Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 28, 2022
A Regional Conference of the Society for Industrial and Systems Engineering

Optimization of Collaborative Autonomous Small Unmanned Aircraft Systems (sUAS)

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Author Note: Austin Patel, Joseph Bruce, Michael Kaminski, and William Allen are First Class (senior) cadets at the United States Air Force Academy in Colorado Springs, CO. Lieutenant Colonel John Miller serves as their primary instructor and Lieutenant Colonel Kevin Treat serves as their primary faculty advisor. The student authors would like to extend thanks to the advisors involved with this project as well as the client organization, MITRE and organizational sponsors, AFOSC and AF Futures.

Abstract: With increasingly complex combat zones and advancing adversaries, developing large swarms of cost-effective Unmanned Aerial Systems may provide compelling capabilities for US (United States) forces. Therefore, the research question concerns the optimal combination of existing Small Unmanned Aircraft Systems that provide the best performance metrics of average / standard deviation of detection time, and mission success while constrained to a given budget and size of swarm. Requirements for these sUAS were that they fall within USAF Group 1-3 UAS's. The study team used a Python simulation to gather individual performance data on different sUASs within a randomized target location in a 5 nautical mile radius. These metrics were then input into an optimization program which selected the optimal combination given certain hard constraints. The results suggest that a mixture of 6 ALADiN and 24 Parallel Firefly's was the optimal combination across all three scenarios tested. The combined cost is 1.6 million dollars. Using insights from the simulation, the team was also able to recommend what attributes were the most important to a successful mission, saving time and money in the development processes.

Keywords: Small Unmanned Aircraft Systems, JADC2 (Joint all Domain Command & Control), F2T2EA (Find, Fix, Track, Target, Engage, Assess)

1. Introduction

According to the 2018 National Defense Strategy; "with the increasing use of unmanned systems in the combat zone, the joint force must strike diverse targets inside adversary air and missile defense networks to destroy mobile power-projection platforms and enhance close combat lethality in complex environments" (2018 NDS 6). Future combat will benefit immensely if a large quantity of small, low-cost UAVs operate synchronously in the low earth region. The goal is to win while maintaining a position of resource superiority. Considering our current weapons systems, The United States Air Force will need more expendable platforms that can accomplish the mission. These low-cost UAVs will help to strike a wider range of target sets in any domain while managing risk. A large mesh of UAVs will allow for reliability as individual aircraft can become immobilized; however, the rest of the mesh will continue to operate efficiently. Also, due to the nature of smaller UAVs grouped in large swarms, we can create a diversity of functionality across all the platforms within a swarm. According to a RAND study conducted by Hamilton and Ochmanek on the topic of low-cost reusable unmanned aerial vehicles in contested environments, some of these functions include intelligence, surveillance, reconnaissance (ISR), position, navigation, and timing (PNT) and communications. The functions present within a swarm are exactly what this project will be optimizing.

In this study, we focused on the first step of the kill chain: find, fix, and track. These are the first three components of find, fix, track, target, engage, and assess chain (F2T2EA). The first step of the chain, find, consists of the collection of ISR, Intelligence preparation of the battlefield (IPB), and gauging a defensive reaction. The second step, fix, consists of locating and identifying the target while assessing the collateral damage. The third step, track, which consists of following, relocation of assets, and prioritization of mission. The fourth step, target, consists of final location, final coordination, ROE's, final approval, and final lock. The fifth step, engage, consists of clearance to engage and weapons launch. And finally, the sixth step, assess, consists of kill confirmation and loss assessment.

As stated before, we are only concerned with the first three steps of this chain. Therefore, the UAS platform must be extremely efficient in the find-fix-track of a target. Once target acquisition is reliable then weapon employment can be studied.

1.1 Client Organization

The primary client for this project is The United States Air Force Special Operations Command (AFSOC) however, this capstone is being facilitated by MITRE which is a not-for-profit organization that works in the public interest across federal, state and local governments. Major Devin Beckwith is our representative from AFSOC A5KU for this project.

MITRE does not seek to sell assets or seek additional clients; it simply wants to provide an increase in impact to the problem set. They operate several federally funded research and development centers (FFRDCs) that assist US government agencies such as the Department of Defense with scientific research and analysis

1.2 Problem Statement

What is the optimal combination of existing small, unmanned aircraft systems (sUAS's) that provide the best performance metrics of time of detection, standard deviation, and mission success while constrained to a given budget and size of swarm?

1.3 Related Work

Outside related work has proven extremely valuable to the scoping of our question, the clarification of physical attributes and capabilities, the development of our own simulation/mathematical models, and the insight needed to fully understand the role of sUAS in the F2T2EA and Joint All-Domain Command and Control (JADC2) frameworks.

