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Heterogeneous Aerial Platform Adaptive Mission Planning Using Genetic Algorithms

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The focus of this study was to examine an automated mission planner that utilized a heterogeneous set of small aerial assets simultaneously surveying several Points of Interest (POI). The concept mission was to aerially search for an unknown Target of Interest (TOI) located amongst a set of POIs. In order to develop a planning system that is capable of meeting mission requirements, an adaptive mission planner, based on a Genetic Algorithm (GA), was investigated that seeks to task a heterogeneous set of unmanned aerial vehicles. Initially, a set of fixed wing UAVs were tasked to survey a set of POIs in search of a TOI, a POI that requires additional or long term surveillance. Once a TOI was located, a multi-rotor UAV was deployed to visit the TOI and additional POIs. Remaining POIs that were not tasked to the multi-rotor UAV were then re-tasked amongst the fixed wing aircraft set. The mission planner was implemented using a GA that planned initial and post TOI identification UAV paths. Mission simulations were conducted and the mission time increase was analyzed against different TOI locations and number of UAVs searching. Simulation results indicated that the deployment of a multi-rotor UAV not only provided additional surveillance of the TOI, but reduced overall mission times as well.

Keywords: UAV mission planning; genetic algorithm; heterogeneous UAV.

1. Introduction

Unmanned Aerial Vehicles (UAVs) have become a commonly used resource for Intelligence, Surveillance, and Reconnaissance (ISR) missions in military operations. In some scenarios, ground teams may have access to multiple UAVs but only deploy one at a time. Multiple UAVs in the air at the same time may provide enhanced area or target coverage capabilities and potentially reduce the surveillance time compared to usage of a single asset. Planning a multi-UAV mission requires a system that allows a UAV operator to both route and fly multiple platforms at once. In addition, different types of UAV assets may be available, further increasing complexity of a mission planning system.

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The scenario considered for mission planning was the tasking of UAVs to search Points of Interest (POI) where one is a Target of Interest (TOI) that requires additional surveillance. The POIs require multiple visits using a heterogeneous set of both fixed wing and Vertical Take Off and Landing (VTOL) multi-rotor UAVs. Initially, a set of fixed wing aircraft were considered to perform overhead fly-by visitations of multiple POIs in search of a TOI. Fixed wing UAVs are typically capable of achieving long duration flight times compared to single and multi-rotor systems. Once the TOI was located, a multi-rotor UAV was deployed to collect further data. The fixed wing UAVs required an updated flight plan such that additional fixed wing aircraft do not revisit the TOI. It was desired that UAV mission times be balanced such that a maximum number of POIs were visited. Additional POIs will also be visited by the multi-rotor UAV by tasking it to visit nearby unsearched POIs en route to and from the TOI. Upon arriving at the TOI, a sensor pod will be deployed to obtain long term ground surveillance and the multi-rotor UAV will continue to visit additional unsearched POIs. Remaining unsearched POIs not tasked to the multi-rotor UAV were then evenly re-tasked and visited by the fixed wing aircraft set.

Tasking the UAVs within the described scenario will require searching millions of possible combinations to find a asset allocation where the vehicle flight times are balanced. Assignment of the UAVs to specific tasks will require an optimizer that is able to scale up beyond traditional deterministic methods [1]. Nondeterministic algorithms, such as the Genetic Algorithm (GA), has been shown to handle asset tasking optimization problems that are NP-hard and scale up to allow multiple vehicles [2]. The final deployment of the algorithm will allow an operator to choose POI locations and number of fixed wing aircraft used. Including VTOL aircraft that are tasked to surveil POIs during their trip to the TOI was explored to determine if the renaming fixed wing search time could be reduced by alleviating the surveillance flyovers required. Performance of the planning system was evaluated by comparing the total mission time with only fixed wing UAVs to fixed wing and VTOL aircraft.

2. Multiple Aircraft Path Planning Literature

Typically, tasking a heterogeneous set of UAVs has required either a human operator or a joint human and robotic operation [3–5]. Fully automated mission planners are an emerging research area that may produce more efficient flight routes than a human operator. Field operators of UAVs now have access to multiple aircraft that may or may not be homogeneous. Additionally, planning when using a set of heterogeneous UAVs that are cooperatively tasked to perform simultaneously is of much interest recently. Fundamentally, UAV mission planners are optimizers that attempt to maximize flight routes and mission specific requirements. There is potential to combine existing UAV mission planning techniques with modifications that allow for the efficient usage of heterogeneous aircraft.

Various types of algorithms have been used to address UAV mission tasking and path planning problems. Mixed Integer Linear Programming (MILP) approaches have shown success in solving UAV tasking problems [6–8]. Additional heuristic approaches [9, 10] and taboo search algorithms [11] have been used to task a homogeneous fleet of fixed wing UAVs in a multi-objective mission. On the other hand, MILP is often undesired due to the long computational time required to solve larger problems making it unsuitable for real-time applications [12]. Markov decision process [13, 14] and agent-based approaches [15, 16] have also been implemented to solve the UAV tasking problems. The complexity of the models used in agent-based approaches offer no assurance of an optimal final result and thus are often avoided [17]. GA are well known optimizer that have been shown to successfully plan balanced missions for simultaneous mutli-UAV sets [18] surveying multiple POIs [2] and are particularly well-suited in UAV tasking and path planning [18–22]. Several GA approaches for coordinated tasking in surveillance missions under number of targets, task load requirements and reconnaissance time constraints exist in literature [23–26].

A flight tested GA method using homogeneous fixed wing UAVs was investigated *et al.* [2] where the fitness function balanced UAV flight times, example shown in Fig. 1, was able to converge on a desktop PC in less than 5 min. Operators picked five of the available eight POIs for three fixed wing UAVs to survey three times. The GA convergence was fixed to a specific number of iterations based on extensive studies of selected POIs within reasonable range of the UAVs.

Mission planning applications, such as the one in [18], are often complemented by road-map [27–29] and pose-based [30–32] path planning methods depending on the path planning application. In addition, the impact of continuous commutation links have been included in flight/path planning [33], something that very soon may be necessary in all UAV flight planning algorithms.

The mission planning methods discussed thus far only pertain to single or homogeneous UAV assets and neglect requirements that may call for heterogeneous UAVs for multi-tear or faceted tasks. Existing GA systems operated assuming a homogeneous set of UAVs, meaning that the fitness function will need to be redesigned to address different UAVs. The existing GA mission planning effort by Darrah *et al.* [2] was chosen as a basis for modifications that would include heterogeneous aircraft that undertake a search and deploy style mission. In order to build upon existing knowledge of GA mission planners, a basic operational concept needs to be developed that will highlight capabilities of fixed wing and multi-rotor UAVs.

3. Concept of Operations

Small fixed wing UAVs, with a wing span less than six feet, and multi-rotor UAVs, with less than 12 inch diameter

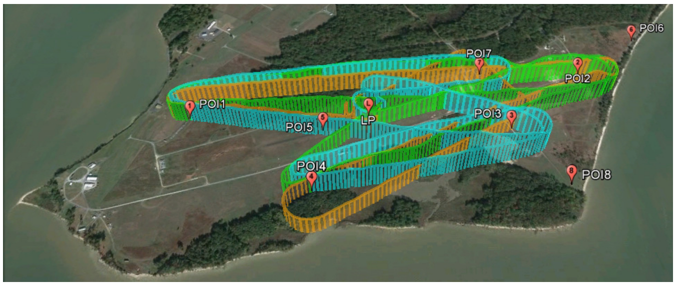

Fig. 1. Fixed wing GA mission planning [2].

