Dynamic Heuristics for Surveillance Mission Scheduling with Unmanned Aerial Vehicles in Heterogeneous Environments

Dylan Machovec, James A. Crowder, Howard Jay Siegel, Sudeep Pasricha, and Anthony A. Maciejewski

1 Introduction

Unmanned aerial vehicles (UAVs) are used in many environments to gather information, such as in active battlefields scenarios. An example of such a scenario is shown in Fig. 1. In this example, seven UAVs are being used to gather information about nine targets. Assuming that a UAV can only surveil a single target at a time, this is an oversubscribed scenario, which means that there are more targets than UAVs and it will not be possible to surveil all targets simultaneously with the fleet of UAVs. To gather as much useful information about the targets as possible, it is necessary to conduct mission planning and scheduling to determine how the UAV fleet should effectively surveil the targets.

As both the number of UAVs that are active simultaneously and the number of targets available in an environment increases, it becomes necessary to reduce the amount of human control and human scheduling required to operate them effectively [1]. This can be accomplished by designing and deploying heuristic techniques that can find effective mission scheduling solutions.

D. Machovec (✉) · A. A. Maciejewski
Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO, USA

J. A. Crowder
Colorado Engineering, Inc., Colorado Springs, CO, USA
e-mail: jim.crowder@coloradoengineering.com

H. J. Siegel · S. Pasricha
Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO, USA

Department of Computer Science, Colorado State University, Fort Collins, CO, USA
e-mail: hj@colostate.edu; sudeep@colostate.edu

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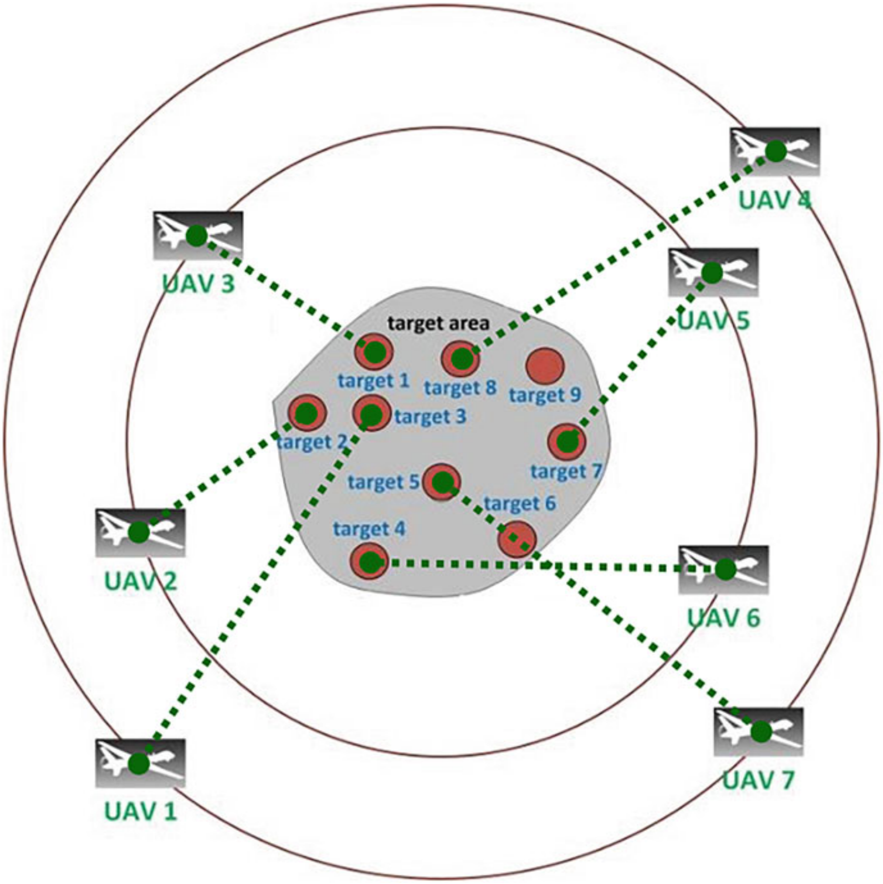

Fig. 1 An example scenario with seven UAVs and nine targets. The UAVs have fixed flight paths, which follow one of two circular paths around the area containing the targets that are candidates for surveillance

In this study, our focus is on the design of mission scheduling techniques capable of working in dynamic environments that are suitable for determining effective mission schedules in real time. Because scheduling problems of this type are, in general, known to be NP-Hard, finding optimal solutions is not feasible [2]. Due to this, we consider fast heuristic techniques to find mission schedules and evaluate their performance when compared to mathematical upper bounds we derive and simple baseline heuristics we generate. These techniques are capable of generating the mission schedules required by our environment in less than a second.

To effectively compare and evaluate these techniques, we measure system-wide performance using a metric called surveillance value. Surveillance value is designed to measure the overall performance of all information gathered by the UAVs, based on the number of surveils that occur, the quality of information gathered by each surveil (e.g., image resolution), the overall importance of each target, and the relevance of the information obtained for a specific target.

This work builds on our previous work in [3, 4], which defined surveillance value as the system-wide performance measure and explored bi-objective trade-offs between surveillance value and energy consumption in a static environment where all mission planning decisions are made once in advance. This work considers a dynamic (instead of static) environment and attempts to maximize surveillance value while considering energy consumption as a hard constraint.

The novel contributions in this work include:

- The design of new mission scheduling heuristics that are used to dynamically determine which UAVs should be used to surveil each target and additionally which sensors should be used for these surveils
- Extending the model of surveillance targets in [4] to require a minimum interval of time between consecutive surveils of the same target
- A model for randomly generating scenarios defined by a set of UAVs and targets for the purpose of effectively evaluating mission scheduling techniques, such as the heuristics considered in this work
- A detailed analysis and comparison of heuristics across many simulated scenarios with varied characteristics

This chapter is organized as follows. In Sect. 2, the system model and environment are described. The methods used by both the novel mission scheduling heuristics and the comparison heuristics evaluated in this study are presented in Sect. 3. Section 4 contains the specific process used to generate all of the scenarios we use in our simulations. In Sect. 5, we show the results of the simulations and use the results to analyze and compare the behavior of the heuristics. Related work is discussed in Sect. 6 and finally in Sect. 7 we conclude and discuss possible future work that could build on this study.

