Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
May 4, 2023
*A Regional Conference of the Society for Industrial and Systems Engineering*

# Determining Autonomous Small Unmanned Aircraft Vehicles Swarm Composition and Search Patterns

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**Author Note:** Josiah DeValois, Jeremy Kappel, Luke Poudel, and Kyle Villacorta are all First-Class (senior) cadets at the U.S. Air Force Academy, partnering with Air Force Special Operations Command and the MITRE corporation. We would like to thank our faculty advisors, Lieutenant Colonel Miller and Dr. Gonzalez, for their expertise in the completion of this capstone research analysis. The views expressed herein are those of the authors and do not reflect the position of the United States Air Force Academy, the Department of the Air Force, or the Department of Defense.

**Abstract:** The United States military is developing large swarms of Unmanned Aerial Vehicles which will reduce risk to pilots and increase flexibility when dealing with peer adversaries. This research provides an evaluation of strategies that the Air Force Special Command is currently considering when determining the expected success rate of Unmanned Aerial Vehicles subject to distance, budget, and specific scenario assumptions. We define mission success as the proportion of targets found and tracked by the vehicle swarm of the assigned targets in a simulated ten-by-ten kilometer search area. Using a simulation, we find that the Altius-900, Dominator, and Voly yield the best mission success rate based on budget and target detection. Our findings support the future application of UAVs and provide a deeper understanding of what attributes are most important to mission success for Air Force Special Operations Command.

*Keywords:* Small Unmanned Aircraft Systems, Adaptive Airborne Enterprise, Surface to Air Missiles

## 1. Introduction

The Air Force currently deploys Groups 4 and 5 Unmanned Aerial Vehicles (UAVs), which are UAVs weighing more than 1320 kilograms, as seen in Table 1, controlled by ground control stations via satellite communications. The future objective is to equip ground-based controllers with the latest insights obtained from our research, enabling them to enhance UAV swarm performance. This new capability will allow for our fight to be less reliant on satellites and minimize human risk, resulting in a more flexible and effective force. General Charles Q. Brown, Secretary of the Air Force stated in his directive *Accelerate Change or Lose,* “We must focus on the Joint Warfighting Concept, enabled by Joint All-Domain Command and Control and rapidly move forward with digital, low cost, high tech, warfighting capacities” illustrating the necessity for a technologically advanced military (Brown, 2022). Currently, Air Force Special Operations Command’s (AFSOC) developmental efforts are in their foundational stages with the use of Vigilant Spirit (VS), a multi-role control station capability that offers software, simulation, and autonomy, designed to task and control multiple unmanned systems. As of 2023, AFSOC’s large UAVs are controlled by a pilot and a sensor operator, but in the future, it aims to deploy smaller UAVs from larger ones that will be able to operate autonomously. Additionally, AFSOC aims to minimize expenses and human casualties by exclusively deploying small UAVs into contested or denied airspace, as depicted in Figure 1.

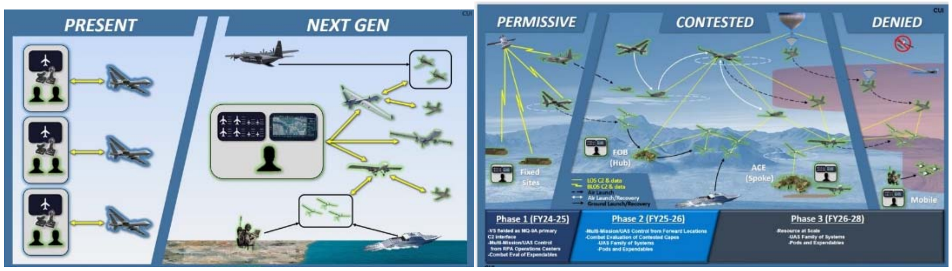


Figure 1. Current State as defined by AFSOC A2E Briefing (left), The Future Fight (Right) (AFSOC, 2022)

The left-hand image of Figure 1 exhibits AFSOC's current and future Adaptive Airborne Enterprise (A2E) generation. Currently, UAVs are operated and controlled from separate ground stations with different crews. However, the future A2E will have a multi-role control station that deviates from the 1:1 control to gain a competitive edge in contested spaces. The right-hand image shows AFSOC's plan to enhance combat capabilities using a kill-chain approach, starting in 2024. Missions are categorized as permissive, contested, and denied areas. The permissive area includes communication components and deployment sites for Group 4 or 5 UAVs. In the contested area, Group 1 or 2 UAVs track, target, and engage enemy forces in denied spaces. For this to be successful, AFSOC needs to know which small UAVs are able to complete the mission successfully, and how they ought to behave after being deployed. This study explores deployment strategies, which UAVs to use, and which configurations are most effective. We focused on using the doctrine provided by AFSOC and MITRE to guide our study.

