Optimization of a Modular Drone Delivery System

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***Abstract*— Drones have recently become a promising solution for rapid parcel delivery due to advances in battery technology and navigation systems. Drones have inherited limitations in battery capacity and payload, which make their efficient operation and management a critical problem for a successful delivery system. Adopting modularity in the drone design can provide operational benefits to increase overall fleet readiness and reduce overall fleet size. This paper discusses the potential value of introducing modular design to a drone delivery system. We propose an optimization method for the operation management of a fleet of modular delivery drones. This paper presents simulation results that compare the proposed method with existing operation management methods. The results show that a simple operation management strategy can make a drone delivery system unstable with increasing demand on certain types of modules in the fleet. The results comparing modular and non-modular drone operation also prove that the proposed operation management method with modular drones can save delivery time and energy consumption during a delivery operation over non-modular drones.**

Keywords—drone delivery system; modularity; optimization; parcel delivery; dynamic programming; operations management;

I. Introduction

Unmanned aerial vehicles (UAVs), or drones, have been successfully applied to disaster management [1], 3D mapping [2] and precision agriculture [3]. Recently, drones are considered as a promising solution to rapid parcel delivery. Parcel delivery using drones has many advantages over existing ground vehicle delivery using trucks. Delivery time can be reduced since drones are not interrupted by the established infrastructure such as traffic lights, and the volume of traffic. It is also possible to reduce the cost of maintenance in a drone delivery system since drones are less expensive than ground vehicles and easier to repair. Various major companies expressed their interest in drone delivery including Amazon with their service “Prime Air” [4], DHL with “Parcelcopter” [5] and Google with “Project Wing” [6].

Several research studies on drones have contributed to making a drone delivery system feasible by increasing flight time and improving navigation capabilities. Studies on lithium-ion batteries with high energy density have shown improvements on flight time compared to nickel-cadmium and nickel-metal hydride batteries [7]. In addition, a wide range of different augmentation systems to assist GPS by providing accuracy and integrity have improved the positioning and navigation of drones [8]. Moreover, technologies to detect and avoid obstacles play significant role in the stability and the robustness of a drone system [9, 10].

There are few studies related to increasing the operational efficiency of a drone delivery system. Drones have limitations in the delivery range and payload, which makes the efficient operation and management more critical compared to ground delivery systems. Previously, Traveling Salesman Problem (TSP) is suggested to optimize the routes of the drones that show substantial savings when drones and trucks are operated together [11]. The suggested TSP lacks a fleet perspective by focusing on a single drone operation. In another study, a TSP problem is formulated for combined truck-drone delivery network systems to optimize truck routes, and a clustering method is proposed to determine the optimal number of drone launch sites and locations [12]. Another study proposes a mixed-integer linear programming formulation for a drone delivery fleet to minimize operation costs by optimizing the delivery routes [13]. The focus in these studies is on routing rather than a complete management of the entire fleet including scheduling, inventory management, maintenance and repair.

Introducing modular architectures to the drone design provides several operational advantages in a drone delivery system [14]. A major drawback in the operation of drones is the limited battery capacity. With lithium-ion batteries used in most commercial drones, flight time is approximately 30 minutes, and non-modular drone is unavailable for delivery for more than one hour when recharging the battery [15]. A modular design with swappable batteries is expected to perform better than drones with integrated batteries in terms of readiness. Furthermore, since a set of drone types with distinct capabilities is necessary to accomplish various types of delivery tasks, modularity can reduce the overall fleet size thanks to module sharing.

In this paper, we propose an operation management strategy based on the optimization of modular drone delivery systems. For a given set of modular designs, this strategy determines the schedule and the assignment of modular combinations to meet the delivery demand. One study introduces fuzzy controller [16, 17] and develop a reinforcement fuzzy learning scheme for robots playing a differential game operation [18]. Another study is stochastic neighborhood approach is used to optimize shift schedule management for tank trucks [19]. We suggest an optimization algorithm with a forward-looking approach and compare with existing methods such as dynamic programming [20] under a randomly generated delivery scenario.

We apply the proposed operation management strategy to a modular and a non-modular drone system to identify potential

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benefits of modularity in rapid parcel delivery. The results show that modular drone operation with the suggested optimization algorithm can save delivery time and energy consumption, compared with, not only, modular drone operation based on existing management algorithms, but also non-modular operation based on either management algorithm.

