Simulation Experimentation of Swarms

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ABSTRACT

Collections of autonomously behaving systems, or swarms, are predicted to be an important component of the US DoD strategy. Therefore, research into how to create swarms with suitable characteristics, behaviors, and function for these different purposes is in the interest of the US military. However, there are challenges in swarm research, including technical limitations of existing hardware, the need to address both individual drone level behavior as well as the complexities of the entire swarm behavior, and the parameter combinatorics that may be relevant to swarm performance in operations. This presentation proposes methodologies for the computer simulation research and analyses for experimentation on swarm behavior. Swarm performance data from computer simulation experimentations were analyzed to investigate how individual and entire swarm characteristics might affect how well the swarm performed a mission.

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Dr. Ross Arnold is the Chief Computer Scientist within the Weapons and Software Engineering Center of DEVCOM-AC and Senior Scientist Technical Manager Lifecycle Software. He has over 1200 citations across more than 30 conference and journal publications in systems science, artificial intelligence, swarm robotics, autonomous systems, and fire control. Dr. Arnold has performed remote assignments as a Visiting Research Scientist for the United States Military Academy at West Point, and as Senior Research Engineer at the Japan Air Systems Research Center in Tokyo, where he led cooperative research efforts between DEVCOM-AC and the Japan Ministry of Defense ATLA in autonomous swarm systems. Dr. Arnold holds a Bachelor of Science in Computer Science, a Master of Science in Software Engineering, and a Ph.D. in Systems Engineering with a focus in Systems Thinking and software simulation. He was the recipient of the 2021 Outstanding Dissertation Award at Stevens Institute of Technology for his research in systems science.

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INTRODUCTION

Swarms are groups of entities of similar characteristics that tend to move together and work cooperatively towards an overarching goal. Swarm intelligence is based on the concept of swarm theory, which proposes that simple entities behaving in a collaborative manner can produce emergent effects. Swarm theory can be regarded as an application of General Systems Theory (Bertalanffy, 1968) to certain biological systems such as beehives and ant swarms. Although separate entities may behave in a certain way, when these entities combine their behavior, a new result may emerge (Navarro and Matia, 2013). This phenomenon is commonly known as "the whole is other than the sum of its parts" or "the whole is more than the sum of its parts," (Koffka, 1922) and has been leveraged across many different fields as an extension of systems science (Arnold and Wade, 2017).

The use of swarm intelligence has been under investigation for many different applications over the last few decades (Arnold et al., 2019). Both centralized and decentralized swarm Artificial Intelligence (AI) have been used in a variety of applications and research efforts such a swarm navigation and biologically inspired swarm behavior (Beni and Wang, 1993, Oh et al., 2017). Swarm-based software algorithms and systems have been explored by the U.S. Department of Defense for many different defense and homeland security applications, to include radiation detection, search and rescue, mapping, reconnaissance, and object detection, among others (Arnold et al., 2020; Chung et al., 2016; Cook, 2017; Savidge et al., 2019; Scharre, 2014).

In general, optimized swarm configurations for these applications are determined through proprietary or application-specific methods. These methods tend not to generalize beyond specific scenarios or application needs. Although such methods are reasonable and suitable for each specific application, we believe there may be more general ways to organize and investigate swarm performance based on specific characteristics. However, research on general ways to determine these optimal swarm characteristics appears to be minimal.

This work describes and demonstrates a design of experiment approach to conducting simulation experimentation of drone swarms. Like prior research, the focus is on one specific application and scenario as our starting point to demonstrate the process. However, this methodology can be easily expanded to more general applications if the simulation software exists to support it. This further software development and expansion upon this initial research is planned in future work.

OVERVIEW

Computer Simulation Experimentation of Swarms

While swarm experiment designers have a high degree of control over the actual configuration of the swarm, many swarms are agent-based systems by nature. Swarm entities are often deliberately designed to behave in a non-deterministic way (Arnold et al., 2020; Vásárhelyi, et al., 2014; Williams, 2015). As a result, many swarm behaviors can be difficult to predict. Especially in high-dimensional dynamic systems such as swarms, emergent unintended consequences may result.

Despite the emergent nature of many swarm systems, the common approach to modeling swarm behavior is often restricted to simulating deterministic solutions to specific problems. For example, optimum solution (Kennedy and Eberhart, 1995), tolerances (Bjerknes and Winfield, 2012), range (Ugur et al., 2007), demonstration of proof of concept of rules (Bahceci and Sahin, 2005), and so on. A more efficient way to recognize and take advantage of the emergent behavior of swarms during computer experimentation may be to derive causal relationships between swarm design parameters and swarm performance. Computer simulations of configured systems can be used to understand, predict, and control these emergent properties in configured high-dimensional systems (Arnold et al., 2020). Understanding relationships among the parameters of a system and the way those relationships affect the resultant holistic swarm behavior has numerous benefits. Such knowledge can be used to design a swarm system to perform many different types of missions, rather than focusing the system on a single narrowly defined scenario.