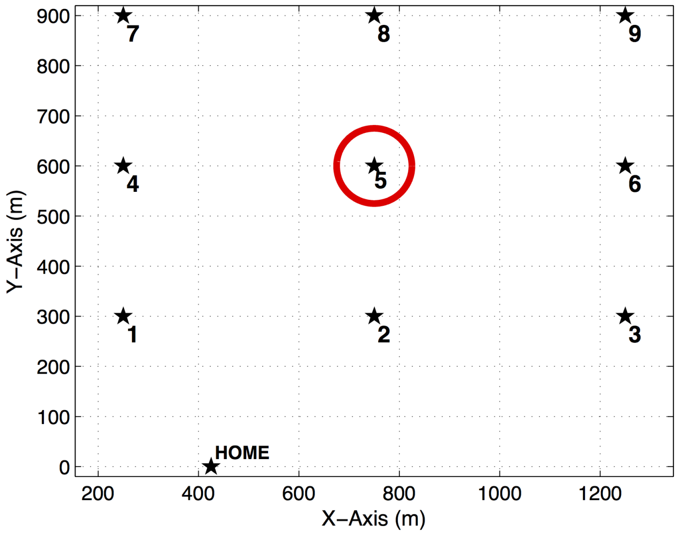

Fig. 2. Scenario search space.

rotors, have different flight and mission duration capabilities, but can typically carry similar sensing payloads. The concept mission is as follows. A set of POIs must be surveyed to locate an unknown TOI which requires additional close surveillance. POIs in the search space require multiple overhead fly-by visitations and no POI can be visited simultaneously within a specified window of time. Three fixed wing and a single multi-rotor UAV are initially available for the mission. An example of a search space containing nine POIs which are equally spaced apart in a three by three matrix configuration, for this study referred to as the square mission, is shown in Fig. 2. The home base location is centered and away from the nine POIs and is where fixed wing aircraft and multi-rotor UAV vehicles will deploy from and return to. The TOI location is initially unknown by the planner, but for illustration purposes the TOI is annotated as POI #5. Search space size is based off of the flight distance range capabilities of a small hand launched UAV such that all POIs can be visited at least three times and then return to home.

4. Adaptive Mission Planner Concept

In order to develop a mission planner for the previously defined operational concept that includes heterogeneous UAV assets, a process breakdown of the envisioned mission planning system was developed. First, an initial mission plan must be developed to task a set of fixed wing UAVs, which are optimized for endurance, to survey POIs simultaneously in search of a TOI. The mission scenario presented takes advantage of both fixed wing UAV flight duration and agility of a multi-rotor UAV. The fixed wing UAVs will be deployed and return to a home base location and are assumed to be flying at different fixed altitudes to avoid aerial collisions.

Once the TOI is located, a mission re-plan must be developed in which a VTOL aircraft, such as a multi-rotor UAV, will be deployed from the home base location to visit the TOI. The multi-rotor UAV will fly at a low altitude so as to deploy a sensor pod over the TOI to obtain additional close surveillance. Additional POIs that have either been unvisited or still require visitations will also be tasked to the multi-rotor UAV. Remaining POIs not tasked to the multi-rotor UAV will then be evenly re-tasked amongst the fixed wing aircraft. Once the TOI and remaining POIs have been visited, the fixed wing aircraft set and multi-rotor UAV will return to the home base location.

Two GA-based mission planners will be required to generate initial and mission re-plan solutions. Mission parameters such as POIs locations and aircraft specifics such as battery life remaining and flight capabilities will be used as inputs to the GA mission planners. Results from the planning will be either an initial mission or a post TOI located re-plan depending upon the inputs. Within each GA mission planner will be several components which include: GA population, fitness functions, convergence verification, selection/reproduction and genetic alterations.

The evaluation system simulates mission flight paths using the Dubins paradigm such that a fitness function can measure the success of the developed mission plan. A GA convergence criterion is then checked to determine if the desired number of GA generations has been satisfied, similar to [2]. If minimum number of generations and minimal change over the past 50 generations were satisfied, then the final mission plan solution is considered converged. Selection/reproduction operators, such as the roulette wheel method and elitist strategies, are applied to select best fit solutions within the population. Genetic alterations, such as crossover and mutation operators, then modify the selected population to produce a new current population of mission plan solutions. Inputs of the initial GA mission planning system will be presented next followed by those of the GA mission re-planning system. The information flow within the GA is outlined in Fig. 3.

Initial GA mission planning was performed to generate a flight path for the fixed wing UAV search of the POIs. Fixed wing UAVs in the set were assigned to visit a balanced number of POIs. The initial mission planner consisted of a fitness function that simulates flight of the fixed wing mission plans and combines the flight paths using an equation that rewards balanced mission times. Initial mission plans were considered valid once the GA converged.

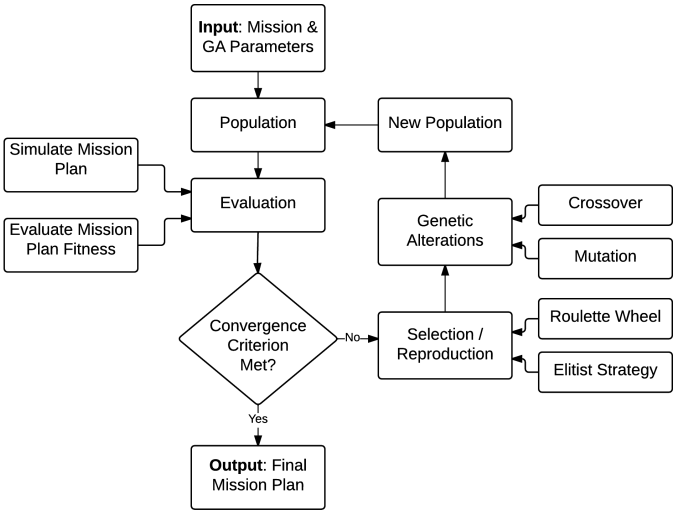

Fig. 3. GA initial mission planner and re-planner components.

Inputs to the initial GA mission planner include the following:

- Home base coordinates,
- POI coordinates and frequency of visitation,
- Number of fixed wing aircraft desired, aircraft turn radius and cruise speed,
- POI visitation window time constraint,
- GA parameters which include population size, chromosome representation and desired number of generations.

The GA mission re-planning was activated once a TOI has been located by one of the fixed wing aircraft. Once a TOI was located, a multi-rotor UAV would be deployed to visit the TOI and additional POIs remaining to be visited by the fixed wing UAVs. Remaining unsearched POIs were then re-tasked amongst the fixed wing aircraft set. Inputs to the re-plan GA mission planner included the following:

- Home base coordinates,
- TOI coordinate location,
- Unsearched POI coordinates and remaining frequency of visitation,
- Constraint restricting re-visitation of POIs that have been visited within a 30-s time window,
- Fixed wing aircraft vehicle states which includes the current coordinate location and remaining battery life,
- Aircraft turn radius and cruising speed,
- GA parameters which include population size, chromosome representation and desired number of generations.

The fitness function of the GA re-plan consisted of simulated mission flight paths and a set of equations for both multi-rotor UAV and fixed wing mission plans that rewarded visiting the most POIs and highest level of battery usage for the multi-rotor UAV along with balanced fixed wing UAV missions. The multi-rotor UAV mission plan was simulated first and remaining POIs not visited by the multi-rotor UAV were simulated in a separate mission plan using fixed wing aircraft set. Multi-rotor UAV and fixed wing mission plans were then evaluated to determine individual vehicle set fitness values. Re-plan mission solutions were considered valid once the re-plan GA converged.