2 System Model

2.1 Overview

For this study, we use a simplified model of a real environment; our future studies that build on this research will continue to enhance this model. The system considered in this study consists of a heterogeneous set of UAVs (with varying sensor and energy characteristics) and a heterogeneous set of targets (with varying surveillance requirements). These sets are constant, meaning that UAVs and targets will not be added or removed dynamically. During the time when we consider mission scheduling, the UAVs fly in continuous concentric circles at a constant speed around the target area, which contains the entire set of targets. This is a simplifying assumption because the techniques we consider in this study do not control the flight path of the UAVs. It is assumed that every UAV is always close enough to every target and has an unobstructed view of every target so that any sensors available to any UAV can be used to surveil any target at any time. A UAV can only surveil a single target at any given time. Because UAVs cannot stay airborne indefinitely, this work considers mission scheduling strategies for a single day. This means that at the end of the day, all UAVs would be able to return to their base of operations to refuel or recharge. The problem space we explore is made up of oversubscribed systems, which means that there are fewer UAVs than targets. This prevents all targets from being surveilled simultaneously; however, the techniques designed and evaluated in this study are still applicable to undersubscribed systems.

2.2 Target and UAV Characteristics

In this environment, each UAV has a single energy source with a fixed amount of total energy available to it. In our subsequent discussions, we normalize this value so that the maximum amount of energy available to any UAV is less than or equal to 1.0. Every UAV is equipped with one or more sensors that can be used to surveil targets. The sensor types considered in this work are visible light sensors (VIS), infrared light sensors (IR), synthetic-aperture radars (SAR), or light detection and ranging systems (LIDAR). Each UAV cannot have more than one sensor of a given type, which is a simplifying assumption in this work. The heuristics presented in this study can be easily modified to function in environments with multiple sensors with the same type. Each sensor available to a UAV also has an associated sensor quality value ranging from 0.0 to 1.0 and a rate of energy consumption, which is normalized to the total energy available to the UAV and ranges from 0.0 to 1.0. All sensors available to a UAV draw from the same source of energy. An example set of characteristics for seven UAVs is shown in Table 1, based on the table in [4].

Targets represent locations of interest to be potentially surveilled by UAVs. Because the environments we consider are often oversubscribed (there are more targets than UAVs), it is possible that some targets will not be surveilled. An unchanging priority value is assigned to each target, which represents the overall importance of surveilling the target. Priority values can be any positive number, where higher numbers represent more important targets. Each target has a fixed surveillance time value, which specifies the number of hours per day that a UAV

Table 1 UAV characteristics

Characteristics	UAV 1	UAV 2	UAV 3	UAV 4	UAV 5	UAV 6	UAV 7
Sensor type	VIS|IR	VIS	SAR	LIDAR|IR	SAR|IR	VIS|IR	SAR|LIDAR
Sensor quality	0.9|0.7	0.5	0.5	0.7|0.8	0.8|0.7	0.9|0.7	0.8|0.8
Energy used/hour	0.08|0.06	0.08	0.08	0.1|0.06	0.125|0.06	0.07|0.06	0.125|0.08
Total energy	1.0	0.8	0.9	0.7	0.8	0.6	1.0

should spend surveilling the target. Because the kind of information that is useful for each target may vary, targets have a set of surveillance types, which defines the sensor types that are allowed to surveil the target, and a list of sensor affinity values, which range from 0.0 to 1.0 and measure how useful or relevant the information gained from that sensor type is for the target. There is a constraint on the number of times a target may be surveilled by all UAVs in a day called the surveillance frequency of the target. Finally, we define a minimum time between surveils for each target because information gained from back-to-back surveils of a target is likely to contain repeat information compared to surveils that are spread throughout the day. Table 2 lists an example set of characteristics for nine targets, which is also based on [4].

2.3 Surveillance Value

To evaluate the performance of different techniques for assigning UAVs to targets, it is necessary to measure the worth of individual surveils by a UAV on a target. We use the concept of surveillance value [4] to achieve this, where for a given surveil, the value of that surveil is given by the product of the priority (ρ), sensor affinity (α), and sensor quality (γ) associated with the UAV (u), target (t), and used sensor type (s):

$$\text{value (surveil)} = \rho(t) * \alpha\,(t, s) * \gamma\,(u, s)\,. \tag{1}$$

The total surveillance value earned over an interval of time is then defined by the sum of values earned by all surveils performed by UAVs in that interval of time:

$$\text{surveillance value} = \sum_{\substack{\text{s} \in \text{surveils} \\ \text{performed}}} \text{value (s)}\,. \tag{2}$$

If a surveil is not fully completed during the day due to being in progress when the day ends, or due to the UAV lacking sufficient energy to finish a complete surveil of the target, then partial value will be earned for that surveil, which is directly proportional to the fraction of the surveil that was completed. For example, if a full surveil of a target takes 4 h and only 3 h of this were completed in the interval of interest, then the value of that surveil in that interval of time would be 75% of the value given by the fully completed surveil.

Table 2 Target characteristics

Characteristics	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9
Priority	1	2	6	7	5	4	3	3	1
Surveillance type	SAR|IR|VIS	SAR|LIDAR	VIS|SAR	VIS|IR|SAR|LIDAR	VIS	IR|LIDAR	SAR|VIS	SAR|IR|VIS	VIS
Sensor affinity	0.8|0.6|0.9	0.9|0.7	1.0|0.8	1.0|0.7|0.9|0.8	1.0	0.8|0.7	0.9|1.0	0.9|0.8|1.0	1.0
Surveillance time	3 h	4 h	1 h	3 h	2 h	1 h	3 h	3 h	4 h
Surveillance freq. (#/day)	4	3	5	2	4	5	3	3	4
Min. time betw. surveils	2 h	3 h	4 h	8 h	3 h	4 h	3 h	6 h	2 h

2.4 Problem Statement

The goal of our proposed scheduling techniques in this environment is to assign UAVs to targets in a particular order to obtain as much useful surveillance information as possible. This problem is constrained by the total energy available to each UAV. In this study, this constraint is only applied to the energy consumed by a UAV's sensors. The energy needed for the UAV's fixed flight plan is not included in the energy available to the sensors. Because the flight plan is fixed, it is also not possible for the UAV to refuel at any point during the day, such as while there are no targets available for it to surveil. Additionally, each UAV can only surveil one target and only operate one of its sensors at any time; similarly, each target can only be surveilled by one UAV at any time. This is a simplifying assumption used in this study. Because there may be duplicate information obtained from surveilling a target with multiple sensors at once, the surveillance value performance measure would need to be adjusted to account for this. Once a UAV begins surveilling a target, this surveil cannot be preempted unless the UAV does not have enough energy to continue (i.e., the surveil cannot be stopped early to allow the UAV to surveil a different target). Given the above constraints, the final goal is to maximize the total surveillance value obtained over a day.