Based on this viewpoint, the behavior of configured swarms can be examined using stochastic simulation programs. There have been several published reports of using simulation programs to explore the impact of a modification to the system as a proof of concept or to study of the impact of single to few factors (Czitrom, 1999). Typically, these efforts can be characterized as a one-factor at-a-time (OFAT) approach. A more powerful method uses Design of Experiments (DOE), whereby more complex analyses simultaneously assessing multiple variables and their interaction occurs. Attention to multiple variables simultaneously is much more effective for adequate testing of multidimensional systems such as swarms (Montgomery, 2012). DOE approaches can be utilized to provide insight into causal relationships between ways in which a swarm is configured and how the swarm as a whole behaves in virtually simulated operational environments.

Virtual Experiment Set Up

US Army DEVCOM Armaments Center has developed a robust, configurable UAS simulation system called DroneLab to support research efforts to expose emergent swarm behavior (Arnold et al., 2021). DroneLab is a software application designed to facilitate simulation of large numbers of UAS operating collectively as a cohesive but decentralized system. DroneLab allows for the definition of an environmental scenario such as a searching for survivors after a major natural disaster (tsunami, earthquake, etc.). The scenario defines the geometry and position of the obstacles (buildings) and the locations of the survivors. DroneLab also allows for the assignment of one of three roles to each entity (drone) within the search swarm. These three roles, which can also be conceptualized as "personality" types, were developed by prioritizing different preprogrammed behaviors from a fixed set of options. Examples from this fixed set of options include behaviors such as collision avoidance, battery recharge, formation control, and waypoint navigation. Additional behaviors can be added relatively easily due to the polymorphic architecture of DroneLab. The three personality types (roles) developed for this experiment were titled relay, social searcher, and anti-social searcher. An entity assigned to the relay role maintains a randomly assigned distance between 50 and 800 meters from the closest member of the swarm to provide a network infrastructure; this enables other agents to continue their behaviors while maintaining connectivity to the other swarm members. The anti-social searcher drones prioritize a loose formation behavior, putting a high value on increasing the spread of the swarm thus maintaining a greater distance between themselves and all other agents of the swarm compared to the social searcher drones. The social searcher role prioritizes a tighter formation between entities in the swarm. All three roles trigger a spiral-out behavior upon detecting four or more survivors within a 10-meter radius. This behavior was designed to more rapidly locate other survivors that are likely to have congregated nearby (Arnold et al., 2018).

DroneLab is highly configurable and allows for the specification of multiple simulation scenarios that can be executed in succession. A single simulation is defined by listing the number of drones of each personality type and the maximum Wi-Fi, or communication, distance for that drone. Each simulation can be run multiple times as the application is not deterministic due to the ability to place survivors at random locations within the scenario. See the section "Design of Swarm Experiments Approach" for more details.

The terrain for this experiment was reconstructed based on a satellite photo of Kobe, a large city in Hyogo Prefecture, Japan. The Kobe photo was taken hours after the Great Hanshin earthquake of 1995 which caused large-scale destruction in the city. In this setup, 919 survivors were placed in the DroneLab simulation; 616 were placed in actual locations based on information available from the earthquake, and 300 additional survivors were randomly placed throughout the city, in different random locations from run to run. This allows for a realistic representation of a post-disaster site that has undergone large scale search-and-rescue operations.

Communication Networks

Communication networks are one possible moderator of swarm performance. Communication networks are a function of the communication range of drones and drone proximity to other drones. Drone proximity to other drones is a function of the prioritized behaviors, which are based on responses to the presence of either 1) other drones, in the case of relay, or 2) location of survivors, in the case of social and anti-social drones. Therefore, swarms consisting of the same number of drones will differ in behavior, performance, and communication networks because of the different configuration or percentages of social, relay, and anti-social drones within the swarm.

Outputs from DroneLab include matrices that identify which drones have communicated for each minute of the mission. These matrices are input to the network analysis software ORA (Netanomics). Swarm-level metrics such as network density, total centrality, and speed of communication can then be calculated and used in the models that predict swarm performance.

DESIGN OF SWARM EXPERIMENTS APPROACH

Design of Experiments (DOE) is used across many industries and application areas with many unique methods tailored to different domains. DOE involves systematically defining a dataset to collect, and then statistically analyzing that data. It is the only accepted and scientifically credible approach to specifying the datapoints which will support a statistical model (Montgomery, 2012). The statistical model generated from the data can be used as a surrogate of the underlying model behavior or system phenomena. The statistical modeling of the data is sometimes referred to as machine learning (ML). Below, The DOE process used for this simulation experimentation is summarized in five phases: plan, design, execute, analyze, and assimilate (Jablonski et al., 2024).

Plan

This phase involves determining the objective, the output(s) of interest, and the modifiable inputs of the simulation that we are interested in understanding or optimizing. The objective of this experiment is to understand the effect of drone swarm size, drone communication distance, and individual drone characteristics on the time it takes to find 90% of survivors after a natural disaster (referred to as mission time). A secondary objective is to understand how communication network parameters of the swarm during the mission are changing and how those influence the mission time output metric.

This directly leads to the outputs that need to be tracked and recorded. The primary output is the time each survivor is found which can be used to determine the mission time. Additionally, several communication network parameters are tracked and calculated based on the swarm behavior during the mission; these include network density, total centrality, and speed of communication.