## 1.1 Background

AFSOC A5/8 oversees strategic plans, programs, and requirements, and is actively engaged in shaping future acquisitions. As AFSOC is shifting its focus from the current fight to the future fight in the INDOPACOM region, they requested assistance in determining deployment strategies and recommendations on UAV acquisitions. Table 1 displays the organization of Unmanned Aerial Vehicles (UAV). The weight, operating altitude, and speed of the UAV increase with the group. AFSOC predominantly relies on larger Group 4 or 5 UAVs, for both attack and surveillance, despite having smaller UAVs at their disposal. UAVs offer a distinct advantage to the United States as they are inexpensive and reduse risk to human life. By improving UAV deployment, AFSOC aims to enhance mission effectiveness and cost savings.

Table 1. Department of Defense UAV Groups and Attributes

| UAV Group | Maximum Weight (lbs) | Nominal Operating Altitude (ft) | Speed (kph) |
|---|---|---|---|
| Group 1 | 0-20 | <1200 AGL | 185 |
| Group 2 | 21-55 | <3500 AGL | <463 |
| Group 3 | <1320 | <18000 AGL | <463 |
| Group 4 | >1320 | <18000 AGL | Any airspeed |
| Group 5 | >1320 | >18000 AGL | Any airspeed |

## 1.2 Problem Statement and Goals

Which combination of deployment strategy and UAV swarm composition will maximize mission success rate subject to budget, distance to target area, and UAV property constraints? Mission success is defined as the proportion of targets found and tracked by the drone swarm of the assigned targets in a ten-by-ten-kilometer search area.

ISBN: 97819384964-4-8

### 1.3 Scenario – Generalized Island

To better model the situation, our scenario focuses on a general island. From discussions with AFSOC, we hold the assumption that the island contains Surface to Air Missiles (SAMs) that are normally distributed throughout the island, thus necessitating the development of new doctrine to defend against vulnerabilities using rapid maneuvering and dispersing forces. Though this is not always the case, it helps to simulate a variety of configurations for enemy SAM arrangements. Additionally, this is the most restrictive case for search algorithms, so if the UAVs can find them in that configuration in some amount of time, finding them in any other configuration will take less time. The mission includes at least one Group 4 or 5 UAV deploying one or several small UAVs from 322 kilometers to go search the island with information it has from satellite imagery to find and fix enemy SAM location and send more accurate location data back to the Group 4 or 5 UAV.

### 1.4 Related Work

This paper builds upon the work of the previous year's capstone: *Optimization of Collaborative Autonomous Small Unmanned Aircraft Systems (sUAS).* The previous manuscript's primary objective was to employ a "lawnmower" search pattern to identify the optimal combination of sUAS that would yield the most favorable metrics: time of detection, standard deviation, and mission success (Patel et al., 2022). In their code, the team simulated one UAV searching for one target and then used those findings to find the required number and types of UAVs (Patel et al., 2022). We later compare our conclusion to theirs, understanding that we will be using a different search algorithm and updated data.

Small UAVs can be dropped from a larger aircraft and then quickly classify SAMs while flying overhead (Siemiatkowska & Stecz, 2021; Yount, 2021). This validates that AFSOC's aim of deploying small UAVs from just outside denied airspace and using them to classify SAMs is feasible. Once the UAVs are deployed, it is important for them to have a predefined search path. Coverage Algorithms for Search and Rescue with UAVs found that a "node count" algorithm, which uses vertices in each grid cell and instructs each UAV to incrementally search by moving towards the closest unsearched and unassigned vertex  was the most effective (Recchiuto et al., 2014). In Multi-objective path-based D* Lite, the author used a path-finding algorithm that makes decisions in accordance with multiple cost objectives as opposed to a singular objective like travel distance (Luo et al., 2020). Because the mission success of UAV swarms is constrained to the endurance of the individual UAV, this application is to integrate a multifactor analysis for UAV performance.