3 Mission Scheduling Techniques

3.1 Mapping Events

Mapping UAVs to targets refers to the process of determining which UAVs will surveil which targets, which sensors will be used for surveils, and when the surveils will occur. A UAV is available to be mapped if it is not currently surveilling targets and has energy remaining. A target is available to be mapped if it is not currently being surveilled and it is eligible for being surveyed based on its surveillance frequency and its minimum time between surveils. A sensor of a UAV is said to be a valid sensor type for a given target if that sensor type is also in the target's list of surveillance types. If a UAV has a valid sensor type for a target, it is called a valid UAV for that target. Only valid UAVs are considered for mapping to a given available target.

The time when a mapping of available UAVs to available targets occurs is called a mapping event. When a mapping event happens, a mission scheduling technique is used to assign available UAVs to surveil available targets based on the current state of the system. In this study, all techniques presented are real-time heuristics to allow mapping events to be completed in less than a second for the problem sizes considered. There are different techniques for deciding when a mapping event should be initiated, e.g., at fixed time intervals or due to changes in the environment. In this study, we consider the case where mapping events occur every 6 min during the day if there are available UAVs and available targets. By using a time interval such as 6 min when the minimum surveillance time of any target is 1 h, any delay where a UAV is not surveilling a target because a mapping event has not yet occurred is small. This 6 min time interval provides some opportunity for multiple UAVs to become available during that window, which increases the number of choices available to the mission scheduling technique. Other values for the time interval can be implemented instead of 6 min. In a real-world implementation, this interval of time can be derived based on empirical evaluations of the characteristics of the actual system. While our resource manager is designed to deal with dynamic environments, such as those with time-varying UAV and target characteristics, in this simulation study the environment is non-varying.

3.2 Comparison Techniques

For comparison, two randomized heuristics are considered. Randomized heuristics are often better points of comparison than heuristics that use extremely simple logic to make mapping decisions. For example, in high performance computing, simple randomized heuristics often perform better than simple ordered techniques like first-come-first-served [5].

3.2.1 Random

At a mapping event, this technique considers available targets in a random order. For each target, a random available valid UAV and a random valid sensor type of that UAV are selected. The selected UAV and sensor type are assigned to surveil the target. This results in both the target and the UAV becoming unavailable for new assignments until this new surveil completes. If there is no available UAV that has a valid sensor type for the target, then no UAV is assigned to the target. This repeats with the next target in the random ordering until there are no more assignments of UAVs to targets possible in the current mapping event.

3.2.2 Random Best Sensor

The random best sensor heuristic is similar to the random technique, but uses knowledge about the sensor quality of UAVs and the sensor affinity of targets to make decisions that are likely to result in higher surveillance value. Like the random heuristic, available targets are considered in a random order and a UAV with a valid sensor type for this target is selected at random. However, instead of selecting a random valid sensor type from the UAV, this heuristic then chooses the sensor type with the maximum product of the UAV's sensor quality and the target's sensor affinity. Because both of these values are directly used along with the target's priority in the calculation for the value of a surveil, this strategy will likely select higher value surveils when compared to the random heuristic if they are available on the selected UAV. After this, the same process used by the random heuristic is followed: the UAV is assigned to surveil the target with this sensor type and the heuristic will continue with the next randomly ordered target until no more assignments are possible.

3.3 Value-Based Heuristics

The value-based heuristics in this study are designed to search through valid combinations of UAVs, targets, and sensor types to greedily assign UAVs to surveil targets based on the surveillance value performance measure. A valid combination is represented by an available target, a valid available UAV for that target, and a valid sensor type of the UAV for the target.

3.3.1 Max Value

At a mapping event, the max value heuristic starts by finding a valid combination of a UAV, target, and sensor type that results in the maximum possible value for a single surveil. If there are multiple valid combinations with the same maximum possible value, then any of these combinations can be selected arbitrarily. The heuristic then assigns the UAV from the selected combination to surveil the selected target with the selected sensor type. This process of finding the maximum value combination and starting a surveil based on the combination repeats until no more assignments of available UAVs to available targets are possible in the current mapping event.

3.3.2 Max Value per Time

The max value per time heuristic is identical to max value except for one difference. Instead of selecting the valid combination that results in the maximum possible value for a surveil, max value per time instead selects the valid combination that results in the maximum possible value divided by surveillance time of the target (based on a complete surveil of the target).

3.3.3 Max Value per Energy

The max value per energy heuristic is identical to max value except for one difference. Instead of selecting the valid combination that results in the maximum possible value for a surveil, max value per energy instead selects the valid combination that results in the maximum possible value divided by the projected energy consumed by the UAV. The projected energy consumption can be easily calculated from the energy consumption rate of the selected sensor type and the surveillance time of the selected target (based on a complete surveil of the target). We have used the general concept of performance per unit time and performance per unit of energy in prior work in a high-performance computing environment, e.g., [5, 6].

3.4 UAV-Based Metaheuristic

The value-based heuristics described in Sect. 3.3 are designed to perform well in specific situations, and using the wrong heuristic for a scenario could result in performance that is worse than using random. Because there may be insufficient information to predict which heuristic should be used, we design a metaheuristic to intelligently combine the best performing value-based heuristics. This does not include the max value per time heuristic because in the scenarios we consider, max value per time never performs better than both max value and max value per energy. The UAV-based metaheuristic uses a two-phase process to find good surveillance options. This is similar in concept to the metaheuristic we designed in [5] for a different environment.