II. Modularity in Drone Delivery

In this section, we describe the process used to modularize a fleet of delivery drones and map the predefined set of modular drones to the delivery demand. A module in this study is characterized by the functionality of its components that defines its type and a set of variables that differentiates variants of a module type. The delivery demand is represented by mass, volume, delivery distance and time of the order. These values are randomly generated following probability distributions to define a reasonable scenario.

A. Modular Architecture

We heuristically define a modular architecture for the drone fleet based on the independent variables in Equations (1) – (5) governing the drone motion. While some studies define the modular system architecture using functional or physical decomposition [21, 22], the focus of this paper is not on modular design but on the feasibility of modularity in the context of drone delivery operation, in this paper. The complete system optimization combining design and operation is left to a future study. Equation (1) defines an approximate relationship based on Newton's second law of motion for the horizontal drone velocity v_h in terms of the total mass m_t, the gravitational acceleration g, the total motor thrust T, the air density ρ, the drag coefficient C_d, and the effective area of drone A_e. The total mass includes the mass of the drone defined by the sum of the weights of its modules m_i and the load/parcel m_p as shown in Eq. (2). n is the total number of modules representing one drone. Equation (3) relates motor thrust to the rotor diameter D, and the motor power P, using static thrust calculation and fluid mechanics. Equation (4) assumes that the effective drone area is related to the carrier volume V_c, which is the space where load/parcel are placed. The energy capacity of the battery C_b must be larger than the energy required to complete delivery in t_{total} amount of time as shown in Eq. (5).

$$v_h = \sqrt{2\sqrt{1-(m_t g/T)^2}\, T/(\rho C_d A_e)}\ , \qquad (1)$$

$$m_t = \sum_{i=1}^{n} m_i + m_p\ , \qquad (2)$$

$$T = \left(\frac{\pi}{2} D^2 \rho P^2\right)^{1/3}, \qquad (3)$$

$$A_e = V_c^{2/3}, \qquad (4)$$

$$P t_t \leq C_b\ , \qquad (5)$$

P, D, V_c, and C_b are the four independent variables related to the physical drone design. Note that the drone mass is not an independent variable since it can be modeled as a function of the four independent variables. m_p is given by the demand, and t_t is determined by both the demands and the drone design.

The four independent variables can be attributed to motor, rotor, carrier, and battery, respectively. We define these components as modules, and use these variables to create different variants of these modules. The definition of modules determines the modular architecture of drones while variants create distinct modular drones with different capabilities. Table I summarizes the module definitions and the associated variables.

TABLE I. MODULE DEFINITIONS

	Modules			
	Module 1	***Module 2***	***Module 3***	***Module 4***
	Carrier	***Battery***	***Propeller***	***Motor***
Number of Variants	$N_1(=2)$	$N_2(=3)$	$N_3(=3)$	$N_4(=3)$
Variables	Volume	Capacity	Diameter	Power

B. Modular Drone Assignment

Mapping a delivery demand to a modular drone can be formulated as an optimization problem. Given a modular architecture with k module types and a set of N_i module variants for each module type as in Table I, the number of possible modular combinations is $\prod_{i=1}^{k} N_i$. Physical constrains exist in practice, which make some of these combinations infeasible. In this study, we focus on a case with four module types. We define the variables describing different module variants as $[\alpha_1, \alpha_2, \alpha_3, \alpha_4] = [V_c, C_b, D, P]$. For given delivery demand, the constraints that a modular drone must satisfy can be formulated as:

$$V_p \leq \alpha_1, \qquad (6)$$

$$m_t g \leq \left(\frac{\pi}{2}\alpha_3^2 \rho \alpha_4^2\right)^{1/3}, \qquad (7)$$

$$0.5(2m_t g)^{\frac{3}{2}} / \sqrt{\rho \pi \alpha_3^2} \leq \alpha_4\ , \qquad (8)$$

$$\alpha_4 \frac{L}{v_h} \leq \alpha_2, \qquad (9)$$

where m_i is the mass of module i, and L is the distance to the delivery location specified by a demand, and V_p is the parcel volume. Equation (6) defines the volume constraint for the parcel to fit into the modular drone. Equations (7) – (8) are the requirements for the drone to be able to lift the load and hover in the air. Equation (9) is the condition for the battery to provide enough energy throughout the delivery. To optimize the drone assignment to the demand, we use the following cost function J_1 in Equation (10) which is the weighted sum of the average power consumptions given by the first term and the delivery time given by the second term. v_h in the cost function J_1 is the function that consists of α_i as represented in Equation (1).