5. GA Mission Planning Framework

The GA framework to generate mission plan solutions is presented in this section. First, the genetic representation used to characterize mission plan solutions is discussed. Next, selection/reproduction and genetic alteration operators are defined. Lastly, fitness functions designed to evaluate fixed wing and multi-rotor UAV mission plans are presented.

5.1. *Genetic representation*

Real Representation (RR) was used to encode the chromosome parameters which means that parameters were represented using real number vectors [23]. Chromosomes were expressed by a $2 \times L$ vector, where L is the length of the chromosome. Vehicle numbers are represented in the top row, which represent both fixed wing and multi-rotor UAV platforms, and POI numbers are represented in the bottom row. Tasking was then defined as the pair assignment between a top row vehicle number and a bottom row POI number. Priority parameters were assigned to POIs which determined the number of times the POI was to be visited during a mission. Summation of priority parameters determined the length, L, of the chromosome. Table 1 illustrates a sample chromosome using 5 POIs and 3 UAVs. POIs 1 and 2 were assigned a priority of 1, POIs 3 and 4 were assigned a priority of 2 and POI 5 a priority of 3.

5.2. *Initial population*

An initial population size of 52 was selected based on a population convergence analysis performed on the GA used to task homogeneous set of fixed wing aircraft in a balanced surveillance mission [2].

Table 1. Sample chromosome.

UAV #	1	3	1	2	3	2	1	2	3
POI #	2	1	5	5	3	4	4	3	5

5.3. *Selection/reproduction*

Roulette-wheel selection, augmented with elitist section, was used in this application. In this case, the roulette-wheel selection determined which chromosomes will engage with crossover alterations.

5.4. *Genetic alterations*

Crossover and mutation operators were implemented to perform alterations on chromosomes. Crossover was applied on even generations on the chromosomes selected by the roulette-wheel and was applied at random chromosome partition locations. Mutation was applied on odd generations to alter random number elements in the population which was represented by a mutation rate. Using the GA design that tasked a homogeneous set of fixed wing aircraft [2], a mutation rate of 21 was selected.

5.5. *Fitness functions*

The fixed wing aircraft are initially deployed to survey a set of POIs in search of a TOI. Since the TOI is initially unknown, the initial GA mission planner was to develop a mission plan that balanced flight times and POI loads amongst the fixed wing aircraft. It was found that no tuning parameters were necessary, thus, none were incorporated into the proposed fitness functions. The initial fixed wing fitness function is expressed as:

$$\text{Fitness}_{F_{WI}} = \frac{D-S}{N+1}, \tag{1}$$

where

$D =$ Summation of all UAV flight times traveled,

$S = d_{\text{MAX}} - d_{\text{MIN}}$ where d_{MAX} is the the maximum UAV flight time traveled and d_{MIN} is the minimum UAV flight time traveled,

$N =$ The number of times in which two planes arrive at the same POI within a specified window of time.

Equation (1) is derived from the following set of requirements from a previous GA application [2] that ensures all initial mission objectives are achieved:

(1) Maximize UAV mission time.
(2) Balance task loads evenly amongst UAVs in the set. Even distribution of POI task loads ensures that the term S is minimized.
(3) UAVs must not reach a POI within too short of a time window which is represented by the N term.
(4) $D-S$ Signifies the range of the minimum and maximum UAV flight times subtracted from the total flight time of all UAVs, wherein a small range suggests that work was effectively distributed amongst the UAVs.

Once a TOI is found in the search space, a multi-rotor UAV was to be deployed to visit the TOI. Remaining unvisited POIs, that will not be visited by the multi-rotor UAV, were to be evenly re-tasked amongst the fixed wing aircraft. Re-tasking the fixed wing aircraft set was evaluated using a summation of the initial fixed wing fitness function and an additional term, expressed as:

$$\text{Fitness}_{F_{WA}} = \sum_{i=1}^{n} \frac{1}{F_{Wn}}, \tag{2}$$

where

$FW_n =$ UAV distance to first POI. Aircraft number is denoted by the term "n".

Adding the term from Eq. (2) ensured that during a mission re-plan the fixed wing aircraft visit a POI closest to their current position in the space first. Since the distance to the first assigned POI should be minimized, the reciprocal of this term was added to increase the fitness score. The re-plan fixed wing fitness function is shown in Eq. (3) with each term carrying a weight of one.

$$\text{Fitness}_{F_{WR}} = \frac{D-S}{N+1} + \sum_{i=1}^{n} \frac{1}{F_{Wn}}. \tag{3}$$

When a TOI was identified by the set of fixed wing aircraft, a multi-rotor UAV was to be deployed with the intention of visiting the TOI and reducing the POI load on the fixed wing aircraft. Alleviating the POI loads on the fixed wing aircraft was achieved by tasking the multi-rotor UAV to visit additional unvisited POIs en route to and from the TOI. The multi-rotor UAV fitness function as well as the mission battery life are presented in Eq. (4) as:

$$\text{Fitness}_{QR} = D_{\text{TOI}} * \frac{\text{POI}_V}{\text{POI}_T} * (100 - \text{Battery}_M), \tag{4}$$

where

$$\text{Battery}_{\text{Mission}} = \frac{\text{Distance Traveled}}{\text{Distance}_{FB}} * 100 \tag{5}$$

and

$D_{\text{TOI}} =$ Reward for visiting the TOI $(D_{\text{TOI}} = 1)$ and or penalty for failing to visit the TOI $(D_{TOI} = 0)$,

$\text{POI}_V =$ Number of POIs visited by multi-rotor UAV,

$\text{POI}_T =$ Total number of POIs,

Distance Traveled $=$ Distance traveled by multi-rotor UAV,

$\text{Distance}_{FB} =$ Total distance traveled on a full multi-rotor UAV.

Equation (4) was used to satisfy the following set of requirements ensuring the multi-rotor UAV mission objectives:

(1) TOI must be visited and is represented by the term D_{TOI},

(2) Visit additional POIs in route to and back from TOI which is represented by the term $\frac{\mathrm{POI}_V}{\mathrm{POI}_T}$,
(3) Maximize the battery usage, represented by the term $(100 - \mathrm{Battery}_M)$.

Next, two-dimensional fixed wing and multi-rotor UAV flight path modeling using the Dubins paradigm is presented to illustrate how vehicle flight paths were simulated.

6. 2D Dubins Path Planning Algorithm

Two-dimensional fixed wing flight paths were generated using the Dubins paradigm [30–32]. Aircraft were to first fly over a POI and then adjust heading until it was in a straight line path with the next POI. Bank maneuvers were described using Dubins arcs and forward movement using Dubins straight paths. Fixed wing flight path was modeled after the 3D Robotics Aero fixed wing aircraft [34] and is shown in Fig. 4. The parameters shown below are representative of the Aero aircraft specifications and an example of the flight path at cruise speed is presented in Fig. 5:

(1) 15 m/s cruise speed,
(2) 11° turn-rate angle per second,
(3) 77 m turn radius,
(4) 30, 40 and 60 m cruising altitudes,
(5) 30-min flight time on full battery. Flight time was a selected percentage of the estimated 40-min flight time by 3D Robotics to account for battery usage during take-off and landing.

Two-dimensional multi-rotor UAV flight paths were modeled using Dubins straight path segments as it was assumed that a multi-rotor UAV can change heading and direction at any moment. Multi-rotor UAV flight path was modeled after the 3D Robotic IRIS quadcopter [34] seen in Fig. 6. The parameters shown below are representative of the IRIS quadcopter specifications and an example of the flight path at cruise speed is shown in Fig. 7:

(1) 25 m/s cruise speed,
(2) 5 m cruising altitude,

Fig. 4. 3DR aero fixed wing aircraft.