The DOE inputs include the total number of drones in the swarm, the portion of drones that were programmed to behave in each of three different ways: social searcher, anti-social searcher, and relay, and the maximum communication range of the drones. Table 1 shows these inputs and the ranges we considered for each in this experiment.

Table 1. DOE Input Factors and Their Ranges

Input Factor	Minimum Value	Maximum Value
Total Drones	10	50
Portion Social	0	1
Portion Anti-Social	0	1
Portion Relay	0	1
Communication Range (m)	50	800

Design

The experimental design involves determining the specific combination of values of the input factors that should be simulated. Typically, a computer-generated optimal design is employed that is appropriate for the type of data being analyzed and the type of model that is expected to be fit to the data. This experiment uses a space filling design with an additional maximum projection criterion to maximize the minimum distance between any two points in the full experiment as well as in lower dimensional projections. Note that there is a mixture-type constraint in the design space for this set of inputs which was accounted for in the computer-generated design: the portion of each type of drone needs to add to one to ensure that the sum of the number of social searcher drones, the number of anti-social searcher drones, and the number of relay drones is equal to the total number of drones assigned to the swarm.

The design has 1,000 total runs but was developed in three parts to support the model fitting process: a training set, a validation set, and a test set. The training set, which is used to fit the model parameters, is 750 runs. The validation set, which is used to determine appropriate hyperparameters, is 150 runs. The test set, which is excluded from the model fitting process and used afterwards for model evaluation, is 100 runs. Visualizations of the space-filling design are shown in Figure 1. This figure only includes the 100 test set points to avoid overcrowding and for clarity. Figure 1a is a pairwise scatterplot matrix which shows each input factor against each of the others, i.e. each two-dimensional projection of the design space. The triangle shaped distribution of points in the three portion vs. portion boxes represent the mixture constraint in the design space: the sum of any two portions will always be less than or equal to one to meet the constraint that all three add to one. The bottom left box, representing the total drones verses the communication range, are two unconstrainted factors, and the points there are distributed throughout the space. Figure 1b is a ternary plot of the three portion factors. In this plot, communication range is represented by color (blue= low ranges, red= high ranges) and the points are labeled by the total swarm size. A sample point is circled in plot 1b as well as shown in black in plot 1a. This represents a single simulation in the experimental design with the following parameters: drone size (total)= 36, portion social searchers= 0.556, portion anti-social searchers= 0.028, portion relay= 0.417, and communication range= 231.7 meters.

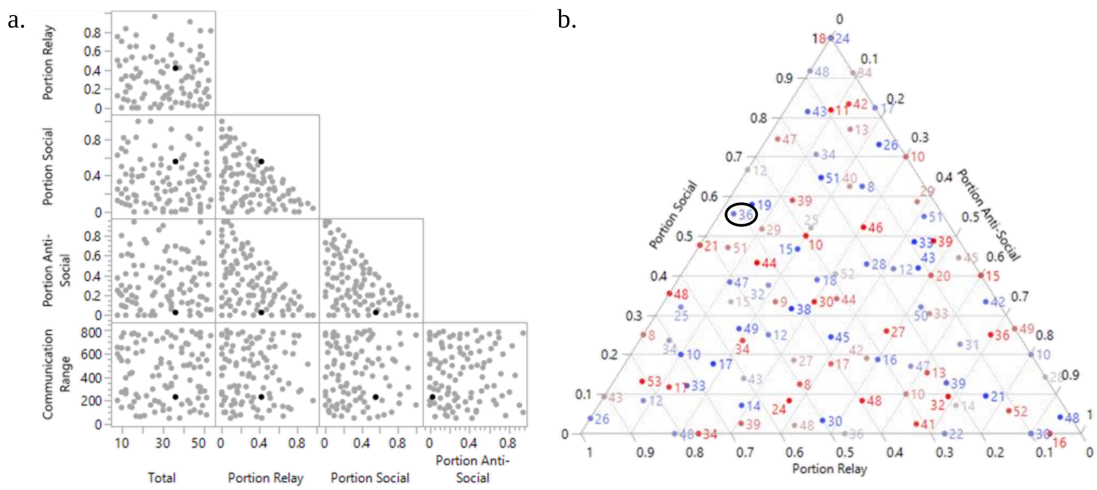

Figure 1. A Pairwise Scatterplot (a) and Ternary Plot (b) of the Test Set Space-Filling Design

Figure 2 is provided to aid in reading and interpreting the ternary plot as they will provide a useful tool for visualizing results later in the paper. Each side of the triangle represents zero of a given drone configuration: bottom is zero social searcher, left is zero anti-social searcher, and right is zero relay. Each point of the triangle represents a swarm of all of one drone configuration: top is all social searcher, bottom right is all anti-social searcher, and bottom left is all relay. Points within the triangle have some mix of all configuration types, with the mid-point of the triangle representing equal portions (one third) of all three types.