### 1.5 Organization

The organization of this paper is as follows: Section 2 describes Methodology, Section 3 describes Results and Analysis, and Section 4 discusses the Conclusion and Future. Finally, Section 5 provides Recommendations and Future Research.

## 2. Methodology

AFSOC faces the challenge of determining the most favorable UAVs and deployment algorithms to employ to achieve the highest possible mission success rate and estimated expected success rate of the mission. This problem is difficult considering there is currently no simulation to calculate a UAV's performance. Instead, AFSOC must choose based on which UAVs are capable of the mission's minimum parameters, meaning that they have the range to reach the island. This results in deploying UAVs without knowing if they will succeed in their mission. Resolving this issue is crucial since it would enable AFSOC to identify which UAVs are best suited for a given mission and save money by not sending more UAVs than required, and by sending the cheapest UAV that can succeed. Furthermore, this could potentially enhance mission success by allowing AFSOC to make better-informed decisions.

In the discrete event simulation, we modeled each different UAV option with its available characteristics: endurance, top speed, range, maximum altitude, payload capacity, and cruising speed. The UAVs were deployed 322 kilometers from the last known location of the nearest SAM and began their search from there. Once a target had been assigned to a UAV, it is no longer available for targeting by another UAV. UAVs were assigned targets upon deployment based on their proximity to the targets. Once a UAV located a target SAM, it sent the Global Positioning System (GPS) coordinates to the UAV which deployed it, at which point it is assigned a new target. This goes on until all the UAVs are out of fuel or all the targets are destroyed. These UAVs are used only once, so there is no plan to bring them back. To find the best swarm composition, this mission simulation was run using various UAV swarm compositions and assignment algorithms and comparing their respective mission success rates. The mission success rate is calculated as the number of located targets divided by the total number of targets.

## 2.1 Model

The model described above uses two objects, SAMs and UAVs. There are, however, several of each, and each contains details regarding its attributes. A SAM's attributes include if it has been assigned to a UAV, if it has been found, and its location. For example, a SAM at a grid point (19, 65) which has been assigned to a UAV but not yet found would have attributes: ([19, 65], 1, 0). UAV attributes can be found in Table 2.

First, before the simulation began, the program determined which UAVs were viable for the mission by testing if the range and endurance would allow the UAV to reach the target island. This eliminated the Altius-600, Coyote, Sparrow Hawk, and Eaglet. Following this, the simulation subtracted the range and time from the flight from the deployment location to the island. Once the UAVs arrived at the target island, they were assigned a target according to the algorithm used in that iteration. From there, time iterated and the UAVs flew from target to target until either they were out of range or there were no more SAMs remaining on the island. At this point, the simulation checks if the mission success rate was 100%. If it was, it stops and returns the success rate for that number of UAVs. If not, it adds an additional UAV and repeats the simulation. This goes on until the mission success rate is 100%, or the maximum tolerance of UAVs has been reached. After testing how many of that type of UAV are needed to yield a successful mission, the simulation moves to the next search algorithm and repeats it with that. First, it tried a greedy search algorithm, only looking one step ahead. Next, it tried a greedy search algorithm broken up by longitude, then by latitude, so each UAV is assigned a specific area and looks only in that area. Finally, the UAVs try an algorithm similar to the D* algorithm in which the UAVs see future steps and not only the step to the next target. Once a UAV has been tested for the number of UAVs required for each search algorithm, it returns a list with all the success rates for search patterns and the number of UAVs of that type required to yield those results. After this has been done for one UAV, it is then repeated for the next UAV in the viable options list. At the end of the simulation, it outputs the number of drones needed to yield 100% success for each type of algorithm. From there, the user can look at it and determine which UAV and search pattern is best or cheapest to succeed in the mission.

$$\text{Mission Success Rate} = \frac{T_d}{T_t} \qquad (1)$$

Where $T_d$ is the variable for the amount of targets accurately detected, and $T_t$ represents the total number of targets.

## 2.2 Data

Due to the unclassified nature of this project, data was collected from open sources, such as the Quantitative Analysis for Autonomous Systems (QUOKKA) data set. The data consisted of information on small unmanned aerial vehicles (sUAVs) gathered by cadets and midshipmen from the military academies. Range, cruising speed, top speed, endurance, maximum altitude, payload, and cost were all the attributes given in the data set. Eight sUAVs were determined to be the most cost-effective by AFSOC. The following table describes the variables present with each of those sUAVs. The Sparrow Hawk and Eaglet had limited data because they are still under development and testing, so approximations were used.