$$J_1 = \sum_t w_1 \frac{\alpha_4 L}{v_h(\alpha_1,\alpha_2,\alpha_3)} + w_2 \frac{L}{v_h(\alpha_1,\alpha_2,\alpha_3)} \qquad (10)$$

The values of the weighting coefficients w_1 and w_2 define the relative importance of energy consumption and delivery time in the optimization. J_1 is minimized by selecting a module combination that satisfies the conditions in (6) – (9). If the number of feasible modular combinations is small, it is possible to find the modular drone that minimizes J_1 for each separate delivery demand using enumeration. The physical attributes of each module, α_i, depends on the drone assignment. This drone assignment considers the availability of the required modules in the inventory as the constraints. In this paper, we use $[w_1, w_2] = [20, 1]$

TABLE II. ORTHOGONAL ARRAY SET OF NON-MODULAR DRONES

Non-modular Drone	Modules			
	Module 1	*Module 2*	*Module 3*	*Module 4*
	Carrier	*Battery*	*Propeller*	*Motor*
1	2	1	1	3
2	2	1	2	2
3	2	1	3	1
4	2	2	1	2
5	2	2	2	1
6	2	2	3	3
7	2	3	1	1
8	2	3	2	3
9	2	3	3	2

C. Non-modular Drone Assignment

The performance of drone delivery operation is affected by the capabilities of drones in the fleet in non-modular drone. To observe the effect of number of different types of non-modular drones on the fleet performance and compare it with that of modular operation, we define two cases with different number of types of non-modular drones and compare each operation; an operation with one type of non-modular drone that can meet all delivery requirement, and an operation consisting of nine types of non-modular drones selected by an orthogonal array based on Taguchi method [23].

In this paper, we assume a non-modular drone consists of the same "modules" used in modular drones. Unlike modular drones, the modules of non-modular drones are fixed and irreplaceable. The drone for the operation with one type of non-modular consists of the second variant of module 1, the third variant of module 2, the first variant of module 3, and the first variant of module 4. This set of modules are chosen based on the Eqs. (1) – (5) to fulfill the maximum delivery distance requirement explained in 'Randomized Order' in Section III-B.

Table 2 shows the orthogonal array set used in the operation with nine types of non-modular drones. Note that 18 non-modular drones can be created with O_{18} ($2{\times}3^3$) orthogonal array in the generated case. We assume that carrier is standardized to be second variant of module 1, for simplicity, thereby modifying to O_9 (3^3) orthogonal array set consisting of 9 types of non-modular drones in delivery operation.

III. OPERATION OF DRONE DELIVERY

In this section, we describe the details of the simulation model for the drone delivery operation, and suggest an algorithm to manage the system operation considering the system stability and the operation efficiency.

A. Simulation Overview

This section describes the high-level process flow in the simulation of drone delivery. We simulate two separate scenarios with modular and non-modular drones to identify potential operational benefits of modularity for parcel delivery. The simulation models for two scenarios have some differences since the operation of modular drones requires additional steps such as assembly and disassembly that are not applicable to non-modular drones. Another important difference is that non-modular drones have an integrated battery system while the battery in modular drones is swappable.