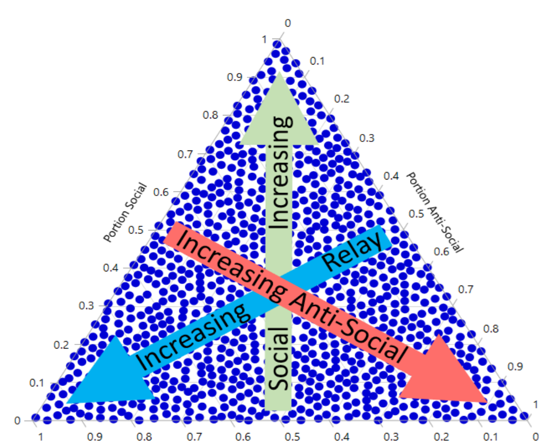

Figure 2. Understanding the Ternary Plot

Execute

In this phase, each point in the design is run through DroneLab and ORA to obtain the outputs of interest. Due to the stochastic nature of the simulation setup and the relatively quick-running simulations, each point was simulated 10 independent times to better detect the true difference from one point to another (signal) from the difference of the same point being run multiple times (noise). DroneLab gives the time each survivor is found, the individual drone locations as a function of time, and a matrix defining how the drones are in communication with each other drone as a function of time. The drone locations and communication matrices over time are input into ORA to calculate the network parameters of interest.

Analyze

The analysis of the data involves taking the design and outputs from the previous two phases and fitting a statistical or machine learning model to that data. In this experiment, the data lends itself well to artificial neural network (ANN), and that is what was used to fit models to the data. For the mission time response, a feed-forward network with two hidden layers (7 nodes in layer 1, 5 nodes in layer 2) is fit using the inputs from table 1 in addition to the number of survivors found. The output of the model is the time it took to find that number of survivors. This model can be used to find the mission time by setting the number of survivors to 828, which is 90% of the 919 total survivors. Figure 3 shows the model fits on the 100 test set runs. Here the grey points are the actual DroneLab output for each of the ten replications of a given run. The blue line is the ANN model fit to the output. There is one run shown (909) where the ANN model significantly underpredicts the DroneLab output towards the end of the mission, but in general, the model shows good prediction capability on this withheld set of data: within the range of the actual DroneLab output.

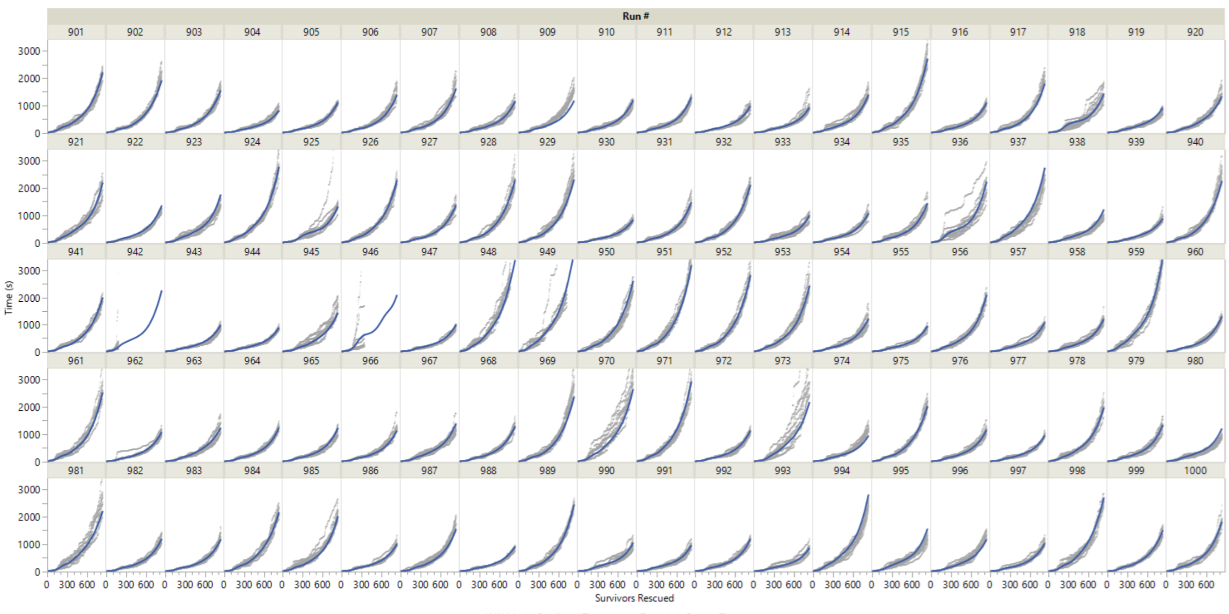

Figure 3. ANN Model Predictions on the Test Set Data

Assimilate

In this final phase, the model is used to obtain knowledge and learn about the phenomenon being studied, typically in relation to the objectives that were defined. In the following Results section, the effect of the input parameters on the mission time is presented in detail. In addition, the relationship and influence of the communication network parameters are also discussed.