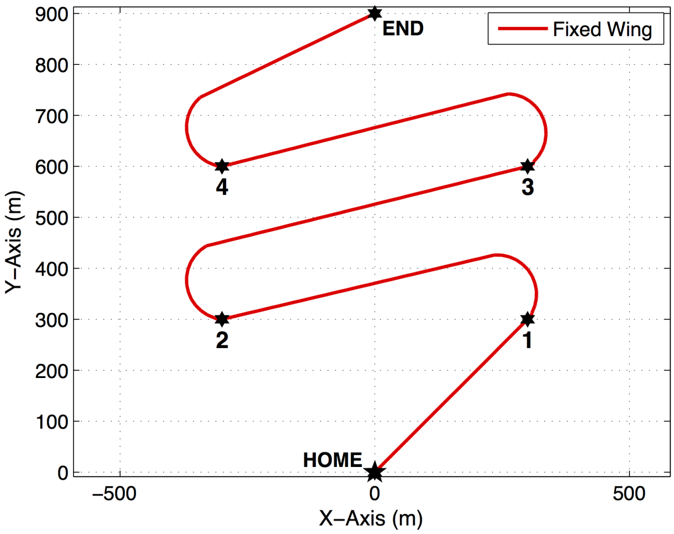

Fig. 5. Fixed wing trajectory.

Fig. 6. 3DR IRIS quadcopter UAV.

(3) 10-min flight time on full battery. Flight time was a selected percentage of the estimated 16–22 min flight time by 3D Robotics to account battery usage during take-off, landing and heading change maneuvers.

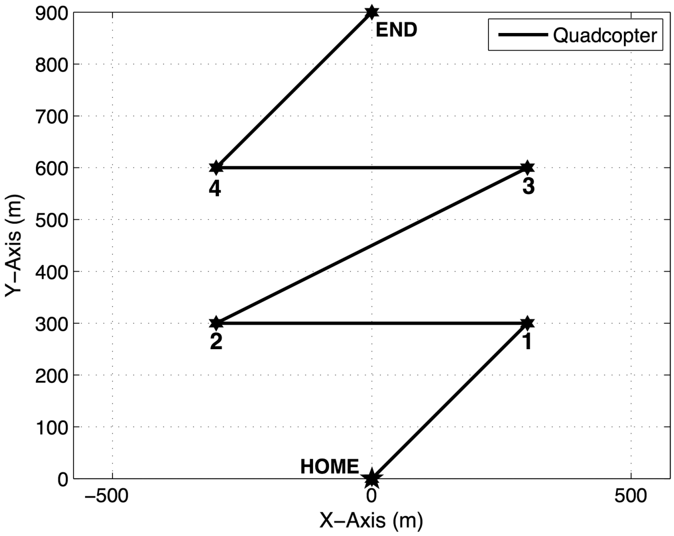

Fig. 7. Multi-rotor UAV trajectory.

7. Simulations

The developed heterogeneous multi-asset adaptive mission planning system was simulated using the previously mentioned fixed wing and multi-rotor UAV platforms and mission concept to ensure that mission plan solutions obtained satisfied both initial and re-plan objectives. Initial mission planning resulted in balanced POI task loading amongst the fixed wing aircraft set. Mission re-planning resulted in the multi-rotor UAV being tasked to visit the TOI and additional POIs. Remaining POIs not tasked to the multi-rotor UAV were then evenly re-tasked amongst the fixed wing aircraft set. Steps to perform the adaptive mission planner simulation were as follows:

- Establish POI search space configuration and size,
- Initialize and run initial GA mission planner,
- Simulate obtained initial mission plan until a preselected TOI has been reached,
- Extract fixed wing vehicle states for mission re-plan,
- Initialize and run re-plan GA mission planner,
- Evaluate mission times as performance metric.

Mission times were evaluating by quantifying the reductions in mission times by the deployment of the multi-rotor UAV. Reductions in fixed wing and overall mission times were examined using Eqs. (6) and (7).

$$\text{Fixed Wing}_R = 100 - \frac{\sum FW_{TT} + \sum FW_{RPT}}{\sum FW_{IT}} * 100, \qquad (6)$$

$$\text{Mission Time}_R = 100 - \frac{\sum FW_{TT} + \sum FW_{RPT} + MR_T}{\sum FW_{IT}} * 100, \qquad (7)$$

where

$\sum FW_{IT}$ = Total initial mission time between all fixed wing aircraft,

$\sum FW_{TT}$ = Total mission time traveled between all fixed wing aircraft prior to locating TOI,

$\sum FW_{RPT}$ = Total re-plan mission time between all fixed wing aircraft,

MR_T = Total mission time of multi-rotor UAV.

The simulation search space was composed of nine POIs equally spaced in a three by three matrix configuration with each POI requiring two visitations as shown in Fig. 2. The home base location was off-center and away from the nine POI configuration. No POI was to be visited simultaneously within a 30 s time window. Three fixed wing aircraft and one multi-rotor UAV was used and POI #5 was assigned as the preselected TOI. Search space size was selected based on the flight distance capabilities of a small fixed wing aircraft. Both the initial and re-plan GAs were allowed to run for 350 iterations to obtain final mission plans.

Table 2. Initial best chromosome.

UAV #	3	3	2	3	2	1	3	2	1
POI #	6	8	1	2	5	2	7	7	3
UAV #	3	3	2	2	1	1	2	1	1
POI #	3	5	9	1	4	6	9	4	8

After 350 generations, the best initial GA mission planner chromosome is shown in Table 2. POI task loads were balanced amongst the fixed wing aircraft as each were tasked to visit 6 POIs each. Figure 8 then shows the initial fixed wing aircraft trajectory.

POI #5 was assigned to be the TOI and further examination of the initial chromosome indicated that fixed wing aircraft #2 was assigned to first visit POI #1 followed by POI #5. This means that fixed wing aircraft #1 and #3 will visit as many POIs in their flight plan before fixed wing aircraft #2 reaches the TOI. Simulation of the initial mission plan is shown in Fig. 9. Fixed wing aircraft #1 reached POIs #2 and #3 and fixed wing #3 was inbound to POI #6 before the TOI was reached.

Current vehicle states of the fixed wing aircraft were then used to generate a mission re-plan. The best re-plan chromosome attained after 350 GA generations is presented in Table 3. Upon further examination of the re-plan chromosome, the multi-rotor UAV was assigned to visit a total of 7 POIs including TOI #5. Fixed wing aircraft #1 and #3 were assigned to visit two POIs while fixed wing aircraft #2 was assigned to visit three remaining POIs. Re-plan trajectory of

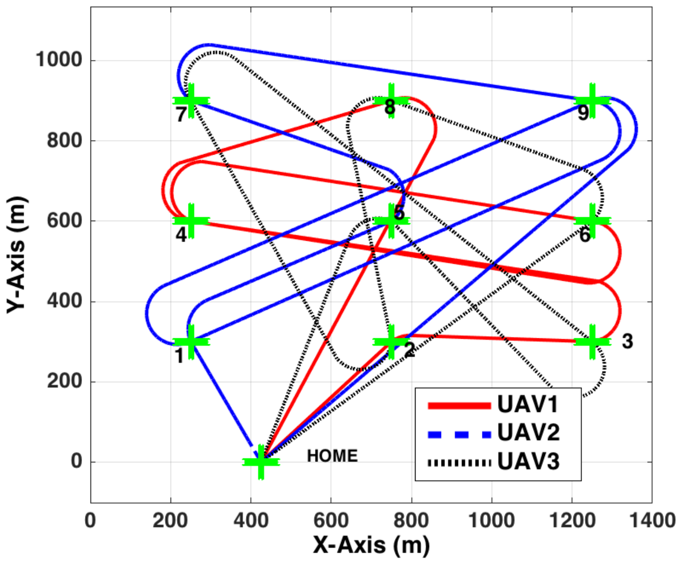

Fig. 8. Scenario initial trajectory.