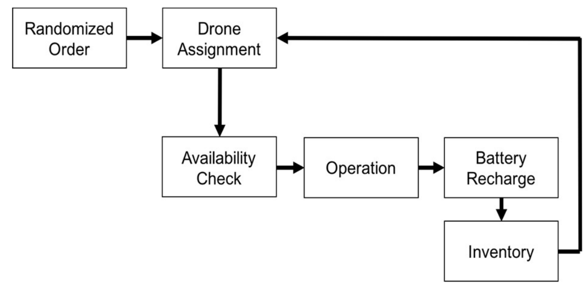

Fig. 1. Operation of non-modular drones

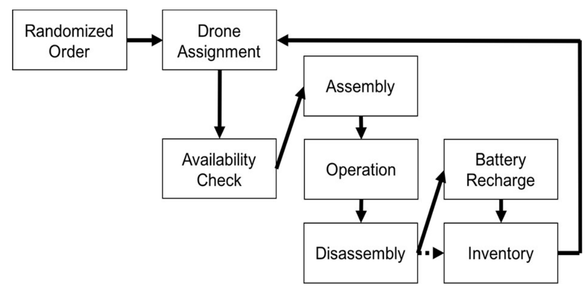

Fig. 2. Operation of modular drones

Figure. 1 and 2 depict the process flow followed in the two different scenarios. The process starts with randomly generated orders defined by mass, volume, travel distance and the time of the order. A drone assignment is performed following the process described in Section II-B and the availability of the required drones/modules is checked. Section III-C elaborates on how this process can be modified by integrating feedback from the inventory. Modular drones undergo an assembly process. When drones are ready, they are dispatched for the delivery operation. After the delivery, modular drones are disassembled. For modular drones, only the battery modules are recharged after disassembly while for non-modular drones, the entire drone is unavailable while its battery is recharged because battery is integrated.

B. Simulation Assumptions

The assumptions involved in each step of the simulation process described in the previous section are summarized rest.

- Randomized Order—We assume that delivery orders do not exceed the capabilities of the available drones. Amazon reports that 86% of all Amazon packages weigh 2.3 kg or below, and the targeted distance is less than 14 km from the drone station [24]. For the simulation scenario, we use a normal distribution with a mean of 1.4 kg and a standard deviation of 0.9 kg for the weight of one parcel and set the range between 0 kg and 2.3 kg. A normal distribution with a mean of 6 km and a standard deviation of 7.5 km is used for the delivery distance of one delivery order and limit the range between 0 km to 13.5 km. This paper considers the volume and the order time of one parcel that follows a uniform distribution with the range between a volume of zero cubic meter and a volume of one cubic meter. The total number of randomly generated orders for each day is 100.

- Drone Assignment—We assume that all modules are compatible with each other but the assigned drones must satisfy the constraints in Eqs. (6) – (10). We assume a drone fleet with four module types as shown in Table I with variants N_1= 2, $N_2 = N_3 = N_4 = 3$. This paper defines the modules as independent variables in Eqs. (1) – (5). Details are explained in Section II-A.
- Availability Check—For a drone to be considered available, all corresponding modules must be available in the inventory.
- Assembly—We assume that the time to assemble a complete modular drone is always less than 5 minutes.
- Operation—Drones can be deployed only during daytime. We assume operation time as a half of one day. At night, drones are not sent for operation but orders are accumulated. We do not model damage or maintenance needs in this simulation. We also do not model the delivery routing problem.
- Disassembly—All modular drones are disassembled after return, i.e., the inventory only contains modules in a modular drone operation scenario. This assumption is necessary in practice since modules might need service after operation and assembly/disassembly time is relatively short compared to the delivery time. All modules besides the battery are sent back to the inventory after disassembly, while battery modules and regular drones go to the recharging.
- Battery Recharge—Non-modular drones and battery modules are unavailable during the recharging process. Battery recharge time is assumed to be one hour in this simulation.
- Inventory—Initial number of non-modular drones and modules are predefined. The inventory levels are recorded and used for the drone delivery.

C. Operation Management

This section elaborates on the three methods for operation management problem that are a preprocessed static drone assignment, dynamic programming, and an assignment with the proposed customized algorithm. All methods can be used in operations with more than two non-modular drones. Since the operation with one type of non-modular drone is a special case where there is only one selection to be made when assigning drones, only Algorithm 1 is applicable. The drone assignment in operation receives the feedback from the inventory regarding the availability of the assigned modules.

Algorithm 1 Static Drone Assignment

Input:
$\mathbf{t_r}$ —Time when a drone is requested
R — The matrix containing order information
S — The vector representing the number of variants for each module type
V — The vector containing predefined module/drone assignments
N — The vector containing the inventory levels, with elements n_{ij} for the variant j of the module i

Output:
$\mathbf{t_r}$ — The time when a drone is requested
$\mathbf{V_f}$ — A vector containing drones/modules send for operation
R — The matrix containing order information

```
// Initialize the set of modules
V_f = V
// Set R_t to the t^th column of R
R_t = R(t,:)
// Iterate over the number of module types
for i ∈ {1, ... length(S)} do
   // Iterate over the number of variants
   for k ∈ {1, ... S_i} do
      // Check predefined assignment corresponding to
        the order
      if V_i = k then
         // Check inventory level is empty
         if n_ik = 0 then
            V_f ← 0
            // Substitute the (t + 1)^th column of R
            R(t + 1,:) = R_t
return (t_r, V_f, R)
```

We refer to the static drone assignment as Algorithm 1. This algorithm chooses the optimal drone that minimizes the cost J_1 in Eq. (10) for a given demand. When the required modules are not available, the only possible decision is to wait until they become available with returning drones from delivery operation. This might not be a preferred approach since it might lead to unnecessary delays in delivery. It is generally possible to have alternative drones that can satisfy the constraints in Eqs. (6) – (9), and a better management strategy can be developed considering these alternatives.