RESULTS

Visualizing Swarm Behavior

The Virtualitics graphic program was used to plot minute by minute x,y,z location of each of the drones. Each drone was color-coded to indicate its behavioral coding, that is, social, anti-social, or relay. This allowed visualization of the overall behavior of swarm. Insights were gained by this novel graphing of drone behaviors. Specifically, it revealed that the drones were programmed to return simultaneously to launch stations for recharging, thus possibly compromising the mission. While an examination of the code could reveal this fact, the visualization shows the impact of that coding of behavior. This insight prompted the suggestion of either staggering the release of drones so that the return for recharging is staggered or launching drones from different launch sites. This is an example of how visualization of the swarm can demonstrate the impact of individual drone behaviors and coding choices on the overall swarm behavior.

DOE Prediction Model: Mission Completion Time

The primary DOE response of interest was the mission completion time, the time it takes to find 90% of the survivors. The ANN model predicts the time as a function of swarm size, portion of each type of drone, communication range, and number of survivors found. To visualize the model and understand how each of those parameters influences mission completion time, the ANN model was used to generate several different types of plots.

In figure 4, snapshot ternary contour plots show how the output varies with all the input factors. The axes of the ternary plots represent the portion of each type of drone: bottom of the triangle is no social searcher drones, left of the triangle is no anti-social searcher drones, and right of the triangle is no relay drones (refer to Figure 2 and its description). The left half of the figure is at a point mid-mission, when 400 survivors have been found. The right half is near the end of the mission when 800 survivors have been found. The top ternary plots show the smallest swarm size of 10 and the bottom plots show the largest swarm sizes of 50. From left to right are three different communication ranges. The plot is colored by the time with the legend in seconds; each color contour represents a 5-minute interval with the blue end of the scale showing the fastest times and the red end of the scale showing the slowest times. The plots show differences in the optimal configurations based on swarm size and communication range. For example, with a swarm of 10 drones and a communication range of only 50 meters, a swarm of all social searcher drones performs the full mission the fastest, as indicated by the lighter red color in the top corner of that ternary plot. With a better communication range of 350 meters, a mix of social and anti-social searchers with no relay drones is optimal (yellow on the right of that ternary plot), with that increased communication range decreasing the mission time by around 20 minutes. At the highest communication range, the 10-drone swarm performs about the same no matter the make-up, given there are some social searchers in the swarm (green everywhere but the very bottom of that ternary plot). However, the mission time is only decreased by about 5 minutes compared to using the optimal configuration when the communication range is 350 meters. Compare that to a 50-drone swarm with the lowest communication; the optimum occurs with a mix of social searchers and relay drones and is about 15 minutes faster than the highest communication range with only 10 drones in the swarm. Increasing the communication range to 350 meters results in a mix of all three types doing well, but only further decreases the mission time by around 5 minutes. Little to no improvements are gained by increasing beyond a 350-meter communication range.

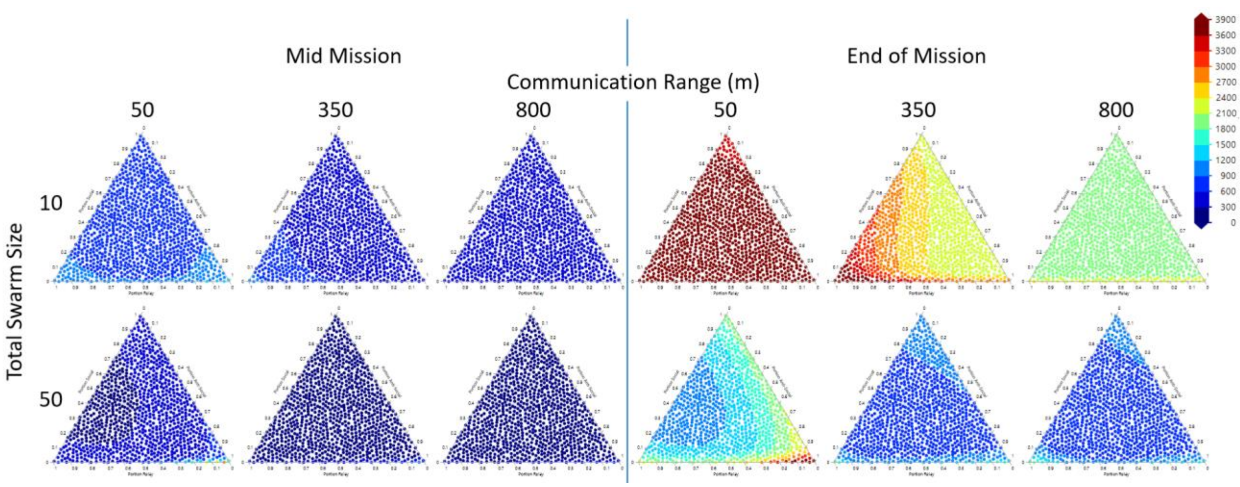

Figure 4. Predicted Rescue Time Ternary Plots

Figure 5 again shows 5-minute contours of the rescue time in seconds; however, in this plot the ANN model is used to find the configuration of drone types that completed the mission fastest for a given swarm size and communication range. This figure can be used to visualize the relationship between swarm size and communication range on the mission completion time, given that the optimal configuration of drone types is used. This plot shows that swarm size matters in our scenario; mission completion time continues to decrease as the swarm size increases and this happens at a higher rate the lower the communication range. The communication range also affects performance with higher ranges resulting in faster missions; however, while this is very prominent with small swarm sizes and lower communication ranges, there are diminishing returns. With 10-drone swarms, a communication range beyond 300-400 meters does not buy too much more performance, and with 50-drone swarms, the mission time remains in the same 10–15-minute contour no matter what the communication range. This reenforces the trend seen in the ternary plots in Figure 4.

