Identifying Suitable Algorithms for Human-Computer Collaborative Scheduling of Multiple Unmanned Vehicles

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Real-time scheduling and task assignment for multiple Unmanned Vehicles (UVs) in uncertain environments will require the computational ability of optimization algorithms combined with the judgment and adaptability of human supervisors. Identifying the characteristics that make a scheduling algorithm suitable for human-computer collaboration is essential for the development of an effective scheduling system. This high-level systems analysis paper begins the process of deriving requirements for collaborative scheduling algorithms by conducting a survey of 117 publications within the past five years in academia and industry on multiple UV scheduling algorithms. The goal of the survey is to determine the types and frequency of scheduling algorithms that are currently in use and to classify the characteristics and capabilities of these algorithms. Results show that academia has settled on meta-heuristic and auction-based algorithms as providing the best balance of performance and computational speed. In industry, however, the most widely used solution methods are "iterative" approaches that monotonically improve the schedule with further iterations. Industry-developed algorithms are more likely to be capable of scheduling heterogeneous UVs, but university researchers have developed more algorithms that can account for uncertainty and provide estimates of robustness. The different objectives of industry practitioners and academic researchers may be driving these disparities. Addressing this gap will be essential to the development and adoption of future human-computer collaborative scheduling systems.

Nomenclature

J	=	objective function of the optimization algorithm
x	=	decision variables
f, g	=	generic functions
θ	=	generic variable

I. Introduction

Real-time scheduling in uncertain environments is crucial to a number of domains, including Air Traffic Control (ATC),[1] rail operations,[2] space satellite control,[3] and Unmanned Vehicle (UV) operations.[4] Specifically, the use of UVs has increased dramatically over the past decade[5-7] and recent advances in the autonomous capabilities of UVs allow for single-operator supervisory control of multiple UVs.[8] Many advanced UVs can execute basic

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operational and navigational tasks autonomously and can collaborate with other UVs to complete higher level tasks, such as surveying a designated area.[9, 10]

In order to effectively control multiple semi-autonomous UVs, some method is necessary for scheduling tasks. For the purposes of this paper, scheduling is defined as creating a temporal plan that assigns tasks among a team of UVs and determines when the tasks will be completed. While this paper will not focus on path planning, it should be noted that path planning is coupled with the scheduling problem, due to the need to estimate how long it will take for a UV to travel to a certain location to accomplish a task. A variety of optimization algorithms have been developed to address the problem of scheduling tasks for multiple UVs.[11-17] While varying in their method of formulating the scheduling problem and solving the optimization, all of these approaches utilize an autonomous scheduler with little to no human input during the development of the schedule.

In the presence of unknown variables, possibly inaccurate information, and changing environments, automated scheduling algorithms do not always perform well.[18, 19] Though fast and able to handle complex computation far better than humans, optimization algorithms are notoriously "brittle" in that they can only take into account those quantifiable variables, parameters, objectives, and constraints identified in the design stages that were deemed to be critical.[20] In a command and control situation such as supervising multiple UVs, where events are often unanticipated such as weather changes and unexpected target movement, automated planners have difficulty accounting for and responding to unforeseen changes in the environment.[21, 22] Additionally, the designers of optimization algorithms often make a variety of assumptions when formulating the optimization problem, determining what information to take into account, or, in the case of receding horizon algorithms, deciding how far into the future to plan.[23, 24]

One approach to deal with the "brittleness" of these algorithms is to have a human operator and an algorithm collaboratively develop schedules. A number of studies have shown that humans collaborating with algorithms can achieve higher performance than either the human or the algorithm alone under certain conditions.[25-31] While extensive research has been conducted to develop better algorithms for planning, comparatively little research has occurred on the methods by which human users utilize these tools, especially when working in dynamic, time-critical situations with high information uncertainty.[32] Additionally, operators can become confused when working with automation, unaware of how the "black box" algorithm came to its solution or the assumptions made by the algorithm in modeling the problem. Fig. 1 is a representation of the fact that there are often differences between the real world, the automation/engineer's model, and the human operator's models of the world.