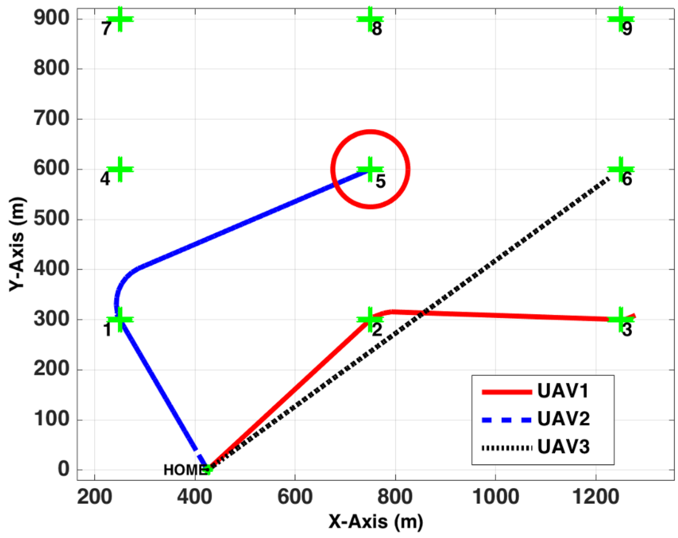

Fig. 9. Scenario simulation

Table 3. Re-plan best chromosome.

UAV #	3	4	1	4	2	2	2	4
POI #	6	2	3	6	8	9	1	9
UAV #	4	4	1	4	3	4	—	—
POI #	8	5	7	7	4	4	—	—

the fixed wing aircraft and multi-rotor UAV are shown in Fig. 10.

Initial and re-plan flight times and distances are presented in Tables 4 and 5. Flight distances and times were balanced in the initial mission plan which was expected as POI loads were balanced evenly amongst the fixed wing aircraft set. During the re-plan, fixed wing aircraft distances and times were also balanced while the multi-rotor UAV traveled for a total time of 2.7 min.

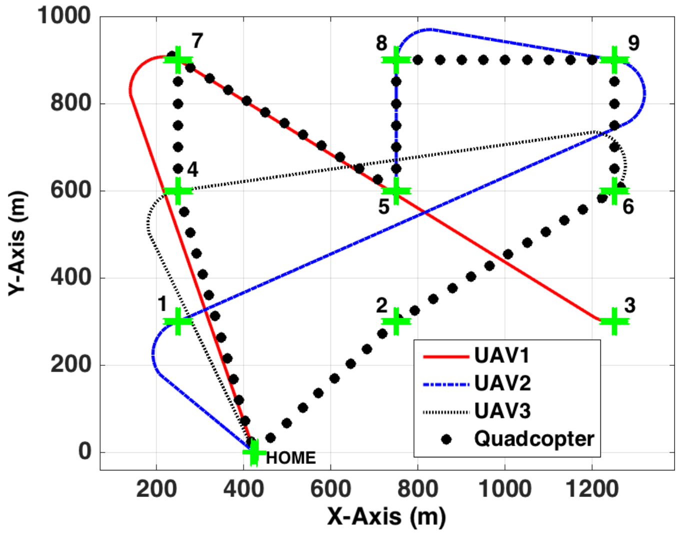

Fig. 10. Scenario re-plan trajectory.

Table 4. Adaptive mission planner flight times (min.).

	FW #1	FW #2	FW #3	Multi-rotor UAV
Initial	7.6	8.2	7.8	
Re-plan	3.9	3.9	3.6	2.7

Table 5. Adaptive mission planner flight distances (m).

	FW #1	FW #2	FW #3	Multi-rotor UAV
Initial	6462	6955	6224	
Re-plan	3490	3555	3239	4095

POI timelines for both the initial and mission re-plan are represented in Figs. 11 and 12. During both the initial and mission re-plan, no two aircraft reached the same POI within the specified window of 30 s.

7.1. *Convergence*

Convergence criteria of the developed heterogeneous GA mission planner was performed by using a Monte Carlo analysis. A set of POIs and a TOI (same as Fig. 2) was run 500 times with different random initial conditions up to 5000 generations. An example of the initial planning stage fitness for the long runs can be seen in Fig. 13 where the maximum, average, and one standard deviation (σ) are highlighted. The maximum fitness was found as the local

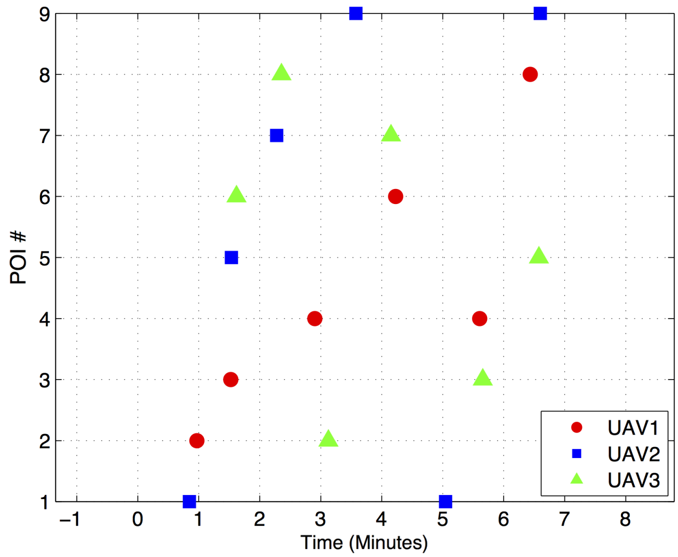

Fig. 11. Initial scenario timeline.

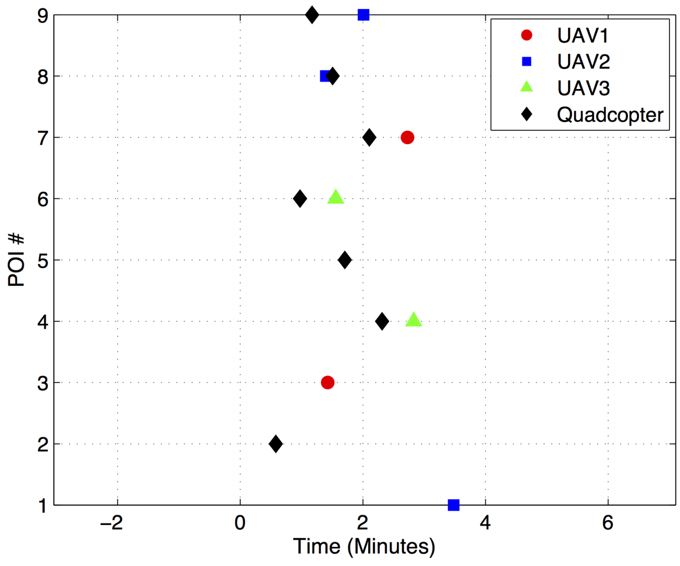

Fig. 12. Re-plan scenario timeline.

