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Experimentation for optimization of heterogeneous drone swarm configurations: terrain and distribution

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ABSTRACT

Computer simulation experimentation examined the effectiveness of different Unmanned Aircraft System (UAS) swarm configurations for identification and localization of survivors after a natural disaster using the DroneLab application. Swarms differed in terms of total number of drones and ratio of entities programmed to perform one of three different "personalities"—Relay, Social, and Antisocial. Relay behavior puts a high priority on maintaining proximity to the centroid of the swarm while also maintaining a distance to closest neighbor drones equal to half of the maximum WiFi range. Antisocial drones prioritize an expanding behavior, increasing the spread of the swarm, while the Social behavior prioritizes a contractive behavior resulting in a tighter swarm formation. All drones performed a local waypoint-based search behavior while conducting a spiral-out search pattern upon detecting four or more survivors within a 10-meter radius. Swarm configurations with different ratios of these behaving entities were assessed for mission completion, defined as time to find 90% of the survivors. Mission completions were recorded for four simulation scenarios consisting of two terrains (urban/rural) with two different distributions of survivors (naturalistic/randomized). Ten replications of 98 different drone configurations were evaluated.

Statistically significant differences between time to mission completion between the terrains, between the two distributions, and among the iterations were revealed. Qualitative comparisons revealed differences in configurations that performed the best in each terrain. A few configurations performed well in all four scenarios. Moreover, the minimum number of entities needed for well-performing swarms was indicated. The work demonstrates the utility of computer experimentation and statistical analyses for developing a framework for swarm design for operational effectiveness.

Keywords: Swarms, statistical analyses, search and rescue, remote autonomous systems

1. INTRODUCTION

There is wide agreement within the United States Department of Defense (DoD) that collectives of artificially intelligent agents, swarms, with various levels of autonomy will be employed for multi-domain operations in the very near future [1] [2]. As a consequence, the DoD requires research addressing quantitative methods for understanding how to build drones and assemble swarms for specific missions. This program of research includes the relationships between design choices and measures of swarm performance and how those relationships change with specific missions and terrains. Engineering design choices include parameters for individual entities as well as for the swarm as a whole.

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Modeling and simulation techniques have proven to be useful in understanding the relationships between small Unmanned Aircraft System (UAS) swarm characteristics and swarm performance in computer simulated operations. This paper demonstrates how the modeling and simulation approach, combined with statistical analyses can result in insight that could be useful for decision-makers when determining how to design, configure and deploy an autonomous swarm for a mission scenario. Performance of a UAS swarm in a search and rescue mission was compared for different sized swarms, under two terrains, with two different distribution of targets in computer simulations. The intent was to identify the swarm configurations (i.e., swarm size, composition of behavior types) that performed best in each terrain (urban, non-urban) and with different distributions of targets. Based on those findings, the configurations of swarms that performed best across all the terrains and target distributions were identified.

2. METHOD

2.1 Computer simulation: DroneLab and entity "personality"

The U.S. Army's DroneLab simulation software was used for experimentation [3] [4] [5]. DroneLab is a software application designed to facilitate simulation of large numbers of UAS operating collectively as a cohesive but decentralized system. The simulated scenario consisted of a search for survivors after major natural disasters (tsunami and earthquake) in a mission space of approximately four square kilometers. The entities in the search swarm were each programmed with one of three roles, which can also be conceptualized as "personality" types. The three roles 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. The three personality types developed for this experiment were titled Relay, Social Searcher, and Antisocial Searcher. An entity assigned to the Relay role maintains a distance equal to half of the maximum range of the WiFi module (approximately 400 meters) from the closest member of the swarm to provide a network infrastructure to enable other agents to continue their behaviors while maintaining connectivity to the other swarm members. The Antisocial Searcher drones prioritize a loose formation behavior, putting a high value on increasing the spread of the swarm thus maintains 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 in order to more rapidly locate other survivors that are likely to have congregated nearby [5].

2.2 Swarm Parameters: Size and percentage of each personality type

Test swarms were configured with two parameters. The first swarm parameter was total number of entities in the swarm. The second was relative proportion of entities assigned one of the three specific "personalities," or roles, within the swarm. All proportions of roles were considered with a swarm size in the range of 10 to 50 drones. The maximum swarm size of 50 was selected as this was estimated to be beyond the point of saturation for the target area. Ninety-eight different configurations were included, with 10 iterations of each run. Swarm performance was recorded in four different scenarios which differed in two terrain/disaster combinations (rural-tsunami, urban-earthquake) and distribution of survivors.