Dynamic programming is a commonly used method in operations research for management problems [25]. We can formulate the problem using the same cost function J_1 in Eq. (10) with following constraint defining module availability,

$$r_{ij} \leq n_{ij} \,, \tag{11}$$

in addition to Eqs. (6) – (9). Here, n_{ij} is the inventory level and r_{ij} is the requested number of variant j of the module i.

Algorithm 3 Custom Drone Assignment

Input:
$\mathbf{t_r}$ — Time when a drone is requested
R — The matrix containing order information
S — The vector representing the number of variants for each module type
V — The vector containing predefined module/drone assignments
N — The vector containing the inventory levels, with elements n_{ij} for the variant j of the module i
Q — A matrix containing the returning modules with elements m_{ij} for the variant j of the module i

Output:
$\mathbf{t_r}$ — The time when a drone is requested
$\mathbf{V_f}$ — A vector containing drones/modules send for operation
R — The matrix containing order information

```
for k ∈ {t_r, t_r + 1} do
  if k = t_r then
    COL ← COLUMN(V(k)) //assign the k^th column
    P ← N(k,:) //assign the inventory level
  else
    COL ← COLUMN(V(k)) + COLUMN(V(k + 1))
    //Add the returned modules to the inventory
  P ← Q(k,:) + N(k,:)
  end if
  //Solve Dynamic Equation
  for i_1 ∈ {1, ... COL} do
    for i_2 ∈ {1, ..., S(1)} do
      //Check whether inventory is empty
      if N(k, n_{1i_2}) > 0 then
        for i_3 ∈ {1, ... S(2)} do
          if N(k, n_{2i_3}) > 0 then
            for i_4 ∈ {1, ... S(2)}do
              if N(k, n_{3i_4}) > 0 then
                for i_5 ∈ {1, ... S(3)} do
                  if N(k, n_{4i_5}) > 0 then
                  //Calculate cost function in (14)
                  f(k) ← cost(R, i_1, i_2, i_3, i_4, i_5, k)
//Find the modular combination to minimize the sum of cost function and information of orders
 [VAL(k), IND(k), R(k)] ← optimize(f(k), P, R)
end for
if VAL(t_r) > VAL(t_r + 1) then
V_f ← IND(t_r + 1) ∧ R ← R(t_r + 1)
else
V_f ← IND(t_r + 1) ∧ R ← R(t_r)
return (t_r, V_f, R)
```

There are several issues when implementing dynamic programming for this problem. First, dynamic programming is computationally expensive when the number of state variables is large. Also, dynamic programming requires the demand over the entire time horizon to be known. Therefore, it is not possible to formulate a general dynamic programming problem over a long period. In this paper, we formulate the problem for one day. We refer to this approach as Algorithm 2. Second, the decision to assign a drone at a time affects not only the decision and inventory levels at the next time, but also that at the time when the drones come back. Thus, we do not guarantee the global optimality.

To account for the impact of the time delay in the management decision, we propose a custom optimization algorithm. We refer to this method as Algorithm 3. We define the following cost function,

$$J_2 = \sum_t (w_1 \frac{\alpha_4 L}{v_h(\alpha_1, \alpha_2, \alpha_3)} + w_2 \frac{L}{v_h(\alpha_1, \alpha_2, \alpha_3)} + w_3 t_d) \tag{12}$$

where t_d is the difference of the time between when drones are requested and when they are actually deployed. Compared with J_1 in Eq. (10), an additional term is added here to the objective function used in Algorithm 2 to penalize the delay in the delivery. The weight coefficients w_1, w_2, and w_3 determine the relative importance of each term. In this paper, we use $[w_1, w_2, w_3] = [20, 1, 1]$

We assume that all the drones dispatched at a certain time eventually return after the delivery without any loss. Therefore, the number of returning drones can be predicted at the time they are sent. Algorithm 3 finds the optimal drones at the time when drones are requested (t_r). Then, it solves the optimization problem again at the next time ($t_r + \Delta\text{t}$) by assuming all requests are delayed. Since the number of modules in the inventory is different from that of modules at the time before (t_r) because of returning drones, the optimal drone to operate changes under the cost function in Eq. (12). After comparing the values of cost function, we determine whether it is beneficial to deploy drones or delay the order to wait for returning drones.