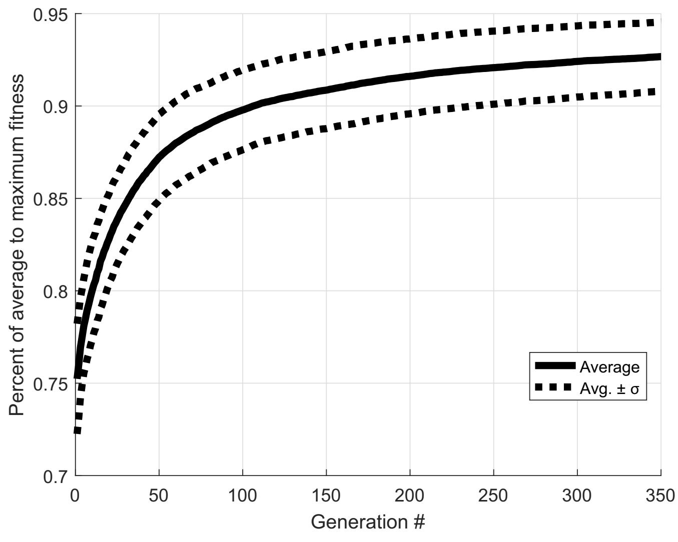

Fig. 14. Fitness approach to maximum.

maximum from within the simulations. The average fitness trend showed a continuous increase that may approach the local maximum, but appears to slow down after 3000 generations. Comparison of the average to maximum fitness found during GA simulations were examined to find how many generations were required to be within 90% of the maximum, shown in Fig. 14. In the case of this particular mission optimization, approaching a fitness value to within 10% of a known maximum was acceptable and was reached in 100 generations on average and 250 generations within one standard deviation of the cases. Therefore, it was recommended to run the developed GA to at least 100 generations past one standard deviation at 350 generations as convergence criteria.

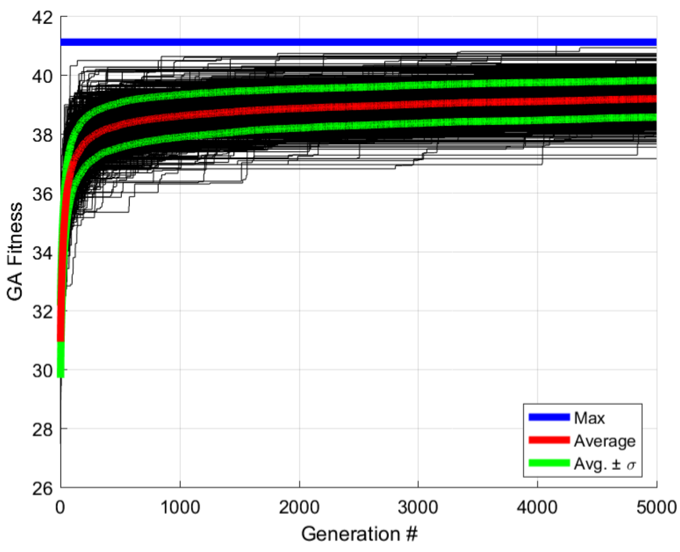

Fig. 13. Fitness of GA over 500 runs for 5k generations.

The GA run time performance for both the initial and re-plan solution is shown in Table 6, where converged generation is the number of generations converged out of the total 350, convergence time is the total time required to converge, sec/gen is the time required per generation, and delta G is the number of generations without an increase in fitness. The initial mission plan was generated in 4.8 min while the re-plan mission plan was generated in 2.6 min. Final and average fitness scores versus generations for both the initial and mission re-plan can be seen in Figs. 15 and 16.

Simulation of the developed heterogeneous adaptive mission planner using the square mission scenario with the TOI located at the center POI, see Fig. 2, indicated that the initial and re-plan GAs generated missions that satisfied mission objectives and reduced the total mission time. Reductions in the fixed wing and overall mission times were achieved by deploying a multi-rotor UAV once the TOI was located, about 4 min into the mission. Summations of the fixed wing flight times during the initial, simulation and re-plan are shown in Table 7. The scenario studied indicated that the deployment of the multi-rotor UAV reduced just the fixed wing UAV mission time by 31% and overall mission including the multi-rotor UAV by 19% compared to only three fixed wing UAVs searching the POIs.

Table 6. Adaptive mission planner GA performances.

	Sec/Gen	Conv. time	Conv. generation	ΔG
Initial	0.8	146.4 s	183	169
Re-Plan	0.5	155 s	310	42

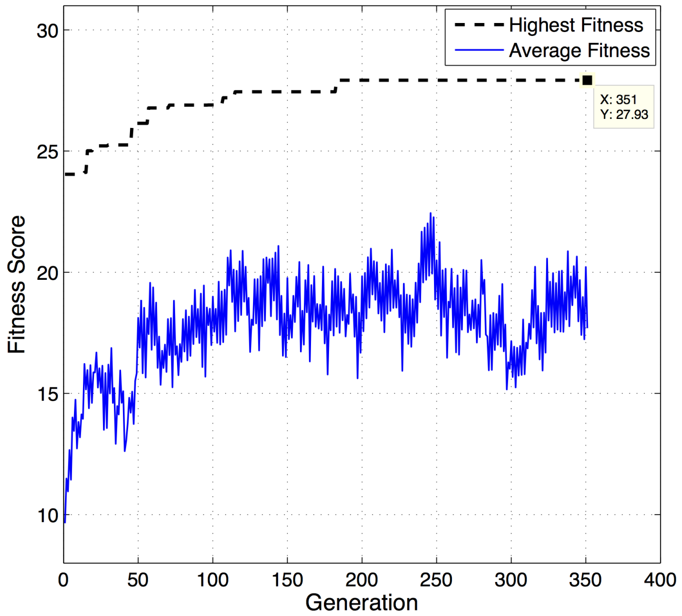

Fig. 15. Initial fitness versus generations.

Table 7. Square mission GA planned heterogeneous overall mission time and re-plan reductions.

Mission stage	Parameter	Quantity
Three fixed wing UAVs	Mission time	23.2 min
TOI located	Time	4.6 min
Re-plan/updated fixed wing UAV	Time	11.4 min
Updated mission plan post TOI including multi-rotor UAV	Time	16 min
Post TOI fixed wing UAVs	Reduction	31%
Mission time w/multi-rotor UAV	Reduction	19%

7.2. *Case study simulations*

Further studies on different mission scenarios were performed where the number of fixed wing UAVs in the heterogeneous set varied along with the location of a single TOI to examine if the overall mission time reduction carries over to different mission configurations. Case studies of TOIs located in different places along with an increased number of fixed wing UAVs were simulated. The search space was composed of nine POIs in a three by three matrix configuration identical to that found in Fig. 2. Each POI required three visitations and no POI was to be revisited within a 30 s time window. In every vehicle set, a single TOI was rotated between one of the nine POIs, which produced nine simulations per vehicle set.

Results comparing the time reduction of varying TOI location and increased number of fixed wing UAVs are presented in Fig. 17 where each data set represents a heterogeneous UAV set containing either two, three or four fixed wing aircraft and a single multi-rotor UAV. Simulation results indicated that for these particular case studies, an average fixed wing mission time reduction of 42% was obtained when the heterogeneous set contained two fixed wing aircraft. Sets containing three fixed wing aircraft resulted in a 20% average mission time reduction while

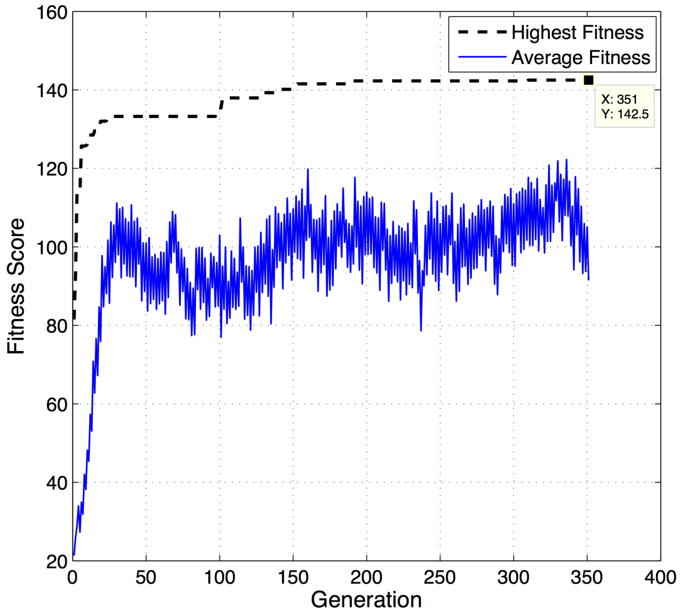

Fig. 16. Re-plan fitness versus generations.