In the first phase, the heuristic selects a candidate target and valid sensor type for each UAV. To make this selection, the UAV's remaining energy is used to determine if the strategy used by the max value or max value per energy heuristic would be most effective. If the remaining fraction of the UAV's energy is greater than the remaining fraction of time in the day, then its energy has been consumed at a relatively slow rate during the day and it makes sense to use the strategy from max value to make decisions without considering energy consumption. Otherwise, the UAV has been consuming energy at a relatively high rate and the strategy from max value per energy can be used to make energy-efficient decisions. Based on this choice, either the valid combination using the UAV that results in the maximum possible value or the maximum possible value divided by energy consumed is selected as the best candidate combination for the current UAV. The first phase ends when every UAV has a candidate combination selected. Note that multiple UAVs can select the same target as their candidate.

The second phase is used to determine which UAV from the first phase should be assigned to its candidate target and sensor type. Unlike the first phase, it is unnecessary to use strategies from multiple value-based heuristics in the second phase. This is because energy is a constraint for individual UAVs and not for the overall system. At the system level, all that is relevant to maximizing surveillance value is the value of each surveil. Thus, we choose the UAV with a candidate combination that results in the maximum possible value earned by its corresponding surveil. This chosen UAV is assigned to surveil its target. This process of selecting candidates in the first phase and making an assignment of the best candidate in the second phase is repeated until no more assignments are possible in the current mapping event.

4 Simulation Setup

4.1 Generation of Baseline Set of Randomized Scenarios

Each scenario that we use to evaluate the heuristics is defined by a set of UAV characteristics and a set of target characteristics. For example, a small sample scenario with seven UAVs and nine targets is defined in Tables 1 and 2. To compare and evaluate the heuristics, we consider a wide variety of scenarios to understand the kinds of scenarios for which each heuristic is most effective.

We randomly generate 100 baseline scenarios by sampling from probability distributions for the number of UAVs and targets in a scenario, in addition to the value for each characteristic of the UAVs and targets. In each case, distributions were selected in a way to attempt to model distributions of parameters that may occur in real-world environments. The details of these distributions are as follows.

The number of UAVs available during the 24 h period of a scenario is sampled from a Poisson distribution with the Poisson parameter $\lambda = 70$. The characteristics of each UAV are then generated. The total energy available to the UAV is sampled from a beta distribution with a mean of 0.8 and a standard deviation of 15% of the mean. The energy consumption rate for each sensor is sampled from a beta distribution with a mean of 0.1 and a standard deviation of 30% of the mean. The total energy and energy consumption rates are sampled in this way so that UAVs can be expected to operate for an average of 8 h, which is enough to allow multiple surveils during the day for most UAVs. The number of sensors available to each UAV is generated by using a Rayleigh distribution with a scale parameter $\sigma = 2$. Any values <1 are increased to one and any values >4 are decreased to 4.

The sensor type for each sensor is selected using probabilities of 0.5, 0.2, 0.2, and 0.1 for the VIS, SAR, IR, and LIDAR sensor types, respectively. Once a sensor has been assigned a type using the listed probabilities, that sensor type is no longer a candidate and the next sensor is chosen among the remaining sensors types after normalizing their probabilities so that the sum is 1.0. The quality of each sensor is found using a beta distribution with a mean of 0.8 and a standard deviation of 10% of the mean.

The number of targets available to surveil during the 24 h period is obtained using a Poisson distribution with $\lambda = 90$. Because the number of UAVs was generated with $\lambda = 70$, this means that these scenarios in general will be oversubscribed. The priority of each target is sampled from a gamma distribution with a mean of 4 and a standard deviation of 20% of the mean. To obtain the required surveillance time for each target, we use a uniform distribution ranging from 1 to 4 h. Differing from what was used for UAVs, we obtain the number of surveillance types for each target by adding 1 to the value obtained from a binomial distribution with $p = 0.5$ and $n = 3$. The surveillance types selected to match this number are uniformly selected from VIS, SAR, IR, and LIDAR. To get the sensor affinity for each surveillance type, we use a beta distribution with a mean of 0.7 and a standard deviation of 20% of the mean. A discrete uniform distribution allowing values of 2, 3, 4, or 5 is used to find the surveillance frequency for each target. Lastly, a two-step process is needed to generate the minimum time between surveils for each target. We sample a value from a gamma distribution with a mean of 2 h and a standard deviation of 20% of the mean. When generating scenarios, we require that it is possible for a target to be fully surveilled a number of times equal to its surveillance frequency within 24 h. The total time (T) needed for these surveils can be calculated from the surveillance time (τ), surveillance frequency (ω), and minimum time between surveils (δ). It is given by:

$$T = \tau * \omega + (\omega - 1) * \delta. \tag{3}$$

To ensure that the total surveillance time for a UAV does not exceed 24 h, the minimum time between surveils is set to the smaller of the sampled value from the gamma distribution and the maximum time between surveils (Δ):

$$\Delta = \frac{24\text{ h} - \tau * \omega}{\omega - 1}. \tag{4}$$

4.2 Generation of Additional Scenarios for Parameter Sweeps

Because the baseline set of 100 scenarios in Sect. 4.1 may have characteristics that are favorable to the performance of individual heuristics, we use parameter sweeps to evaluate the heuristics in a diverse set of environments. We generate 22 additional sets of 100 scenarios each for the parameter sweeps of five characteristics of the UAVs and targets. The characteristics we vary are the mean time between surveils of targets (five sets in addition to the baseline), the mean number of targets in a scenario (four sets in addition to the baseline), the mean number of UAVs in a scenario (four sets in additional to the baseline), the mean rate of energy consumption for sensors (five sets in addition to the baseline), and the mean total energy available to each UAV (four sets in addition to the baseline). The number of sets for each characteristic was selected such that the impact of each characteristic on the performance of the heuristics is clearly shown.

To vary the minimum time between surveils of targets, we vary the mean of the gamma distribution used over the integers ranging from 1 to 5. Additionally, we consider the case where the minimum time between surveils is 0 h for all targets. For each of these cases, 100 scenarios are generated. We examine the effect of varying the number of targets and number of UAVs by generating 100 scenarios each for the cases with λ values of 50, 70, 90, 110, and 130 for the number of targets and 30, 50, 70, 90, and 110 for the number of UAVs. Finally, we vary the mean energy consumption of sensors and mean total energy available to each UAV. Instead of sampling all of the distributions again in this case, we take the 100 baseline scenarios from Sect. 4.1 and scale the values to match the new means.