2.3 Scenarios: Terrain

Of the two terrain sets, the Rural terrain is based on actual data gathered from primary sources on-site at Arahama, Japan, which is a small coastal town destroyed by the 2011 tsunami that struck and disabled the Fukushima Daiichi nuclear power plant, located approximately 100 kilometers to the south. The Urban terrain is 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. Both sets of terrain provide representations of post-disaster sites that had undergone large scale search-and-rescue operations.

2.4 Scenarios: Survivor distribution

Swarm performance in both terrains was tested against two different survivor distributions (i.e., Distribution A, B, see Table 1). A total of 650 survivors were located in the rural terrain, 300 of which were randomly distributed. The remaining 350 survivors were placed in two different ways. Distribution A in the rural terrain was based on real data of survivors after a tsunami, where most people gathered on top of an elementary school. Distribution B rural placements were fictitious, but reasonably spread across the buildings and terrain.

A total of 2620 survivors were to be found in the urban earthquake scenario, where 2000 were randomly distributed in the terrain. The remaining 620 survivors were placed in again two different ways. Distribution A placed survivors concentrated in tall buildings. Distribution B placed survivors in large clear areas, such as school fields.

Table 1: Scenarios

Terrain	Distribution A	Distribution B
Rural-tsunami (total of 650, 300 randomly placed)	Real survivor data, collected from interviews and information collected on-site, survivors concentrated on top of an elementary school and several other structures	Survivors spread across buildings and terrain
Urban-earthquake (total of 2620 survivors, 2000 randomly placed)	Survivors concentrated in tall buildings	Survivors concentrated in large clear areas

2.5 Swarm Performance Metric

Time in seconds to locate 90% of survivors was the performance metric of interest.

2.6 Experiment and Analysis

Performance (time to find 90% of survivors, $t_{90\%}$) was compared in 100 swarm configurations. Swarm configurations were based on the parameters of swarm size (10-50 entities) and percentage (0-100%) of each of the three different personalities (Relay, Social, Antisocial). Two of the 100 configurations returned spurious results and were deleted from the analyses. Each of the remaining 98 configurations was simulated 10 times in each of the four scenario conditions in Table 1 (rural-tsunami Distribution A, rural-tsunami Distribution B, urban-earthquake Distribution A, urban-earthquake Distribution B) for a total of 3920 simulation runs.

To identify top performing configuration for each scenario, calculations of means and standard errors of $t_{90\%}$ for each of the 98 configurations for each of the conditions were calculated and compared. Each of the configurations was ranked according to the performance in each of the four scenarios in Table 1 and the top 20 performing configurations were identified for each. The configurations that were well performing across all four scenarios were identified.

To explore the extent to which the scenario characteristics affect $t_{90\%}$, a general linear regression was applied using the Statistical Product and Service Solutions (SPSS) software, predicting $t_{90\%}$; within subject factors were Terrain (rural-tsunami, urban-earthquake), Distribution (A,B), and Repetition Number (1-10). Because each of the scenarios differed in number of survivors, placements, and features (e.g., buildings, open spaces), performance differences can be expected.

3. RESULTS

3.1 Performance of configurations in each of scenarios

An overall qualitative analysis is presented in Figure 1. The four graphs correspond to one of the four scenarios. Each of the 98 configurations is represented by a sphere on the graph. The percentage of Relay, Social, and Antisocial entities is represented on the axes, the size of the sphere indicates the size of the swarm. The color indicates the ranking of the configuration, from high performing (shorter times to find survivors) blue spheres to poor performing (longer time to find survivors) red spheres. Note that the pattern of colors changes in each of the graphs, showing that one swarm configuration may perform well in one scenario and poorly in another.