Moving forward with this project and simulation requires a good understanding of sUAS capabilities and what they could potentially bring to the fight. A relevant simulation is completely based on the quality of our assumptions so correct and proper information on these entities is important. Much of the literature that we have explored has dealt with the capabilities of drones in congested environments. For example, Lacher and Maroney (2016) ask how small UAS (sUAS) change the reachable domain by aircraft systems. Using multiple different scenarios, the authors explore the implications and risks that using small UAS in high congested and hard-to-reach environments would pose

F2T2EA concepts are the cornerstone of this project. We wanted to gain more understanding of how small UAS plays a role in this framework. Samad, Bay, and Godbole (2007) studied how in tight operating environments with several obstructions, information gathered from multiple UASs can be combined to find most effectively, fix, and track targets compared to a singular drone.

1.4 Current State of Operations

Currently, to conduct F2T2EA missions, the Air Force utilizes a heterogeneous mixture of manned and unmanned aircraft. For example, the F-22 and F-35 are equipped with a multitude of radar systems and collect an immense amount of data that can be passed onto Intel troops to assess the battlefield. However, these assets are extremely costly as the F-22 costs an estimated $334 million and the F-35 is $78 million. Furthermore, unmanned aircraft such as the MQ-9 Reaper are less expensive at only $4 million, however, the United States Air Force currently only has 195 MQ-9 Reapers in its inventory. This places a heavy burden on current supply and in future conflict this could prove to be inadequate as they are expensive and not expendable. The Air Force Air Superiority 2030 Flight Plan focuses on the necessity to overcome the lack of air superiority that "leads to increased risk of joint force mission failure as well as cost to achieve victory in terms of resources and loss of life." In addition to this focus on air superiority, it is vital to be able to contest and be effective against our near-peer adversaries in the modern domain.

2. Data Collection

The data relevant to this capstone project is in the form of capabilities and attributes of certain sUAS's and enemy ground targets. Due to the unclassified nature of the project, we are only able to use open-source data on what current sUAS can perform and their limitations. Some of the data was provided by MITRE and Air Force Special Operations Command in an unclassified "data dump". However, in some files, key metrics such as range or top speed were omitted and needed to be supplemented by external research.

The key metrics for sUAS capabilities include: range in nautical miles (nm), maximum speed in Knots Indicated Air Speed (KIAS), maximum flight endurance in hours (hrs), maximum payload capability in pounds (lbs), cost of a single aircraft in dollars and field of view (FOV) of the sensor in degrees. See Table 1 to view the specific attributes for 12 different sUAS's.

Table 1. Current Small Unmanned Aircraft Systems and their Respective Attributes

sUAS	Range (nm)	Max Speed (KIAS)	Endurance (hrs)	Payload (lbs)	Cost ($)	FOV (degrees)
ALADiN	310.00	405.00	0.580	50.00	250000	74.14*
ALTIUS-900	680.00	45.00	12.670	20.00	10000	84.51*
Boeing Dominator	250.00	75.00	19.000	6.00	50000	75.67*
Parallel Firefly	250.00	55.61	4.500	50.00	4500	73.87*
Voly M20	304.00	65.17	8.000	30.00	75000	81.13*
Inspire 2	21.00	50.40	0.416	2.00	3499	71.01*
Matrice 100	10.08	37.90	0.266	2.64	3299	78.82*
Matrice 200	17.72	44.32	0.400	5.15	6500	77.06*
Matrice 600	9.84	34.76	0.283	12.12	11999	79.19*
Mavic 2 Pro	9.71	38.84	0.516	2.00	1699	77.00
Mavic Pro	8.00	34.76	0.450	1.62	1299	77.00
Phanton 4	18.11	38.87	0.466	1.76	1990	84.00

Some issues that we ran into with regards to data collection are that some systems such as the Boeing Dominator are extremely new, and certain metrics such as range and maximum speed have not been published to the public domain. The team decided to assume values that fall in line with other similar sUAS's. These hypothesized values are noted with an asterisk (*).

Data for ground targets will be reflective of current US military capabilities to best emulate a near-peer adversary. We will not be able to find true and relevant data about ground targets currently in use by China and Russia or any other near-peer adversary. Therefore, in our simulation we will use Mobile SAM sites such as the AN/TWQ-1 Avenger and the Terminal High Altitude Area Defense Battery. Some passive targets such as the AN/FPQ-16 PARCS and the AN/FPS-117 Radar System will also be implemented. Acquiring data was difficult to varying degrees as the internet would fail to provide accurate information about the system whether that be because the manufacturer never released it, or it was hidden behind doors that we did not have access to. As mentioned, some data was unavailable and thus an assumption of similar models had to be made. A web crawler to search and index any information from the web about these drones would be a useful tool to aggregate as much information as possible.