5 Simulation Results

5.1 Upper Bounds on Performance

We calculate upper bounds on the possible surveil value that can be obtained in each scenario. While the optimal result is likely significantly below these bounds, they provide additional insight when evaluating the results. Two different methods of calculating upper bounds are used. The minimum of these upper bounds is then selected for each scenario to produce the final upper bound shown in our results.

The target-based upper bound is found by first calculating the maximum possible surveillance value that can be earned by each target individually. This is done by assuming that the UAV that would produce the most value for a single surveil will surveil the target the maximum number of times allowed by the surveillance frequency of the target. For example, consider using UAV 1 from Table 1 to surveil Target 1 from Table 2. The valid sensor types are VIS and IR. Following the process for calculating surveil value in Sect. 2.3, VIS results in a surveillance value for a single surveil of 1.0 * 0.9 * 0.9 * = 0.81 and with IR the surveillance value is 1.0 * 0.7 * 0.6 = 0.42. The best option for this UAV is to use the VIS sensor with 0.81 surveillance value for a single surveil. This is greater than or equal to the surveillance value from a single surveil for all UAVs that can surveil Target 1. If we assume that UAV 1 is used to surveil Target 1 four times (the surveillance frequency of Target 1), a total of 3.24 surveillance value will be gained, which is an upper bound on the surveillance value earned by Target 1. This process can be repeated for all targets to find an upper bound on surveillance value for the entire scenario.

The energy-based upper bound is calculated by finding an upper bound for each UAV individually and then summing the results. For a given UAV, this method finds the best possible way that the UAV's energy can be spent assuming there are no other UAVs surveilling targets in the scenario. To do this, we first construct a list of all possible valid combinations of targets and sensor types that can be surveilled by the UAV. The surveillance value divided by projected energy consumed for each combination is then calculated and the list is sorted in descending order based on these amounts. This list is then traversed in order starting with the most energy-efficient combination. For each combination, assume that the UAV spends as much energy as possible on that option. This is constrained by the surveillance frequency of the target in addition to the total energy remaining for the UAV. For example, consider the simple example of UAV 1 from Table 1 and the first three targets from Table 2. The most energy-efficient option here is using UAV 1 to surveil Target 3 with its sensor of type VIS. Each surveil of Target 3 takes 1 h and the VIS sensor consumes 0.08 units of energy per hour of surveillance. This would result in a surveillance value per unit of energy of (6 * 1.0 * 0.9)/(1 * 0.08) = 67.5. This target can be surveilled at most five times. Each surveil requires 1 h and consumes 0.08 units of energy per hour. This results in 5 * 0.08 = 0.4 of the UAV's 1.0 total energy. This set of surveils earns 27 surveillance value with Target 3. As the UAV still has 0.6 of its energy remaining, we move to the next best option in terms of energy efficiency, which is Target 1, again with the VIS sensor resulting in 0.81 value for each completed surveil. This target can only be surveilled 2.5 times before UAV 1 will consume the rest of its energy. Considering half of a surveil worth of value for the partial surveil, this will result in 2.5 * 0.81 = 2.025 surveillance value for Target 1. Considering just this set of three targets, the maximum possible surveillance value that can be earned by UAV 1 is 27 + 2.025 = 29.025. After repeating this process for all UAVs, we sum up the resulting maximum possible surveillance values from each UAV to get the energy-based upper bound on surveillance value for an entire scenario.

5.2 Comparisons of Mission Scheduling Techniques

As described in Sect. 4.2, the results shown in this section consist of parameter sweeps where the means of the distributions described in Sect. 4.1 are varied. In addition to the upper bounds on performance (Sect. 5.1) for the results that quantify value obtained, the results that quantify energy consumed also include upper bounds on energy consumption. Calculating the upper bound for energy consumption is very simple: By summing the total energy values from all UAVs. This upper bound can be obtained because the total energy of each UAV acts as a hard constraint on the energy it can expend. It is important to note that the upper bounds for energy and for values (performance) shown in the result figures are average upper bounds over the 100 scenarios considered. This means that in some cases, individual scenarios will surpass these upper bounds, but the average over all 100 scenarios will not. It is also possible that the 95% mean confidence intervals shown for each set of results will surpass these upper bounds for the same reason.

5.2.1 Effect of Minimum Time Between Surveils

In Fig. 2, we vary the mean minimum time required between surveils. Because this value is sampled from a gamma distribution and a mean of 0 is not possible for a gamma distribution, the set of bars marked with a 0 mean corresponds to the case where all targets have no time required between surveils. There are three main points to observe from this comparison. First, as the minimum time between surveils is increased, the value earned by max value per time decreases significantly and becomes less than the value earned from the random heuristics. This occurs because the max value per time only considers the time the UAV spends surveilling a target and not the time afterwards where the target will be unavailable. Due to this, max value per time is generally not a suitable heuristic for the environment considered in this study where the minimum time between surveils is not 0. Second, the other value-based heuristics are always the three best heuristics and earn similar amounts of value. Third, despite the max value per energy heuristic earning a significant amount of value, it consumes far less energy than most other heuristics, which