In Algorithm 3, not only the given time but also the next time is considered. In case of the optimization at the given time, Algorithm 2 is used to solve optimization problem. Since the inventory level has changed due to returning drones at the next time, the constraints have changed with time. Similarly, the optimization problem at the next time can be solved with the different constraints using Algorithm 2. Algorithm 3 calculates and compares the minimum value of the cost function J_2 at both time, thereby leading to better decisions than dynamic programming. This method does not guarantee global optimality but we propose it as a computationally efficient way to account for time delay.

IV. RESULTS

In this section, we show the simulation results corresponding to the three different algorithms discussed in this paper. We compare the results to justify the need for a custom algorithm in the operation of modular drone delivery. We run a 5-day simulation for each algorithm for the modular and non-modular drone fleet under the same conditions. The trend of accumulated orders after one-day simulation is shown to demonstrate that modular and non-modular drone fleet operation are both stable with Algorithm 2 and 3.

nine non-modular drones has a similar tendency with the modular drone operation in Figure 6.

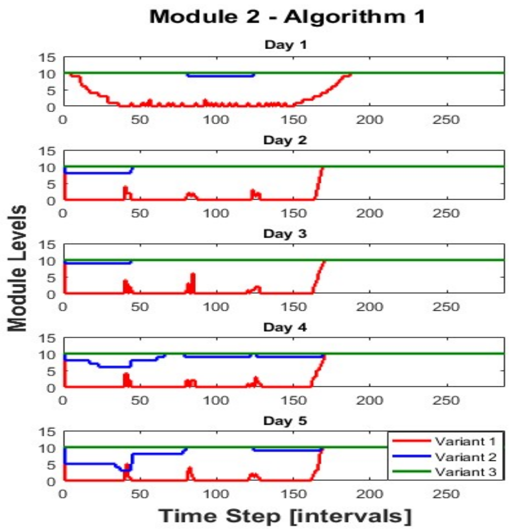

Fig. 3. Battery modules in the inventory with Algorithm 1.

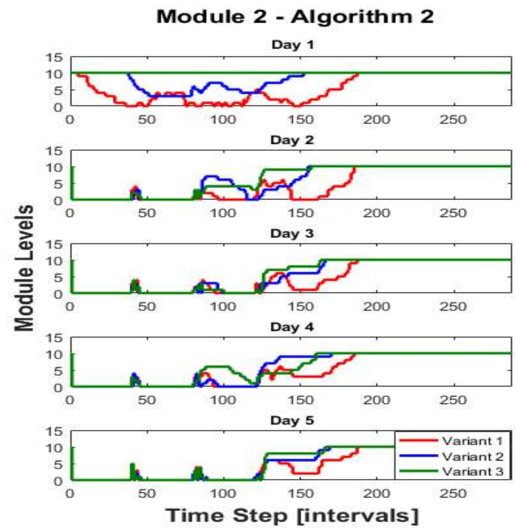

Fig. 4. Battery modules in the inventory with Algorithm 2.

Modular drone fleet simulation starts with an initial inventory of ten modules for each variant of module 2, 3, and 4, and fifteen modules for each variant of module 1 to have thirty modules for each type initially. The non-modular simulation with one drone has an initial inventory of thirty non-modular drones, and the non-modular simulation with orthogonal array has that of three drones for each non-modular drone, thereby meeting the same initial total number of modules as modular drone simulation has.

Figures 3–5 present the inventory levels corresponding to the battery modules for 5 days with three different algorithms. The results for battery modules are the most critical since it takes more time for the battery modules to become available after the delivery operation unlike other modules. As seen in all three figures, the inventory levels for some battery module variants reach zero several times throughout the time horizon. It shows that same orders are delayed during these intervals. As seen in Figure 3, the first variant is out of stock and other variants have barely been used, implying that the orders requiring the first battery module variant are delayed and accumulated. Other variants are actively used in Figures 4 and 5, showing that drone delivery operation with either Algorithm 2 or Algorithm 3 outperforms Algorithm 1 in terms of timing.

