate $\mathcal{N}$: the simulation software will create a drone fleet of $2n$ (two times the desired swarm size). When drones in the swarm reach a critical energy threshold and signal for a replacement, the simulation determines if there are any drones in the Ready state to relieve them. If not, the simulation automatically adds new drones to the fleet. Once complete, the total number of drones ($\mathcal{N}$) required to maintain a perpetually flying swarm of size n is displayed to the user (as seen in Figure 4).

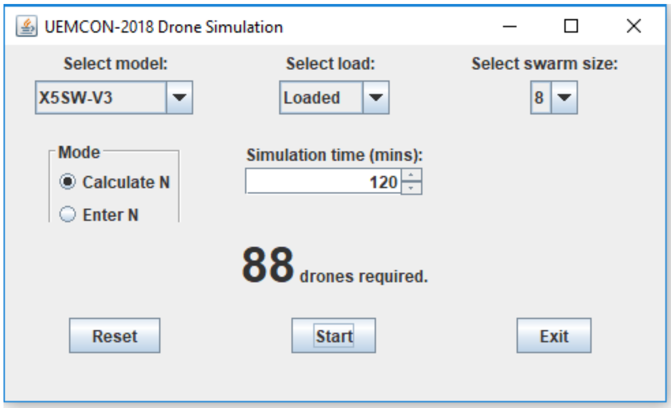

Fig. 4. Screen shot of the simulation software (created in Java) to test for the minimum number of drones necessary to ensure perpetual flight ($\mathcal{N}$).

ii Specify $\mathcal{N}$: the simulation software will create a drone fleet of the user-entered size. The simulation will terminate either when no drones in the Ready state are available to relieve drones in the swarm with depleted energy, or when the desired simulation time has elapsed. The software gives the user a Boolean result (true or false) indicating whether or not perpetual flight was possible with the specified $\mathcal{N}$.

D. Simulation Settings

As discussed in Section III-A, all drones in the fleet exist in one of seven states. Depending on the drone's state, energy will be lost (used in flying) or gained (charged) with each clock tick. The simulation triggers state changes to form the initial swarm, when a drone has completed a charging cycle, when a drone in the swarm reaches a critical energy threshold, when a drone arrives at a charger, when a drone begins charging, when a drone arrives at the swarm, and when a drone leaves the swarm to fly to a charger.

The critical energy threshold that signals a drone in the swarm to call for a replacement is defined in Equation 14, where $\mathcal{T}_{\text{flying}}$ is the same as derived in Eq. 1. Table I further details each parameter used in the simulation.

$$\mathcal{E}_{\text{critical}} = \lambda \times \mathcal{T}_{\text{h}} + \mathcal{T}_{\text{flying}} \tag{14}$$

It should be noted that the simulation software makes various assumptions. The distance from the swarm to any of the charging stations is assumed to be constant, and charging stations are assumed to be able to accommodate an unlimited number of *resting* drones (i.e., an unlimited number of drones can land on the charging station), though the number of drones charging at any given time is bound. The speed at which a drone flies to or from the swarm is assumed to be constant, based on the drone model's maximum speed. Charging is assumed to be linear (if a drone takes 100 minutes to charge, and has 0% energy, each minute will increment the drone's energy by 1%), rather than a more realistic logarithmic model. The energy consumed by each done, whether in flight or hovering, is approximated to constant (based on the specific drone model). When the drone fleet is first created, the drones comprising the initial swarm go straight to the Flying in Swarm state from the Ready state. This means they start flying with 100% battery power, rather than consuming energy on their flight to form the initial swarm. The simulation was created to accept a time quantum of at least one second. The simulation was programmed with a quantum of 1 second to produce the results presented. Depending on the quantum used, it is assumed that state changes, energy updates, and distance flown will all update at the beginning of the next quantum. If one minute is chosen, even if a state change (such as a drone has finished Charging and is now Ready) occurs in the middle of the quantum, the fleet may not be immediately updated.