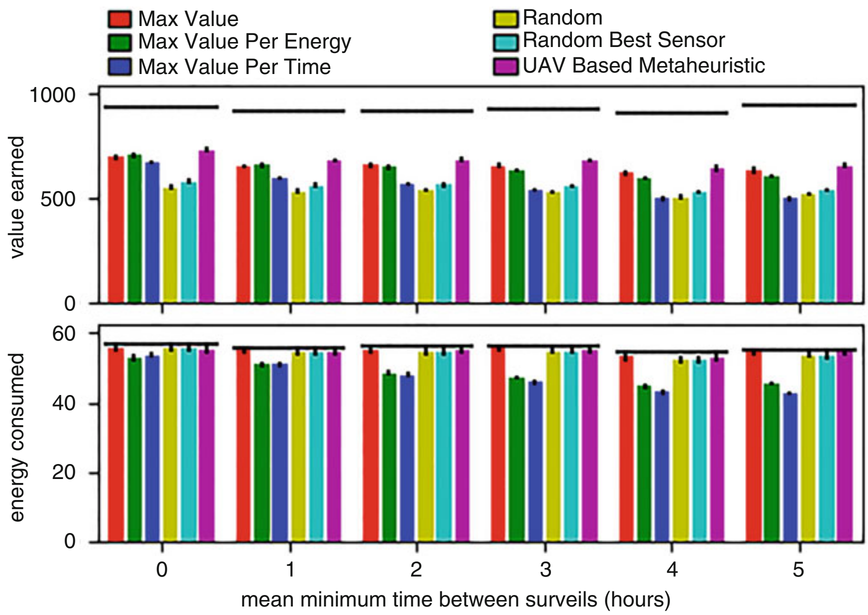

Fig. 2 A comparison of the average total energy consumed and average surveillance value earned for 100 randomized scenarios where the mean minimum time between surveils for targets is varied from the baseline set of scenarios with a mean minimum time between surveils of 2 h. Except for the minimum time between surveils, which is varied, the other parameters have the same value as the baseline case described in Sect. 4.1. Average upper bounds are indicated by horizontal black lines above each set of bars and 95% mean confidence intervals are shown for each bar

always consume energy close to the upper bound for these scenarios. This means that as the minimum time between surveils increases and max value per energy consumes less energy, max value and the metaheuristic start to earn more value.

5.2.2 Effect of Energy Consumption Rate

Results of simulations where the mean energy consumption per hour is varied are shown in Fig. 3. It can be seen that when the rate of energy consumption is low, none of the heuristics is able to reach the upper bound for energy consumption because there is not enough time in the day for the UAVs to do so. These cases also get much closer to the upper bound on value earned because energy is no longer a significant constraint. It can be observed that the max value heuristic earns high value when the energy consumption rates are lowest and drops below the max value per energy heuristic when the energy consumption rates are at their highest. This shows that both heuristics are working as designed and was the motivation for creating the UAV-based metaheuristic, which can intelligently use the strengths of both options.

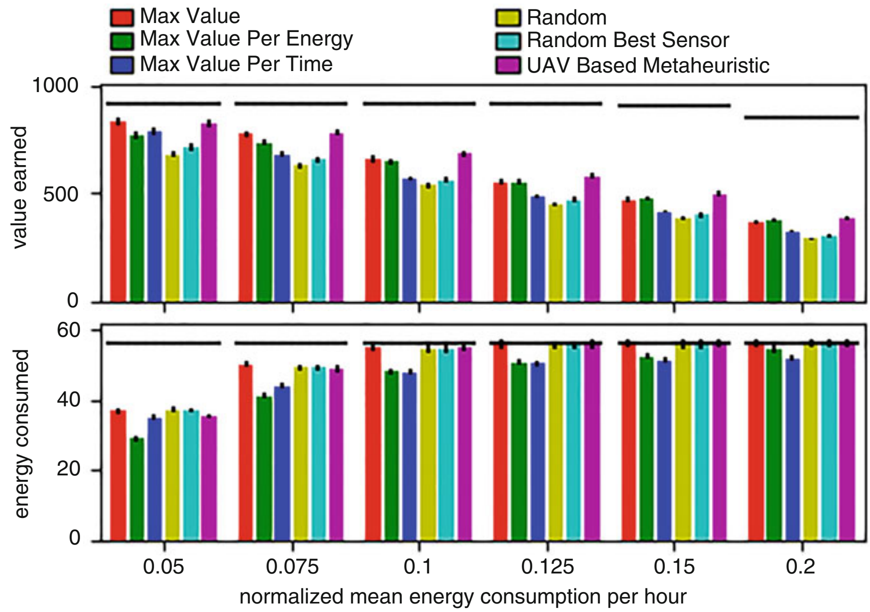

Fig. 3 A comparison of the average total energy consumed and average surveillance value earned for 100 randomized scenarios where the mean energy consumption per hour for each UAV sensor is varied. This variation is achieved through scaling the energy consumption values from the baseline with a mean energy consumption per hour of 0.1. Except for the mean energy consumption per hour, which is varied, the other parameters have the same value as the baseline case described in Sect. 4.1. Average upper bounds are indicated by horizontal black lines above each set of bars and 95% mean confidence intervals are shown for each bar

In these results, it can be seen that the metaheuristic always performs as well or better than both max value and max value per energy.

5.2.3 Effect of Total Energy

The results in Fig. 4 show what happens when the mean total energy available to each UAV. These results show similar behavior to the results with varied energy consumption rates, except that the difference among the max value, max value per energy, and UAV-based metaheuristic heuristics is not as large. This is partially because none of these scenarios result in the heuristics consuming significantly less energy than is available. This can be seen when comparing the energy consumption upper bounds in Figs. 3 and 4.

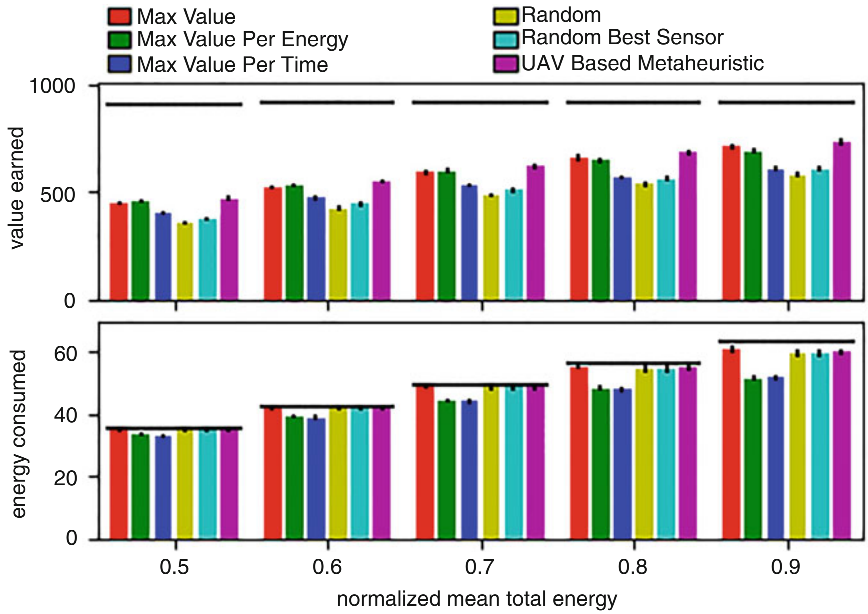

Fig. 4 A comparison of the average total energy consumed and average surveillance value earned for 100 randomized scenarios where the mean total energy of each UAV sensor is varied. This variation is achieved through scaling the total energy values from the baseline with a mean total energy of 0.8. Except for the mean total energy, which is varied, the other parameters have the same value as the baseline case described in Sect. 4.1. Average upper bounds are indicated by horizontal black lines above each set of bars and 95% mean confidence intervals are shown for each bar