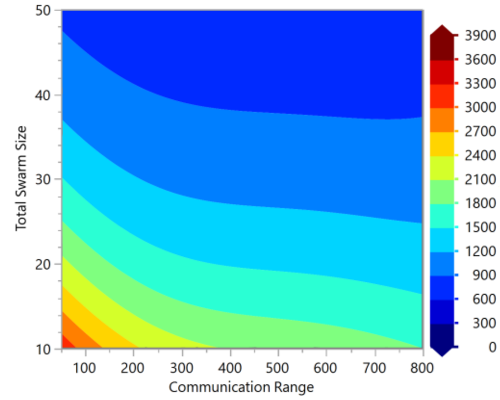

Figure 5. Predicted Mission Time in Seconds Given an Optimal Configuration

In Figure 6, the focus is no longer on mission completion time, but instead on the optimal configuration of drones. The axes show the number of survivors rescued verses the optimal portion of each drone type: relay in blue, social searcher in green, and anti-social searcher in red. Subplots are shown for five different drone swarm sizes, increasing by 10 from left to right, and for six different communication ranges, increasing by 150 meters from top to bottom. A key finding from this plot is that the optimal configuration changes significantly over the course of the mission. For example, before any survivors are found, spreading out the swarm with anti-social searchers optimizes the time it takes to find those first survivors; however, unless the swarm size is smaller or the communication range is higher, anti-social searchers have limited use over the remainder of the mission. This change in optimal configuration over time leads us to hypothesize that there are further gains in mission completion time from re-programing drone types throughout the mission based on the current optimal configuration. Future work is planned to investigate this approach.

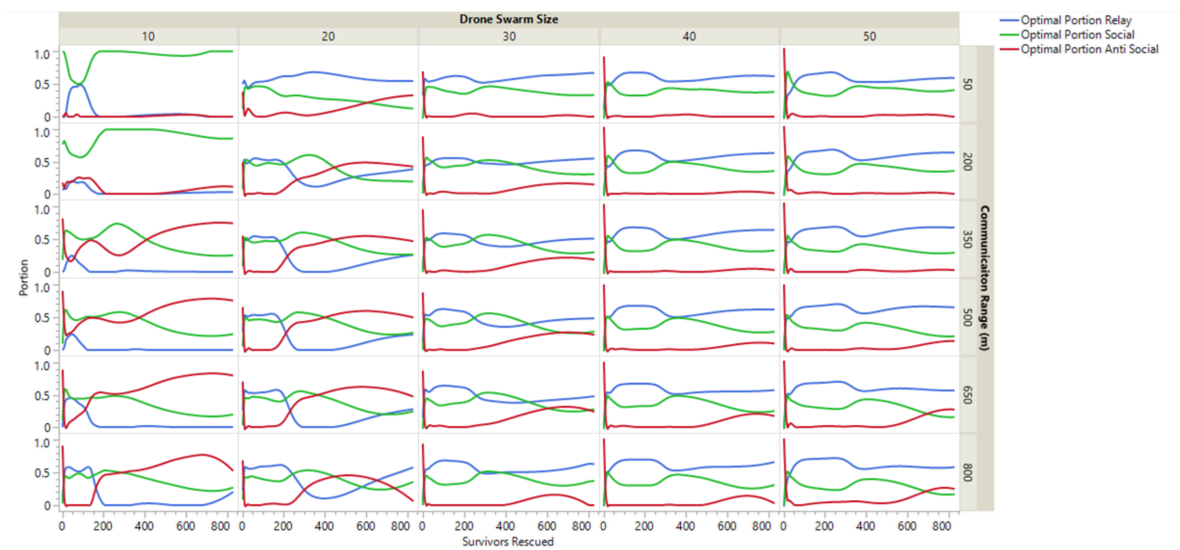

Figure 6. Optimal Configurations over the Mission Time

Communication Network Analysis

A starting point to the communication network analysis involved looking at 30 different swarm configurations. This analysis was completed on older data that had been generated where the total number of drones and their communication range was kept constant (Mezzacappa et al., 2021). As in this experiment, each swarm had varying percentages of entities with one of three different operational behaviors (i.e., social searcher, relay, anti-social searcher). Results indicated significant differences in time-to-mission-completion among the 30 configurations. Statistical analyses of the network parameters revealed significant differences in these variables. The best performing swarm configuration had a greater number of communication linkages and faster speed of communication pathways through the swarm network. Figure 7 shows the network linkages at the beginning, middle, and end of the mission for both the fastest and slowest performing swarms.