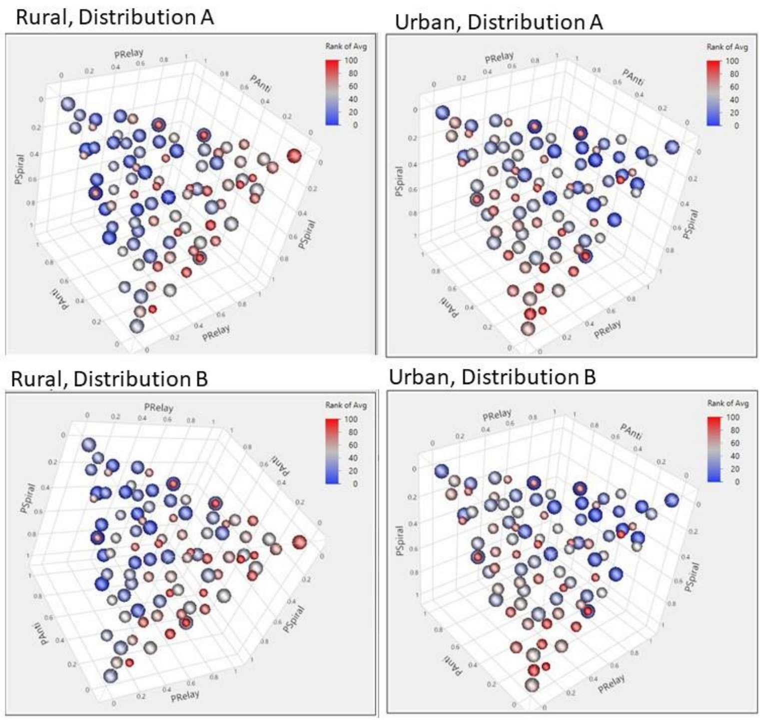

Figure 1: Configurations ranked by $t_{90\%}$ in each of the four scenarios

Tables 2-5 show the top 20 swarm configurations that resulted in the fastest time to detect 90%^ of survivors ($t_{90\%}$). Configuration characteristics (size, number of each personality type), average rescue time and associated standard deviation, minimum and maximum time are listed for each of the swarm configurations. Note that although average time to locate is the primary metric of performance, the reliability of the system is also reflected in the standard deviation. Decision makers may opt to configure a slower swarm in order to have a more reliable estimate of $t_{90\%}$. Minimum and maximum times are also useful with respect to planning, showing the range of times to expect until mission completion. Finally, an estimate of the total number of drones associated with expected average times gives decision makers a range of effective total numbers. Not surprisingly, larger swarms generally outperform smaller swarms in a search and rescue mission, though some smaller swarms are effective certain configurations. For example, configuration 13 in Table 2 only contains 33 entities in its swarm, yet performs nearly as well as configuration 12 which contains 44 entities.

Table 2: Swarm configurations with the shortest location times in the Rural Distribution A scenario

Top 20 Config #	# Drones Total	# Relay	# Social	# Antisocial	$t_{90\%}$ (sec)	Standard Deviation	Minimum Recorded Time (sec)	Maximum Recorded Time (sec)
1	50	0	20	30	932.7	158.84	706	1220
2	50	17	17	16	937.3	138.81	780	1273
3	50	1	10	39	958.0	114.99	756	1100
4	50	0	30	20	990.6	158.97	756	1306
5	45	1	21	23	1006.1	118.01	783	1196
6	49	13	12	24	1007.0	141.51	833	1200
7	46	8	20	18	1013.7	180.88	763	1386
8	47	21	5	21	1026.3	106.46	870	1193
9	39	1	13	25	1026.7	166.93	853	1406
10	43	9	9	25	1065.1	332.39	730	1923
11	46	5	2	39	1106.2	234.35	870	1596
12	44	7	6	31	1117.0	361.10	763	2063
13	33	2	6	25	1119.3	327.27	716	1880
14	41	12	3	26	1132.7	149.59	856	1360
15	37	14	3	20	1140.6	122.65	936	1336
16	39	9	0	30	1195.1	284.82	753	1820
17	50	20	0	30	1197.0	258.94	706	1623
18	50	31	6	13	1213.3	213.20	803	1530
19	48	8	31	9	1221.7	224.23	936	1650
20	41	6	22	13	1222.2	197.66	933	1626

Table 3: Swarm configurations with the shortest location times in the Rural Distribution B scenario

Top 20 Config #	# Drones Total	# Relay	# Social	# Antisocial	$t_{90\%}$ (sec)	Standard Deviation	Minimum Recorded Time (sec)	Maximum Recorded Time (sec)
1	50	1	10	39	922.0	146.99	773	1216
2	50	0	20	30	930.5	93.99	776	1126
3	50	0	30	20	962.0	122.63	786	1163
4	44	7	6	31	990.4	136.09	763	1130
5	43	9	9	25	1027.3	159.14	780	1276
6	49	13	12	24	1042.0	181.02	786	1306
7	45	1	21	23	1064.6	243.34	703	1646
8	46	5	2	39	1106.3	325.61	763	1650
9	39	1	13	25	1106.6	248.29	856	1773
10	46	8	20	18	1135.0	112.99	933	1333
11	41	12	3	26	1140.5	184.43	856	1440
12	48	8	31	9	1167.6	159.86	766	1326
13	50	20	0	30	1178.5	266.07	870	1630
14	36	9	14	13	1183.8	225.10	923	1676
15	47	21	5	21	1203.1	170.84	893	1480
16	50	17	17	16	1211.4	251.06	860	1686
17	33	2	6	25	1232.6	130.28	1033	1383
18	39	9	0	30	1237.6	385.25	866	2016
19	38	4	23	11	1237.8	161.82	1000	1630
20	37	14	3	20	1262.9	201.92	1006	1653