Figure 6 shows the trend of initial orders after one-day of modular drone operation, suggesting that the system is unstable when managed with Algorithm 1. On the other hand, Algorithm 2 and Algorithm 3 achieve system stability by keeping these orders at manageable levels of 'Night-time' represents the orders accumulated throughout the night when drones do not operate. This result indicates that modular drone operation has finished the all orders during the day-time when operated by Algorithm 2 or 3. As seen in Figure 7, the drone delivery operation with

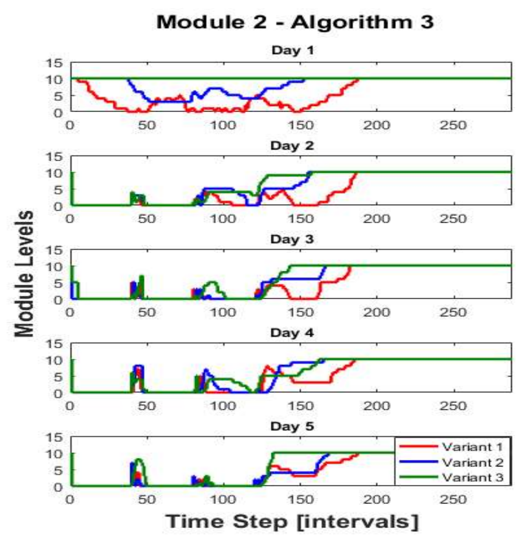

Fig. 5. Battery modules in the inventory with Algorithm 3.

Figure 8 indicates that the drone delivery operation with one type of non-modular drone is stable when operated by Algorithm 1, on contrary to the operation with nine types of non-modular drones. The main reason is that different types of drones are not allowed to replace one another in Algorithm 1, causing delays in delivery orders when nine types of drones are used.

Figure 9 compares the average energy consumption of non-modular and modular drones when each algorithm is applied. Modular drone operation with Algorithm 3 takes approximately 8.6 % less energy than one with Algorithm 2. In case of the non-modular drone operation with nine types, the energy consumption does not have significant difference between with Algorithm 2 and 3. In addition, the energy consumption of the non-modular operation with nine types has no improvement compared that of the operation with one type of non-modular drone.

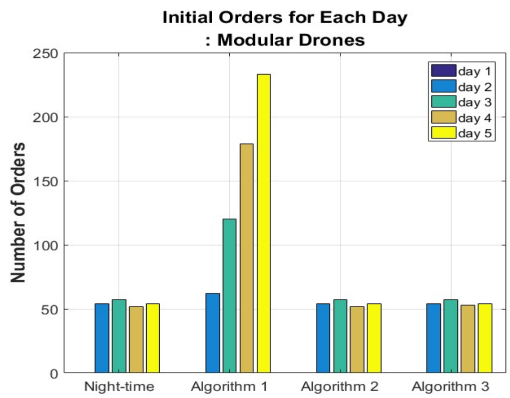

Fig. 6. Initial orders for each day after modular drone fleet operation.

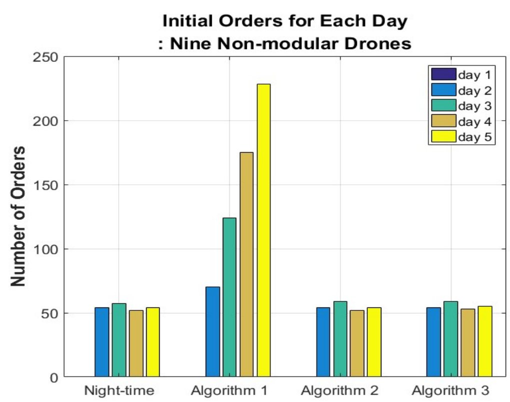

Fig. 7. Initial orders for each day after non-modular drone fleet operation with nine types of drones.