5.2.4 Effect of Number of Targets

In Fig. 5, a comparison of different scenarios with a varied mean number of targets is shown. When there are few targets available, it is not possible to consume all of the energy available to the UAVs because there are more UAVs than targets on average and some UAVs will not be able to surveil targets for a significant portion of the day because all targets will be under surveillance already by other UAVs. As the number of targets in a scenario grows, it can be seen that it becomes very easy to consume all of the energy available to the UAVs. This is because there are many targets and all UAVs are likely to be able to surveil targets continuously. The upper bounds for value earned increase significantly as the number of targets increase. In addition to UAVs being able to operate simultaneously, this effect is due to the fact that with more targets there is a higher probability that a high priority target with a sensor affinity that matches up well with each UAV will appear in a scenario. Lastly, it can be seen that the UAV-based metaheuristic again performs as well or better than both max value and max value per energy in all cases.

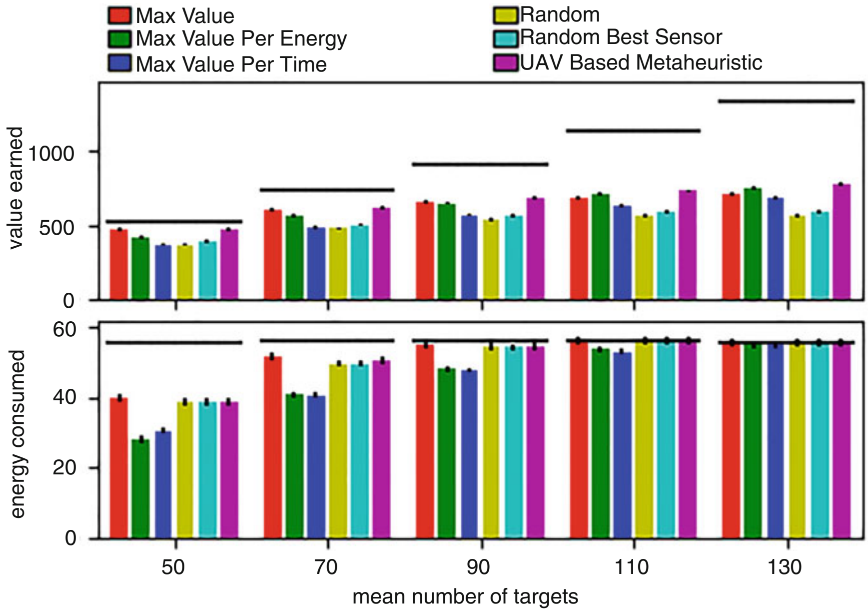

Fig. 5 A comparison of the average total energy consumed and average surveillance value earned for 100 randomized scenarios where the mean number of targets is varied through generating new scenarios in addition to the baseline, which has a mean of 90 targets in a single scenario. Except for the mean number of targets, which is varied, the other parameters have the same value as the baseline case described in Sect. 4.1. Average upper bounds are indicated by horizontal black lines above each set of bars and 95% mean confidence intervals are shown for each bar

5.2.5 Effect of Number of UAVs

Figure 6 shows simulation results for a set of randomized scenarios where the mean number of UAVs in a scenario is varied. These results show the biggest variance in value earned between max value and max value per energy. When there are a small number of UAVs, it is important to use each UAV efficiently, which means that max value per energy performs well. When there are many UAVs, it is more important to carefully pick which UAVs will get the most useful information for each target and energy is no longer a significant constraint because there will be unused UAVs still available when some UAVs start running out of energy. In this case, max value is most effective at picking the best target for each UAV. Once again, the UAV-based metaheuristic still earns value similar to the better of max value and max value per energy.

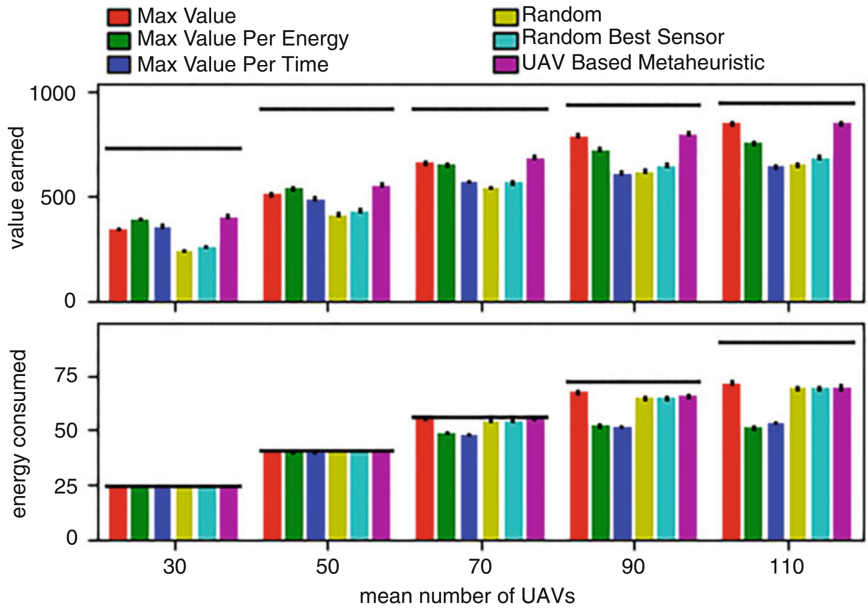

Fig. 6 A comparison of the average total energy consumed and average surveillance value earned for 100 randomized scenarios where the mean number of UAVs is varied through generating new scenarios in addition to the baseline, which has a mean of 70 UAVs in a single scenario. Except for the mean number of UAVs, which is varied, the other parameters have the same value as the baseline case described in Sect. 4.1. Average upper bounds are indicated by horizontal black lines above each set of bars and 95% mean confidence intervals are shown for each bar

5.3 Discussion of Results

The results in Sect. 5.2 indicate that depending on the scenario, either max value or max value per energy is an effective real-time heuristic for maximizing surveillance value. The UAV-based metaheuristic combines the strengths of both heuristics and is effective in all scenarios. The max value per time heuristic was shown to be ineffective in scenarios where there is a minimum time between surveils of targets, and resulted in poor performance in most of the scenarios that we considered. Additionally, when considering scenarios where the energy of UAVs will not be fully consumed during the day, max value per energy is ineffective. Based on these results, our proposed metaheuristic is the best option to use in all cases where the characteristics of the scenario may change unexpectedly.