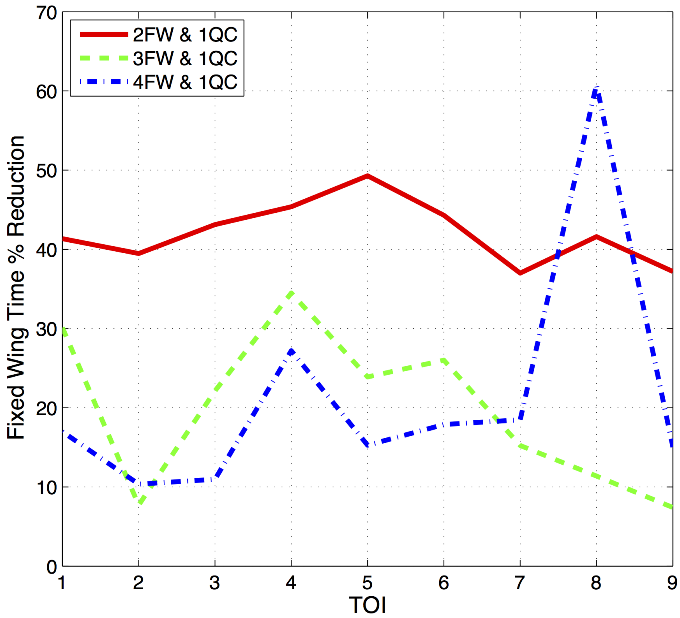

Fig. 17. Case study of fixed wing UAV time reductions.

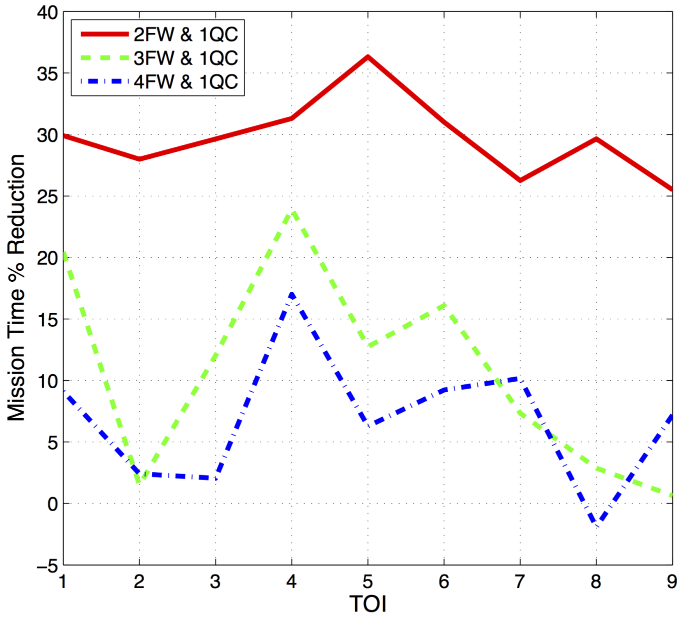

Fig. 18. Case study of mission time reductions.

four fixed wing aircraft resulted in a 21% average mission time reduction. Overall mission time reductions after the deployment of a single multi-rotor UAV can also be seen in Fig. 18. Simulation results of the previously mentioned case studies indicated that average overall mission times were reduced by 30% using two fixed wing aircraft, 11% using three fixed wing aircraft and 7% using four fixed wing aircraft.

8. Summary

A heterogeneous UAV TOI searching adaptive mission planning system was developed and simulated with a goal of tasking multiple aerial assets with working together during a search mission. The mission scenario was to first utilize a set of UAVs (fixed wing) to search and to collect surveillance data from a set of POIs with the goal of locating a specific TOI. Once the TOI was identified, in this case, a multi-rotor UAV was directed towards the TOI with the intent of visiting near-by POIs and then loitering for an extended period of time, landing, or delivering a payload. At the same time, the fixed wing UAVs received an updated flight path that reflected POI visits by the multi-rotor UAV. The developed planner had two goals, first to evenly utilize the fixed wing UAVs and second to minimize mission duration. In order to further reduce mission time, the multi-rotor UAV was routed over POIs and collect surveillance information on its way to or near the TOI to alleviate the work load of the fixed wing UAVs. The multi-rotor UAV had a flight duration lower than that of the fixed wing aircraft and was therefore tasked to optimally balance the flight time with visiting as many additional POIs as possible.

The developed mission planner was implemented as a dual GA system consisting of an initial and post TOI-located planners. Each GA had different fitness functions and otherwise operated similarly with respect to the initial population, mutation rate, crossover and elitism. The fitness functions relied upon two-dimensional flight path models for a fixed wing and multi-rotor UAVs using the Dubins method for simplicity. In reality, three dimensions would be necessary, but the two-dimensional case significantly simplifies computational requirements allowing for larger parameter studies to be performed.

Case study simulations of missions were then conducted in which heterogeneous UAV sets contained either two, three or four fixed wing aircraft and a single multi-rotor UAV to understand the impacts of moving the TOI and increasing the number of fixed wing UAVs on the overall mission times. The simulation search space size was selected based on the flight distance range capabilities of a small fixed wing aircraft. Initial mission plans to search the set of POIs were obtained using the GA and the initial fixed wing fitness function and flight path planner. Once the TOI was found, mission re-plans were generated using the GA and a combination of the re-plan fixed wing fitness function, multi-rotor UAV fitness function and vehicle flight path planners. Case study results indicated an average overall mission time reduction of 30% with two fixed wing aircraft, 11% with three fixed wing aircraft and 7% with four fixed wing aircraft in the heterogeneous set.

In conclusion, the proposed methodology was capable of tasking a heterogeneous set of UAV assets to successfully satisfy mission requirements for the scenarios studied.

Selected simulation case study scenarios revealed that a post TOI located re-plan, including an additional VTOL multi-rotor UAV that visited POIs on its way to the TOI, reduced overall surveillance times compared to a homogeneous set of UAVs. Also, investigations into the use of more than three search aircraft found an inversely proportional relationship to mission time as the number of aircraft increased. In conclusion, the developed system will enable ground operators in the field to plan missions utilizing different classes of UAVs and provide intelligence faster than single assets.

References

[1] M. Flint, M. Polycarpou and E. Fernandez-Gaucherand, Cooperative path-planning for autonomous vehicles using dynamic programming, in *Proc. IFAC 15th Triennial World Congress*, (2002) pp. 1694–1699.

[2] M. Darrah, J. Wilhelm, T. Munasinghe, K. Duling, S. Yokum, E. Sorton, J. Rojas and M. Wathen, A flexible genetic algorithm system for multi-UAV surveillance: Algorithm and flight testing, *Unmanned Syst.*, **3**(1) (2015) 49–62.

[3] T. Perkins and R. R. Murphy, Active and mediated opportunistic cooperation between an unmanned aerial vehicle and an unmanned ground vehicle, *2013 IEEE Int. Symp. Safety, Security, and Rescue Robotics (SSRR)*, (IEEE, 2013), pp. 1–8.