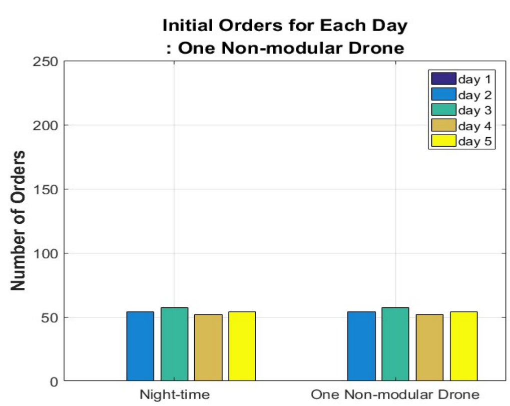

Fig. 8. Initial orders for each day after non-modular drone fleet operation with one type of drone.

Comparing modular and non-modular drone operations, the average energy consumption of modular drone operation is lower by 4 percent, indicating no significant improvement in terms of energy consumption.

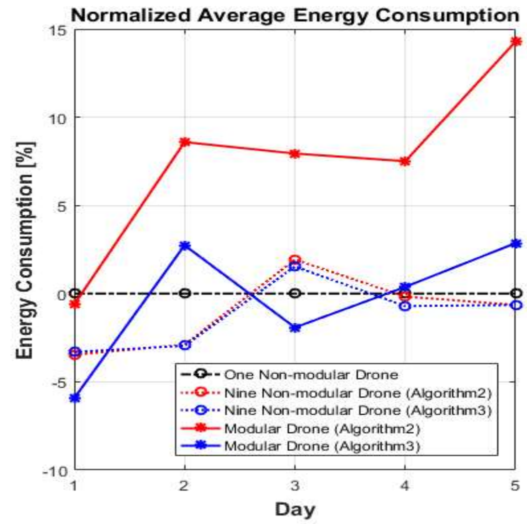

Fig. 9. Averaged energy consumption percentage of drones, normalized based on single non-modular drone operation.

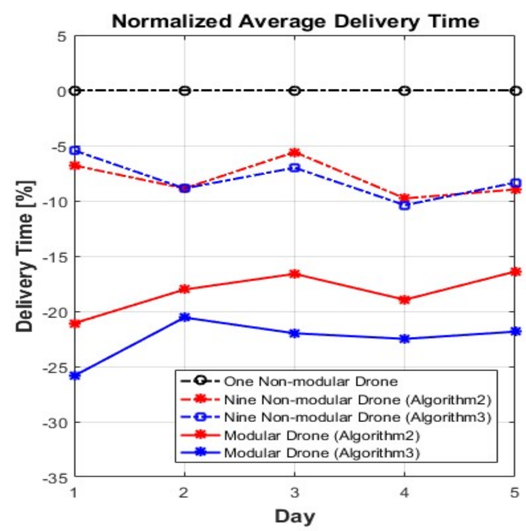

Fig. 10. Average delivery time percentage of drones, normalized based on single non-modular drone operation.

We compare the average delivery time in Figure 10. Comparing non-modular drone operations, the operation with nine types takes less time to deliver the packages than the operation with one type, indicating that the proper management of drone delivery operation with nine non-modular drone can reduce delivery time.

When Algorithm 3 is applied to modular drone operation, the package can be delivered 23.5 % faster than non-modular drone operation with one variance, 14.5 % faster than non-modular drone operation with nine variances, and 4.4 % faster than modular drone operation where Algorithm 2 is implemented. This result shows that the proposed algorithm outperforms existing methods due to the forward-looking nature. Modular drone operation takes less time to deliver packages regardless of the operation algorithm, showing that modularity in drone design has the potential to improve delivery time.

V. CONCLUSION

This paper discusses the potential value of introducing modularity to a drone delivery system. We propose a forward-looking fleet operation management strategy to improve the performance of drone delivery. We compare the proposed method with a stable management strategy and Dynamic Programming. We apply all three management strategies to both modular and non-modular drone delivery operations to identify the potential benefits of modular design for drone delivery.

The results in this paper show that the drone delivery system is unstable with the static management strategy for both modular and non-modular drone operations. Although the drone delivery system is stable with both dynamic programming and the proposed method, the latter can save a delivery time and energy. Also, the results show that modular drone delivery system has potential to improve delivery time compared to a non-modular system.

In this paper, we compare a fully modular system with a non-modular drone system. The results indicate that a semi-modular system with a replaceable battery is an interesting case to analyze for future work. We also define the modules for our analysis heuristically. In a future study, we plan to combine the design decisions on the module definitions with the operation management strategy under an integrated framework. Performing a long-term analysis with such an integrated framework can be used to investigate the profitability of a modular approach in drone delivery with a business perspective.

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