Table 4: Swarm configurations with the shortest location times in the Urban Distribution A scenario

Top 20 Config #	# Drones Total	# Relay	# Social	# Antisocial	$t_{90\%}$ (sec)	Standard Deviation	Minimum Recorded Time (sec)	Maximum Recorded Time (sec)
1	50	31	6	13	1774.3	105.48	1556	1920
2	50	30	0	20	1781.7	153.00	1450	1976
3	50	20	0	30	1898.7	245.54	1600	2326
4	48	37	10	1	2044.4	389.12	1533	2770
5	47	21	5	21	2077.1	233.18	1720	2443
6	50	30	20	0	2099.0	337.72	1693	2636
7	43	25	3	15	2125.7	361.66	1830	3050
8	47	25	16	6	2260.0	335.65	1946	3093
9	46	33	8	5	2330.6	325.73	2006	3056
10	50	17	17	16	2345.7	452.01	1790	3140
11	34	25	3	6	2361.9	224.11	2006	2750
12	41	20	11	10	2378.7	267.76	1990	2970
13	40	34	2	4	2489.3	359.66	1860	2993
14	49	13	12	24	2560.1	516.62	1860	3226
15	50	1	10	39	2732.6	461.29	1966	3493
16	50	0	0	50	2754.6	566.99	1810	3373
17	50	20	30	0	2784.3	504.42	2026	3306
18	50	50	0	0	2788.0	285.37	2370	3170
19	35	23	10	2	2925.0	326.35	2393	3323
20	33	18	5	10	2951.1	258.83	2433	3190

Table 5: Swarm configurations with the shortest location times in the Urban Distribution B scenario

Top 20 Config #	# Drones Total	# Relay	# Social	# Antisocial	$t_{90\%}$ (sec)	Standard Deviation	Minimum Recorded Time (sec)	Maximum Recorded Time (sec)
1	50	30	0	20	1754.0	169.00	1603	2103
2	50	31	6	13	1790.8	70.46	1680	1890
3	50	20	0	30	1958.0	292.13	1606	2540
4	46	33	8	5	2056.9	194.01	1826	2343
5	48	37	10	1	2110.6	289.33	1850	2626
6	43	25	3	15	2188.5	367.88	1690	2926
7	40	34	2	4	2210.5	369.88	1916	3130
8	47	21	5	21	2219.4	452.80	1863	3133
9	50	30	20	0	2243.4	347.61	1933	3143
10	47	25	16	6	2372.5	350.69	1783	2963
11	50	17	17	16	2487.7	416.39	1893	3060
12	50	50	0	0	2648.6	361.66	2223	3370
13	34	25	3	6	2719.7	264.88	2280	3116
14	49	13	12	24	2756.4	503.91	2030	3246
15	50	1	10	39	2761.9	452.41	2056	3483
16	50	20	30	0	2868.6	403.00	1946	3246
17	50	0	0	50	2894.1	178.57	2623	3166
18	41	20	11	10	2910.6	254.01	2420	3170
19	35	23	10	2	2951.1	296.35	2363	3210
20	33	18	5	10	3065.0	318.69	2456	3496

Five of the swarm configurations performed in the top 20 across all the scenarios, as shown in Figure 2. Tentatively, swarms configured in these manners may be expected to perform well across a broad range of conditions.