Table 2. Current Ground Targets and their Respective Attributes

Ground Targets	Size (m)	Speed (mph)	Range (miles)
AN/TWQ-1 Avenger	11	55	275
THAADB	7	40	120
AN/FPQ-16 PARCS	30	0	2622
AN/FPS-117 Radar	12	0	290

ISBN: 97819384962-2-6

3. Methodology

Some assumptions in this capstone are that we will only be employing UAS's that fall in groups 1-3, not groups 4-5 as those are larger drone assets with a separate mission set such as the MQ-9 Reaper. Drones in group 1-3 must weigh less than 1320 lbs and operate at an altitude less than 3500 ft above ground level (AGL). Another limitation for this study is that aircraft in question will only be assessed on their ability to find, fix and track. If a sUAS can effectively accomplish those three tasks, then we will assume that weapon employment to destroy targets would also be feasible. Another assumption is that attributes of enemy ground targets, both passive and active targets, mirror current unclassified US capabilities. This will replicate what Yeadon accomplished in his paper for the Armored Brigade Combat Team as using our own best ground systems will emulate a near peer adversary as best as possible. Lastly, we will assume that there may be different ground environments such as urban or mountain terrain. However, the search attributes within a single ground environment will remain homogenous.

This project will employ two types of models to reach the final answer. The first will be a python simulation of a one drone versus one target to obtain Monte Carlo probabilities of detection within certain time intervals. This produced data will then be piped into the second model that will optimize the bundle of drones given certain constraints such as budget and total swarm size.

4. Modeling

The first part of the project was the simulation of a singular drone versus a singular target. Replicating a technique that Yeadon utilized we will use open-source data on US Army vehicles to set the size of our target. This will provide us with results that would best mirror a near-peer adversary. For this example, we will be using the Heavy Expanded Mobility Tactical Truck (HEMTT) which is a modular truck that can be adapted to launch THAAD Missiles and provide Ground to Air Defenses. This will best mirror the capabilities of the Russian S-400 system. The variables of dimension can easily be adjusted in the Python code to fit the size of any vehicle or radar system.

The drone system being tested will fly at a set altitude and the sensor will have a specific field of view. This will result in a certain ground area being covered at any given time. See figure 1 for a visual representation of this.

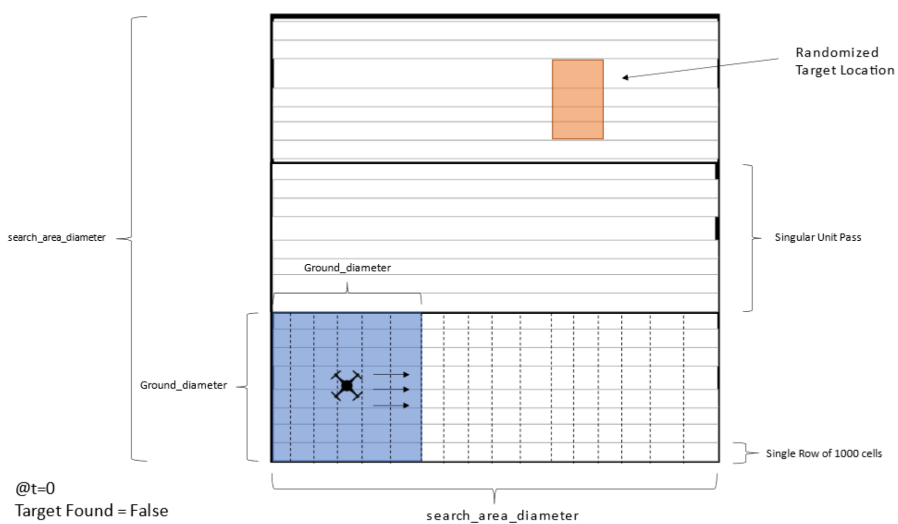

Figure 1. Model of Simulation at time=0

Lastly, the code creates a modular search area in which many variables such as search area diameter and drone attributes can be adjusted to best fit the scenario. The drone in the simulation will follow a "lawnmower" pattern where it will begin in the bottom left corner and progress to the right until it reaches the last cell and then it will transition north and then

ISBN: 97819384962-2-6

proceed to the left to search all those cells. The process will repeat until the target is positively identified and then the tracking will begin. See figure 2 to see a visual representation of the simulation at the beginning of the simulation at time 0. Depending on the flight altitude and FOV, the code with appropriately adjust certain calculations such as the size of the visible search area that the drone can see at any given time.