6 Related Work

Developing a complete mission schedule for UAVs involves solving multiple problems, many of which have been studied in the past such as planning the specific routes used by UAVs, which we do not consider in this study, and assigning specific tasks to UAVs. Some studies solve these problems through time-consuming optimization techniques such as mixed integer linear programming (MILP), while others use techniques ranging from expensive metaheuristics like genetic algorithms (GAs) to fast and efficient greedy heuristics to find effective solutions.

In [7], mission planning is divided into two subproblems: task scheduling and route planning. The task scheduling problem is the one we consider in our study. The task scheduling problem is solved using a MILP approach to minimize the completion time of all tasks as opposed to our work which aims to maximize surveillance value. This also differs from our work in that our environment does not have a specific set of tasks that must be completed and finds solutions in real time, while the MILP approach is time consuming and is used to construct a solution in advance. Similarly, in [8] a swarm of UAVs is also optimized to perform tasks while minimizing total completion time using a MILP approach. In [9], UAVs are assigned to attack and attempt to destroy clusters of targets through expressing three objective measures into one weighted measure (the success probability of the attack, the cost of the attack, and how well the timing of the attack will match a desired window), which is used to apply integer programming methods to find a solution. No-fly zones are considered in [10], which compares MILP and heuristic techniques to solve a task assignment problem where UAVs must complete a sequence of tasks. A solution here is represented by a DAG. In comparison to all these techniques, our methods can compute in real time and can be adapted to incorporate changes in the environment, such as dynamically adding and removing targets and UAVs. Furthermore, our performance measure considers the attributes of individual sensors and the energy consumption by individual UAVs.

Mission planning for UAVs is sometimes studied as an orienteering problem [11, 12]. For example, in [11] the authors utilize a model where UAVs originate from a depot and gain profit from traveling a path through nodes and back to the depot at the cost of fuel. Robust optimization techniques are used to maximize profit while taking uncertainty into account to avoid running out of fuel early. This work differs significantly from ours because distance between targets and UAVs is considered and the focus is on optimization of UAV movement instead of sensing. In [12], UAVs again depart from a depot, but before departure can select a specific set of sensors, which will impact their weight and the information they can gather. The authors solve this problem using both a MILP approach when ample time is available for finding solutions and several heuristic techniques for larger problem sizes that cannot be solved in a reasonable amount of time using the MILP approach. Our work differs significantly from these studies in part because a full mission plan is generated by the MILP approach and it is not modified during the day. In our work, the heuristics dynamically schedule UAVs to assign targets many times throughout the day and these decisions depend on the current state of the scenario. Additionally, our work considers the energy consumption of each sensor, which can greatly impact scheduling decisions.

Some studies have a greater focus on motion planning of the UAVs, which is beyond the scope of our contribution in this work. The work in [13] considers an environment where UAVs must keep track of targets moving throughout regions. This is done by probabilistically sending the UAVs to regions where useful information is likely to be found. A detailed three-dimensional space is considered in [14] where a single UAV must minimize the expected cost of ignorance, which is a measure of the information that was not gathered in a timely matter by the UAV. This is done using a greedy agent-based heuristic approach. In [15], MILP and a GA are used to minimize the total travel distance required for the time-constrained surveillance of objects with known flight paths. Base stations are also present in the field, which can be used to refuel the UAVs as needed.

In [16], UAVs launch with heterogeneous loads taken from bases and must scout targets using those loads. The goal of this study is to minimize the number of UAVs needed to fully scout all targets, which is achieved by seeding a genetic algorithm with an initial solution from a greedy heuristic. In [17], possible solutions for mapping a UAV to any combination of targets is represented by a tree where moving from the root to a node represents assigning the UAV to the target corresponding to that node. A best first search (BFS) method is used to find solutions to this problem. This differs significantly from our work because this heuristic produces a full mission plan for the UAV while our heuristics make decisions for a single surveil only for each UAV at mapping events throughout the day. The work in [18] is to design a method for assigning UAVs to targets in a disaster response scenario. UAVs originate at rally points and use a greedy approach to find short paths to move to and surveil targets based on the capabilities of each UAV.

7 Conclusions and Future Work

We designed a set of value-based heuristics used to conduct mission planning for UAV surveillance of a set of targets (max value, max value per time, max value per energy, and the UAV-based metaheuristic). We conducted a simulation study to evaluate, analyze, and compare these heuristics in a variety of scenarios. We found that while max value and max value per energy are each good techniques in a subset of the scenarios considered, the UAV-based metaheuristic found solutions with among the highest surveillance value for all scenarios. In environments where the best approach is not known, this makes the metaheuristic the obvious choice to employ.

In the future, we are interested in exploring more dynamic environments where a scenario experiences significant changes throughout the day. For example, changes in weather could dynamically affect the quality of outputs produced by different sensors. This is something that could be handled with a performance measure that can capture how the weather will affect the quality of outputs (sensor quality) and how useful different outputs are for different targets (sensor affinity). Additionally, some real environments will have targets of interest that are not in static positions. To address this, the model we use in this study could be expanded to accurately model the movement of both UAVs and targets. Lastly, the mission scheduling techniques in this study are heuristics with relatively simple functionality to allow mission schedules to be constructed in real-time. In the future, we would like to consider more complex techniques that can be used to produce better mission schedules in some cases when there is enough time available to do so.

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