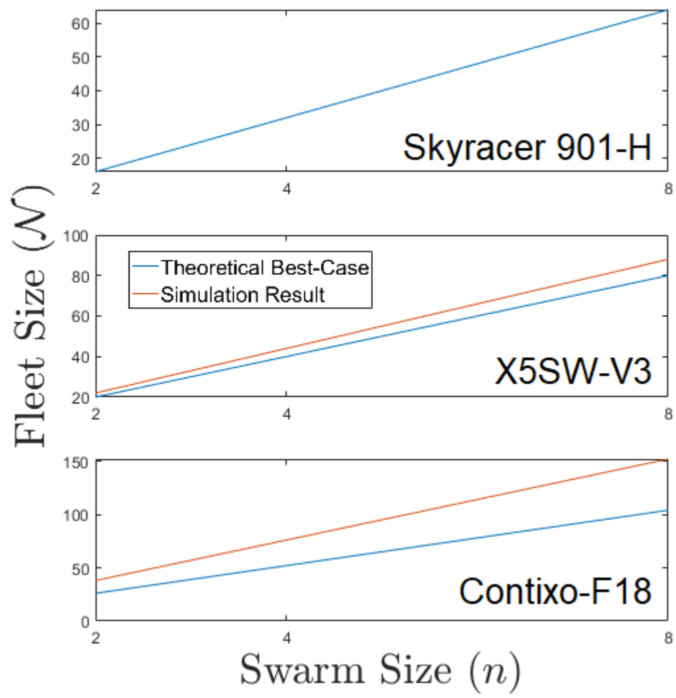

Fig. 5. Comparison of theoretical best-case based on the equations in Section III-B and the simulation results described in Section IV-E for the three drone models that were purchased for this study.

E. Experimental Results

Table III lists experimental results with varying drone models and swarm size. It would appear, as expected, that the largest factor impacting $\mathcal{N}$ is the ratio of flight- to charge-time. The longer a drone can fly without being recharged, the lower $\mathcal{N}$ is necessary to maintain perpetual flight. Other factors include $\mathcal{R}$, the distance from the swarm to the charging station (which determines both how long a drone must wait for a replacement and how much reserve energy a drone needs to return to a charger after being relieved from the swarm), and $\mathcal{V}$, the maximum speed of the drone.

V. Conclusion

As indicated by the study conducted in this paper, perpetual flight is indeed a viable concept. Clearly, the drone fleet must contain a certain number of drones, $\mathcal{N}$, and a sufficient number of charging stations to ensure fully charged drones are always available to relieve swarm drones whose energy has been depleted. The expected, theoretical best-case $\mathcal{N}$ (as derived in Section III-B) and the $\mathcal{N}$ calculated by simulation software can be seen in Table III. The theoretical best-case vs. simulated results for the three drone models purchased for this study can also be seen as plots in Figure 5. The numbers determined from both the best-case scenario and the simulation software are not prohibitive; the perpetual flight of a homogeneous UAV swarm can be attained with inexpensive and a sufficient number of readily available COTS drones. For example, to sustain a swarm size of $n = 4$, a fleet size of $\mathcal{N} = 32$ is necessary for the **Skyracer-901H**, while the theoretical best-case for **X5SW-V3** is $\mathcal{N} = 40$ and **Contixo-F18** is $\mathcal{N} = 52$. The difference in $\mathcal{N}$ between the various drone models is primarily influenced by the battery capacity ($\mathcal{B}$) and charge time ($\mathcal{C}$).

The results indicate a disparity between the theoretical and simulation values. This stems from the fact that the simulation imposed a limit on the number of drones charging at any time, while the equations assumed that an infinite number of drones were able to charge. In the simulation, in order to more closely model real-world situations, there were 4 charging stations that could each charge 8 drones at a time, restricting the number of charging drones. The effect of this added restriction was more pronounced in drones that require longer charge times, forcing the addition of more drones to the fleet to compensate. This indicates that, in a real-world situation, the number of charging stations and how many drones each station can charge at given time are equally important as the flight to charge ratio.

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