As time progresses and the drone changes location, the time when the drone finally spots the target will be recorded as will the standard deviation of the time it took and the mission success rate of the individual drone.

5. Analysis

With the metrics collected from the Monte Carlo simulation we then fed this data into a nonlinear optimization solver to determine the optimal mix of drones to successfully track a target in a larger area. Three separate scenarios were run for each drone varying the altitude that the drone flew at and the search area responsible it had to cover. The first scenario was an altitude of 30m and a search area of 2000 meters^2. The second scenario kept the search area the same, however, the drones now flew at an altitude of 60m above ground level. The third scenario reverted to a 30m altitude but decreased the search area to 1000 meters^2.

The Python simulation models a single drone tracking a single target. However, the final operational solution will include multiple drones and targets. In the optimization of the mix of drones, we must maximize the probability of success throughout the whole 5 nm target zone. The metrics we evaluate each drone on are time to detect target, standard deviation of detection time, and overall mission success rate. Ideally, we would like a drone to have a low time to detect and small standard deviation. However, certain drones fly at a lower velocity than others and have other FOV characteristics that determine how quickly they can survey the area. The mission success rate takes a few parameters into consideration such as the maximum range and maximum endurance of the sUAS. If the drone must fly further than the target location within the search grid, then we will lose the sUAS in a hostile environment and the mission will not be successful as we would like to have the drone in our possession after the mission. Furthermore, if the total time of flight exceeds the endurance of the sUAS then the drone will also fail and therefore the mission will be unsuccessful.

Our optimization function as seen in Equation 1, looks to select the best combination of drones as maximizing the inverse of both times to target and standard deviation while using mission probability as a third metric.

$$Maximize \sum_{i=1}^{n} x_i * \left(\frac{1}{\mu_i} + \frac{1}{\sigma_i} + \rho_i\right) \tag{1}$$

Two hard constraints we input into this model were that the total drone swam must not exceed 30 drones for the 5 nautical mile radius, see equation 2, and that the total swarm must cost less than \$1.64 million, see equation 3.

$$\sum_{i=1}^{n} x_i \leq 30 \tag{2}$$

$$\sum_{i=1}^{n} x_i * cost_i \leq \$1{,}638{,}213 \tag{3}$$

After using the solver module on Microsoft Excel, the optimal mix of sUAS's across all three scenarios is a combination of 6 ALADiN and 24 Parallel Fireflies. This swarm costs approximately 1.608 million dollars. Comparing across the three scenarios we also found an approximate +21.32% mission success for increasing drone altitude from 30m to 60m, for drones that did not already obtain a 100% mission success rate. Likewise, by decreasing the search area diameter from 2000 m to 1000 m we noticed a +53.86% mission success rate.

6. Future Work

In our simulation we took the approach to test the probability of detection of a singular drone versus a singular passive target. This enabled us to obtain some basic probabilities which were then fed into the optimization program to obtain a final mixture of drones. In future work it would be beneficial to add more features to this simulation. In our work we have a singular environment, however in reality there can be a change in environment from urban to rural and the code should represent that swap using obstacles to match the difficulty of the contested area. Another improvement would be to insert more than one target and track the time it takes to successfully find all targets in the region. There would be more than a singular target and therefore the code should be modified to include multiple targets, both passive and active. Also, the model is easy to change based on evolving parameters and priorities. For example, if speed is more important than endurance, then the appropriate change can be made in minutes. Lastly, it would be interesting to investigate the differences between other geometric search patterns other than a simple "lawnmower" search pattern and their effect on mission effectiveness and optimal mixture of sUAS's.

7. Conclusion

The optimal mix consisting of 6 ALADiN and 24 Parallel Firefly's provides the best option to find a target within the 5 nm search area. We know from examining these drones' capabilities that they each offer distinct aspects that contribute to the mix. The ALADiN's speed and the Parallel Firefly's cost supplement each other to create a highly effective team that is still attritable. As stated before, the future fight will benefit immensely if a large quantity of small, low-cost UAVs could be able to operate synchronously in the low earth region. This mix accomplishes exactly that. However, it is important to note that our work is optimal for only our assumptions and situation but moving forward our clients can build upon our work to tailor it to more specific situations and practical applications. That is only possible because of the intelligible nature of our simulation which provides a great foundation for future work in both the assessment of capabilities and the "fix" step of the F2T2EA model.

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