[4] S. Ponda, H.-L. Choi and J. P. How, Predictive planning for heterogeneous human-robot teams, *AIAA Infotech@ Aerospace* (2010).

[5] R. Kilgore, K. Harper, C. Nehme and M. Cummings, Mission planning and monitoring for heterogeneous unmanned vehicle teams: A human-centered perspective. In *AIAA Infotech@Aerospace 2007 Conference and Exhibit* (2007), p. 2788.

[6] A. Richards, J. Bellingham, M. Tillerson and J. How, Coordination and control of multiple UAVs, *AIAA Guidance, Navigation, and Control Conf.* Monterey, CA (2002).

[7] C. Schumacher, P. Chandler, M. Pachter and L. Pachter, Constrained optimization for UAV task assignment, in *Proc. AIAA Guidance, Navigation, and Control Conf.* (American Institute of Aeronautics and Astronautics Inc, Reston, VA, USA, 2004), pp. 1–14.

[8] M. A. Darrah, W. M. Niland and B. M. Stolarik, Multiple UAV dynamic task allocation using mixed integer linear programming in a sead mission, *Infotech@ Aerospace* (2005), pp. 26–29.

[9] J. J. Wang, Y. F. Zhang, L. Geng, J. Y. H. Fuh and S. H. Teo, Mission planning for heterogeneous tasks with heterogeneous UAVs, *13th Int. Conf. Control Automation Robotics & Vision (ICARCV), 2014* (IEEE, 2014), pp. 1484–1489.

[10] J. Wang, Y. F. Zhang, L. Geng, J. Y. H. Fuh and S. H. Teo. A heuristic mission planning algorithm for heterogeneous tasks with heterogeneous UAVs, *Unmanned Syst.* **3**(3) (2015) 205–219.

[11] W. Zheng, L. Qiaoqiao, T. Hongtao and L. Jianxun, Multiple task planning based on ts algorithm for multiple heterogeneous unmanned aerial vehicles, *Guidance, Navigation and Control Conf. (CGNCC), 2014 IEEE Chinese* (IEEE, 2014), pp. 630–635.

[12] S. Leary, M. Deittert and J. Bookless, Constrained UAV mission planning: A comparison of approaches. *2011 IEEE Int. Conf. Computer Vision Workshops (ICCV Workshops)*, (IEEE, 2011), pp. 2002–2009.

[13] B.-M. Jeong, J.-S. Ha and H.-L. Choi, Mdp-based mission planning for multi-UAV persistent surveillance, *2014 14th Int. Conf. Control, Automation and Systems (ICCAS)*, (IEEE, 2014), pp. 831–834.

[14] S. Ragi and E. K. P. Chong, UAV path planning in a dynamic environment via partially observable markov decision process. *IEEE Trans. Aerosp. Electron. Syst.* **49**(4) (2013) 2397–2412.

[15] K. Tulum, U. Durak and S. K. Yder, Situation aware UAV mission route planning. *Aerospace Conf. 2009 IEEE*, (IEEE, 2009), pp. 1–12.

[16] Y. Wei, G. R. Madey and M. B. Blake, Agent-based simulation for UAV swarm mission planning and execution, in *Proc. Agent-Directed Simulation Symposium* (Society for Computer Simulation International, 2013), p. 2.

[17] J. M. Galán, L. R. Izquierdo, S. S. Izquierdo, J. I. Santos, R. D. Olmo, A. López-Paredes and B. Edmonds, Errors and artefacts in agent-based modelling, *J. Artif. Soc. Soc. Simulat.* **12**(1) (2009) 1.

[18] D. Rathbun, S. Kragelund, A. Pongpunwattana and B. Capozzi, An evolution based path planning algorithm for autonomous motion of a UAV through uncertain environments, in *Digital Avionics Systems Conf. 2002. Proc. The 21st*, Vol. 2, (IEEE, 2002), p. 8D2–1.

[19] S. N. Sivanandam and S. N. Deepa, Genetic algorithms, in *Introduction to Genetic Algorithms* (Springer, 2008), pp. 15–37.

[20] I. K. Nikolos, K. P. Valavanis, N. C. Tsourveloudis and A. N. Kostaras, Evolutionary algorithm based offline/online path planner for UAV navigation. *IEEE Trans. Systems, Man, Cybern. B, Cybern.* **33**(6) (2003) 898–912.

[21] C. Zheng, L. Li, F. Xu, F. Sun and M. Ding, Evolutionary route planner for unmanned air vehicles, *IEEE Trans. Robot.* **21**(4) (2005) 609–620.

[22] X.-G. Gao, X.-W. Fu and D.-Q. Chen, A genetic-algorithm-based approach to UAV path planning problem, in *Proc. 5th WSEAS Int. Conf. Simulation, Modelling and Optimization* (World Scientific and Engineering Academy and Society (WSEAS), 2005), pp. 523–527.

[23] M. Darrah, E. Fuller, T. Munasinghe, K. Duling, M. Gautam and M. Wathen, Using genetic algorithms for tasking teams of raven UAVs, *J. Intel. Robot. Syst.* **70**(1–4) (2013) 361–371.

[24] J. Tian, L. Shen and Y. Zheng, Genetic algorithm based approach for multi-UAV cooperative reconnaissance mission planning problem, in *Foundations of Intelligent Systems* (Springer, 2006), pp. 101–110.

[25] W.-L. Yang, L. Lei and J.-S. Deng, Optimization and improvement for multi-UAV cooperative reconnaissance mission planning problem. in *2014 11th Int. Computer Conf. Wavelet Active Media Technology and Information Processing (ICCWAMTIP)* (IEEE, 2014), pp. 10–15.

[26] J. Redding, J. Amin, J. D. Boskovic and J. Jackson, Collaborative mission planning, autonomy and control technology (compact) for unmanned surface vehicles, *AIAA Guidance, Navigation and Control Conf.* Chicago, Illinois, (2009), pp. 10–13.

[27] X. Chen and X. Chen, The UAV dynamic path planning algorithm research based on voronoi diagram, *Control and Decision Conf. (2014 CCDC), The 26th Chinese* (IEEE, 2014), pp. 1069–1071.

[28] J. N. Wilburn, M. G. Perhinschi, B. K. Wilburn and O. Karas, Development of a modified voronoi algorithm for UAV path planning and obstacle avoidance. In *AIAA Guidance, Navigation, and Control Conf.*, Minneapolis, Minnesota (2012), p. 4904.

[29] J. F. Araujo, P. B. Sujit and J. B. Sousa, Multiple UAV area decomposition and coverage, *Computational Intelligence for Security and Defense Applications (CISDA), 2013 IEEE Symp.* (IEEE, 2013), pp. 30–37.

[30] L. E. Dubins, On curves of minimal length with a constraint on average curvature, and with prescribed initial and terminal positions and tangents, *Am. J. Math.* **79**(3) (1957) 497–516.

[31] D. J. Grymin and A. L. Crassidis, Simplified model development and trajectory determination for a UAV using dubins set, *AIAA Atmospheric Flight Mechanics Conf.* (2009), p. 6050.

[32] M. Shanmugavel, A. Tsourdos, B. White and R. Żbikowski, Co-operative path planning of multiple UAVs using dubins paths with clothoid arcs, *Control Eng. Pract.* **18**(9) (2010) 1084–1092.

[33] A. N. Kopeikin, S. S. Ponda, L. B. Johnson and J. P. How, Dynamic mission planning for communication control in multiple unmanned aircraft teams, *Unmanned Syst.* **1**(1) (2013) 41–58.

[34] 3D Robotics Inc. Aero operation manual, Retrieved September 2016 from http://3dr.com/support/articles/208396893/user_manual/.