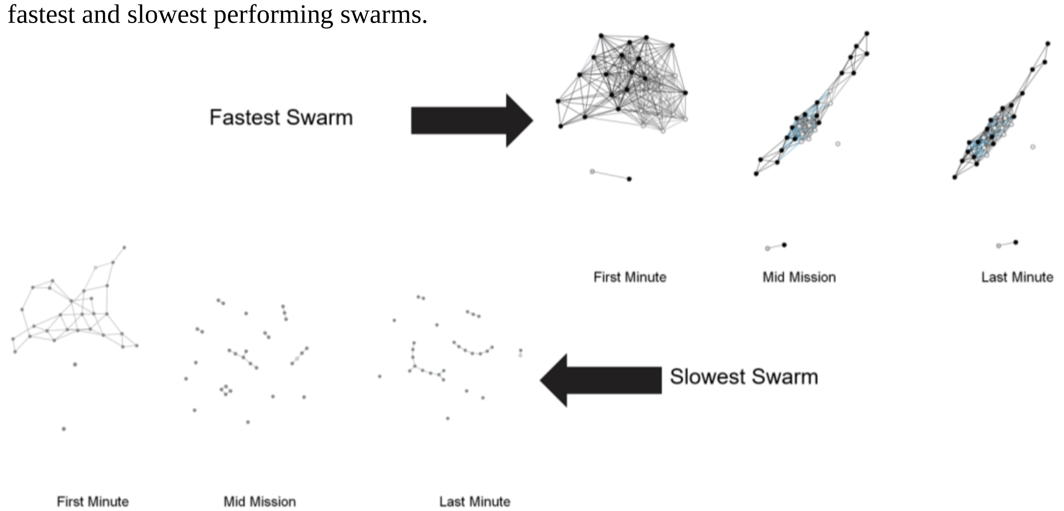

Figure 7. Network and Linkages in Fastest and Slowest Performing Swarms

That previous work generated the hypothesis that the communication network parameters were an important part of the swarm performance. This led to fitting preliminary ANN prediction models to some of the communication network parameters of interest on the current experimental data as a function of the DOE input factors. The communication network parameters considered were network density, speed of communication, and total degree centrality. Figures 7 through 9 show these preliminary results, in the same ternary sub-plot format as Figure 4. Although trends change over the communication network metrics based on swarm size, communication range, and mid verses end of mission timing, the most common trend is a change in network metrics over the relay drone configuration ternary axis. Most prominently, as the number of relay drones increases, the network density tends to decrease (Figure 7). This can be explained by the fact that the relay drones serve to spread out the swarm network by allowing subgroups of searcher drones to form in different areas of the terrain and not necessarily remain in communication range with other searcher sub-groups. Similar trends can be found in some of the speed of communication (Figure 8) and total centrality (Figure 9) sub-plots; however, other configuration axes (social or anti-social searchers) can be more prominent depending on the mission completeness, the swarm size, and the communication range.