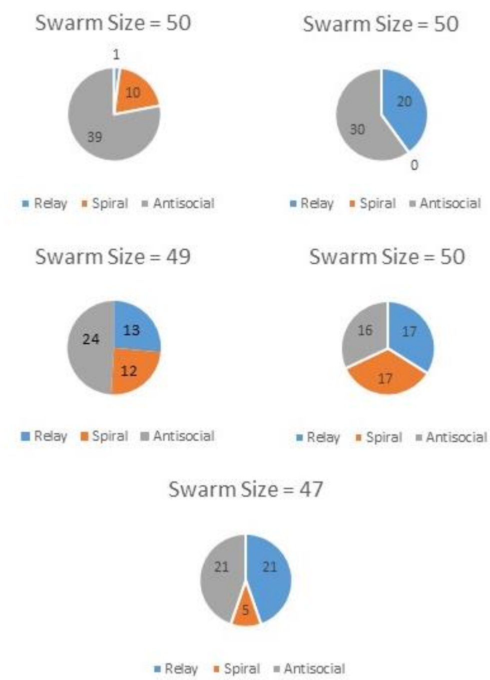

Figure 2: Top performing configurations across all scenarios

3.2 Characteristics of scenarios and time to find survivors

Figure 3 shows the means and standard errors for detecting survivors in each of the four scenarios. Statistical analyses reveal that there are significant differences in these times. Results from the general linear regression revealed significant main effects of Terrain (Rural, Urban, $F_{(1,97)}=282.71$, $p \leq .0001$), Distribution (A,B; $F_{(1,97)}=35.16$, $p \leq .0001$), and Run (1-10; $F_{(9,89)}=2.35$, $p \leq .05$) and an interaction effect of Terrain x Distribution ($F_{(1,97)}=8.25$, $p \leq .005$). These findings suggest that time to find survivors is significantly different among the four scenarios, and is longer in the Urban versus the Rural scenarios, and in Distribution B versus Distribution A.

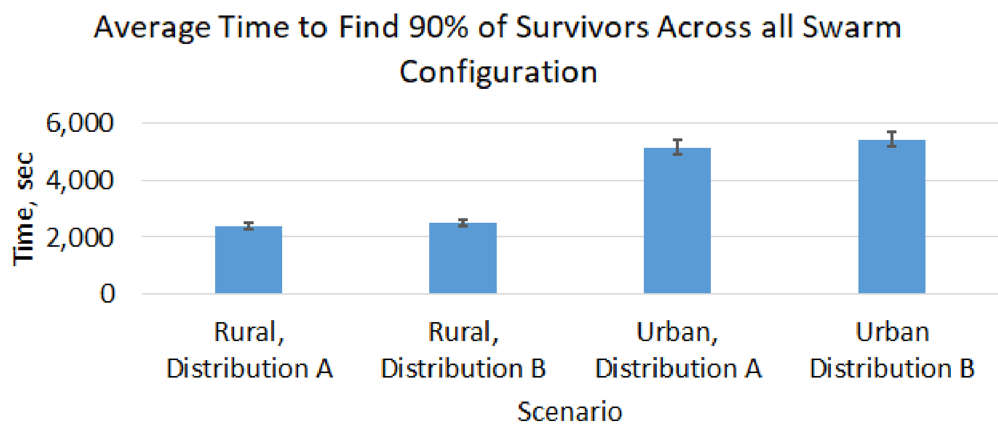

Figure 3: Comparison of times to detect across the four scenarios

4. DISCUSSION

As the previous sections indicate, modeling and simulation techniques can be used to explore the relationship between swarm configuration and swarm performance in different scenarios. Simple statistical calculations yield quantitative metrics (average, standard deviation, range) which can be used to make decisions and analyses of alternatives. Statistical analyses also reveal characteristics of the swarm and scenario that impact swarm performance, along with the extent and reliability of those impacts.

More sophisticated analyses are available that would increase the power of prediction for swarm performance. For example, Design of Computer Experiments [6] or more specifically Design of Swarm Experiments [7] offer the possibility to consider additional parameters of study (e.g., size, WiFi range, velocity, inter-drone distance, communication, etc.). Using this approach, a scalar function relating the average time to find 90% of survivors is statistically modeled with inputs including swarm size, role distribution, and other variables of interest. The resulting function is used to estimate the performance of swarm configurations not explicitly simulated and can be used for optimization studies and sensitivity analyses. This is contrasted by the statistical analysis used in this work which solely considers individual simulations and is, thus, limited in that the entire design space of swarm configurations is not considered. Future experimentation using these more advanced methods will give engineers and planners far more tools to configure swarms and to plan operations.

5. CONCLUSION

Computer modeling and simulation results subjected to statistical analyses offer design engineers and mission planners a method for exploring different swarm configurations for different operational scenarios. Using these methods, swarm configurations that performed universally well across all simulated scenarios were discovered. Additionally, under certain configurations, swarms of smaller size (lesser number of entities) were found to perform as well as, or better than, swarms of larger size up to a factor of one third. These results indicate that decision-makers, when made aware of the optimal configurations for a given mission, may be able to decrease their deployed number of swarm assets by 33% while retaining a similar level of mission capability. As a result, logistics footprint and operational burden can be decreased significantly. Further research is warranted.

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