Table 4. Consolidated Data from AFSOC containing Small Unmanned Aircraft Systems and Attributes

| | Range (kilometer) | Cruising Speed (kph) | Top Speed (kph) | Endurance (hr) | Altitude (ft) | Payload (lbs) | Acquisition Cost per UAV |
|---|---|---|---|---|---|---|---|
| ALADiN | 574 | 630 | 750 | 0.58 | <30,000 | 50 | $250,000 |
| Altius-600 | 440 | 74 | 96 | 4.00 | <30,000 | 7 | $70,000 |
| Altius-900 | 1000 | 111 | 130 | 15.00 | <30,000 | 12 | $75,000 |
| Dominator | 463 | 115 | 139 | 24.00 | <30,000 | 38 | $50,000 |
| Coyote | 167 | 111 | 130 | 1.50 | <30,000 | 5 | $20,000 |
| Voly M20 | 556 | 102 | 120 | 8.00 | <30,000 | 30 | $75,000 |
| Sparrow Hawk* | 322 | 120 | 137 | 4.00 | <30,000 | 30 | $25,000 |
| Eaglet* | 200 | 113 | 124 | 4.00 | <30,000 | 21 | $22,000 |

ISBN: 97819384964-4-8 

## 3. Results and Analysis

It was concluded that range is the biggest factor to consider when evaluating sUAV performance in this context. Four of eight of the UAVs were quickly dismissed from consideration due to a lack of range, as they were unable to even reach the target area to start the mission. Part of the consideration for the range being the most important factor is that all UAVs had very comparable speeds and top speeds, so none had a distinct advantage in any of those things, though that could change as those gaps grow. Among the UAVs, only the Voly M20, Dominator, and Altius-900 succeeded in finding and fixing SAMs on a small island from 320 kilometers away. After flying to the island from a location 322 kilometers out, the UAVs searched for targets using their onboard sensors and a last known location given by satellite imagery. Upon finding the SAMs, the UAVs sent the more accurate location back so that the information could be used to target the SAMs or know areas to avoid. Our findings indicate that the best UAV for this mission is the Altius-900 in instances in which it is beneficial to deploy from further distances or to search a larger area. In situations on a smaller scale, the Boeing Dominator can do the same job for a lower cost, making it the best choice. Additionally, we found that for this situation only one UAV is needed, and it is indifferent to search patterns. As the area being searched increases, this will change these factors, but for this particular situation, one of those three drones using any of the above search patterns will work. This simulation can be enhanced in the future by outputting more data visualizations and by adding a method for the user to enter the island with the location of the targets, as well as the deployment location for the small UAVs. All of these would contribute to greater variance in the results and make them more usable for AFSOC. This can be used for a similar, but larger-scale operation by utilizing the same program and methodology for an island chain rather than just a solitary island.

## 4. Conclusion and Future Work

This paper ran an analysis of UAV performance in a simple simulation of a small island with surface-to-air missiles on it. After flying to the island from a location 322 kilometers out, the UAV searched for targets using its onboard sensors and a last known location given by satellite imagery. Upon finding the SAMs, the UAVs sent the more accurate location back so that the information could be used to target the SAMs or know areas to avoid. Our findings indicate that the best UAV for this mission is the Boeing Dominator, which yields a 100% success rate at the lowest cost. We recommend AFSOC uses the simulation to aid in mission planning and be more informed about possible mission success. For missions outside of the scope we considered, AFSOC would have to change the search area and the deployment location. This simulation can be enhanced in the future by outputting more data visualizations and by adding a method for the user to enter the island with the location of the targets, as well as the deployment location for the small UAVs. All of these would contribute to greater variance in the results and make them more usable for AFSOC. This can be used for a similar, but larger-scale operation by utilizing the same program and methodology for an island chain rather than just a solitary island. In the future, the simulation can be made more user-friendly so that it can be used regularly by AFSOC in mission planning. Additionally, it would be beneficial to add a method through which a user can enter his or her own island or island chain with specific target locations. This would add to the accuracy of a specific mission so that AFSOC would be able to use it for several missions rather than those only mirroring this situation. Lastly, varying sensor payloads onboard the UAVs could help to gain more variance in the results and improve mission success.

ISBN: 97819384964-4-8

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