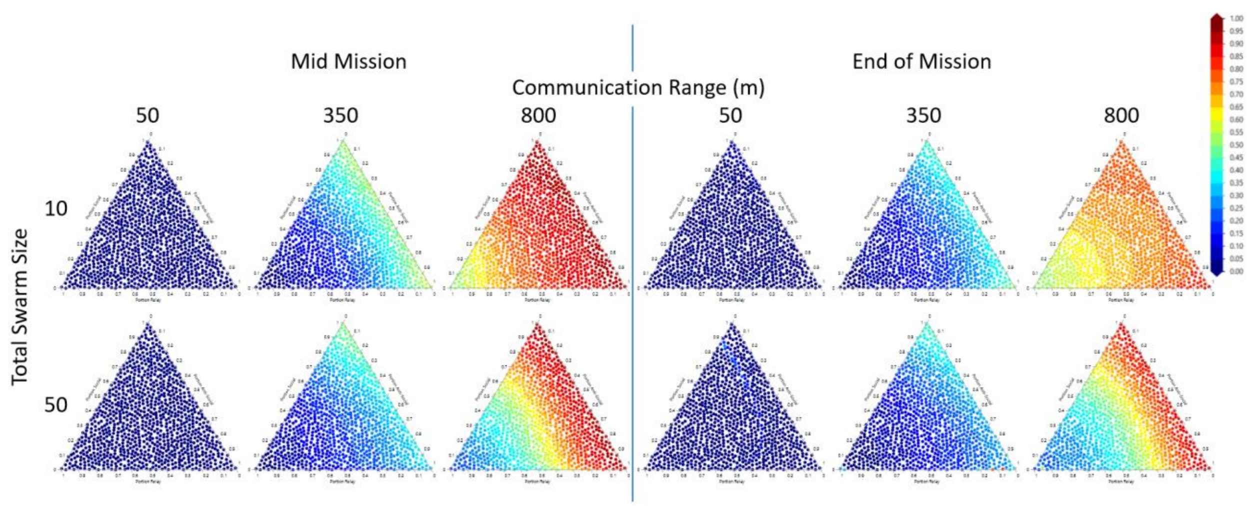

Figure 8. Network Density Ternary Plots

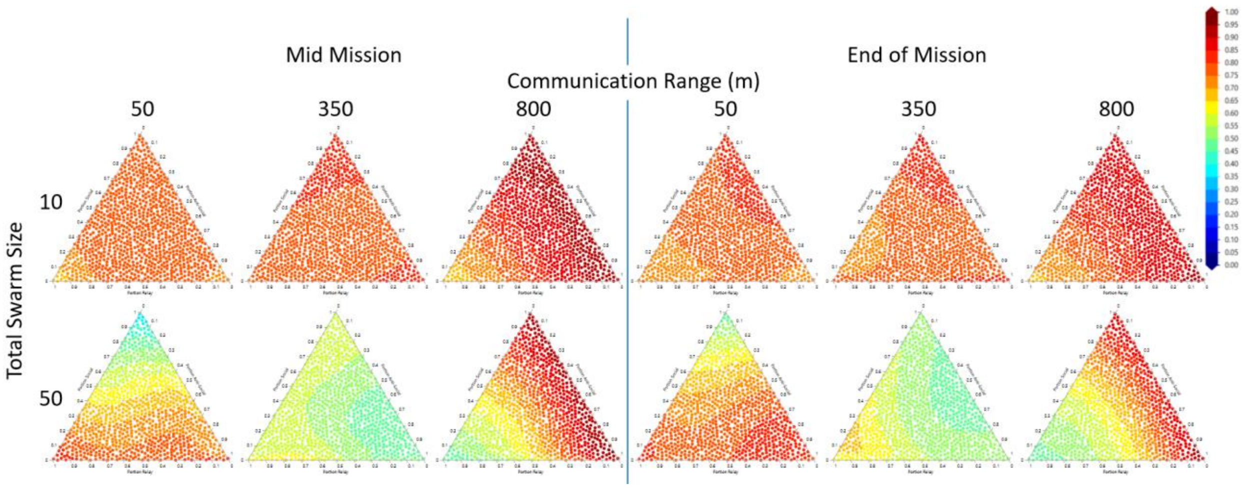

Figure 9. Speed of Communication Ternary Plots

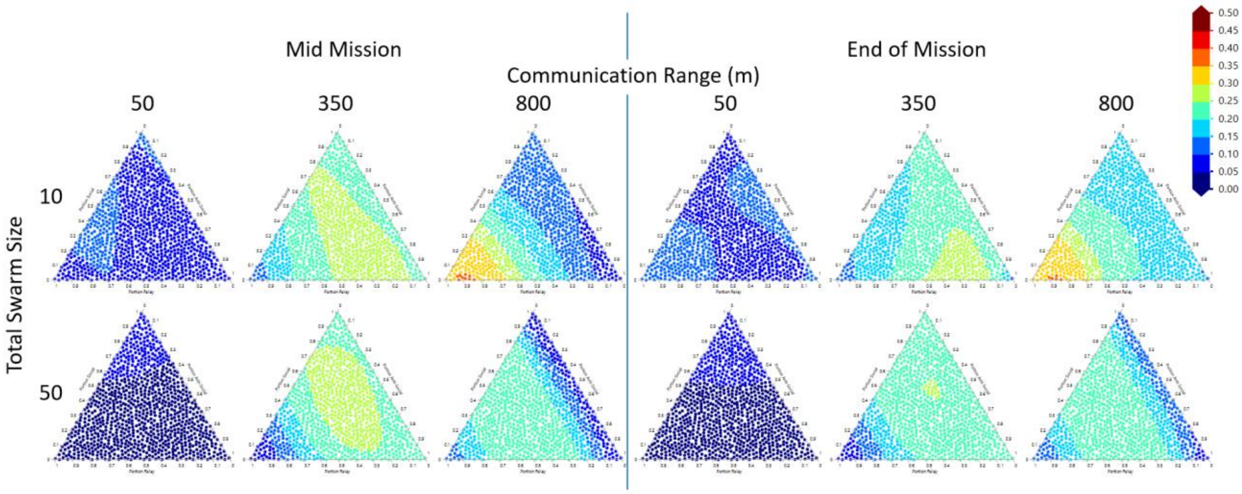

Figure 10. Total Centrality Ternary Plots

CONCLUSION

In this paper, the benefits of conducting simulation experimentation of swarms using design of experiments techniques and model fitting is demonstrated. The experiments revealed how design parameters (individual drone configurations) and real-world constraints (swarm size and communication range) influence the time it takes to complete a mission. For example, in this scenario, given a swarm of optimal configuration, there are diminishing returns to increasing communication range beyond a certain point; however, increasing swarm size, at least up to the maximum of 50 tested, consistently reduced the mission completion time. A look at optimal swarm configurations over the mission time indicated differences in the optimal configurations at different points of the mission which has led to the hypothesis that mission times can be further reduced by re-programing individual drones throughout the mission to match the optimal configuration at any given time.

Initial work looking at communication network parameters of drones was also shown. This revealed a correlation between network parameters and overall drone performance with a greater number of communication linkages and faster speed of communication pathways through the swarm network leading to higher performing swarms. Additionally, preliminary ANN models were fit to this data and those results were plotted to reveal the effect of the input factors on a select set of communication network parameters. Much more work in this area remains to be completed including delving further into the three models fit and shown above, modeling additional parameters, and linking the communication network parameters throughout the mission to both the input factors and the resultant mission completion time.

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