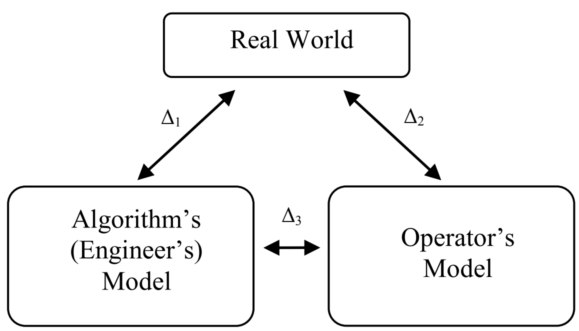


Figure 1. Differences between real world, algorithm's model, and operator's model of the world.

Designing an effective human-computer collaborative scheduling system could provide the ability to supervise multiple UVs while addressing the inherent brittleness and opacity of algorithms. As shown in Fig. 2, the system could include the human operator, the graphical interface which displays information to the operator and allows the operator to interact with the system, the scheduling algorithm, and the semi-autonomous UVs which act in the environment, all with information flowing between components. It should be noted that the scheduling algorithm could exist as a stand-alone component, as pictured, or as sub-system of each UV, as in many decentralized systems.[33, 34] In the development of any complex system, the definition of requirements is a fundamental step in the systems engineering process.[35] While others have attempted to develop requirements for the graphical interfaces in human-computer collaboration,[20, 32, 36, 37] few have attempted to develop requirements for the scheduling algorithms to be used in such systems.

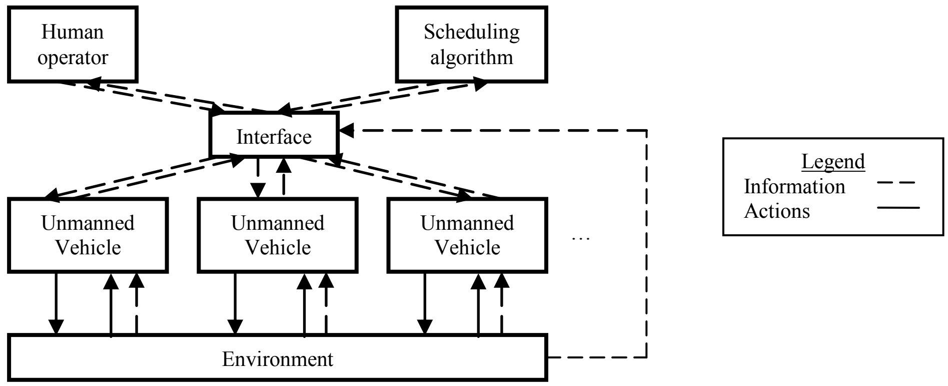


Figure 2. Human-computer collaborative scheduling system diagram.

The goal of this paper is to begin to identify algorithms that have the sufficient or required properties to support real-time human-computer collaborative schedule creation for multiple UVs in uncertain environments. While some algorithms may provide optimal schedules almost instantaneously, the algorithm may lack certain characteristics that are essential for effective human-computer collaboration. For example, the algorithm may not be capable of taking into account uncertainty in the environment, taking real-time feedback or guidance, or providing a level of certainty about the merits of the schedule that it produced. Our goal here is not to criticize the tremendous amount of important work that has been done towards developing better scheduling algorithms. Instead, this high-level systems analysis paper aims to analyze how these scheduling algorithms can successfully be paired with a human operator to operate in real-world scenarios. By identifying the characteristics of the most suitable algorithms from a systems-level perspective, we can guide the development of algorithms that will enhance the performance of human-computer collaborative systems.

As a first step towards identifying suitable algorithms for human-computer collaborative scheduling, this paper describes a survey of algorithms developed in both industry and academia for multiple UV scheduling. The purpose of the survey was to determine the types and frequency of scheduling algorithms that are currently in use and to classify the characteristics and capabilities of these algorithms. A secondary purpose was to compare the algorithms in use in academia and industry, which provided some insight into the differences in objectives between researchers and practitioners. Finally, the survey provided data on the algorithms that are available for use in human-computer collaborative scheduling systems and identified the areas where more research is necessary to enhance the capabilities of such systems.

II. Methods

The survey was intended to cover a broad spectrum of publications in order to analyze the types and frequency of scheduling algorithms for multiple UVs that have been developed in both academia and industry. The survey utilized conference papers, journal articles, and technical reports, primarily relying upon papers that have undergone some kind of peer-review process. The survey covered the years 2006-2011, in order to emphasize what is currently in use or in development. Papers included in the survey were chosen based on searching for resource allocation or scheduling algorithms specifically meant for assigning tasks to multiple UVs in real-time. A general assumption was that the authors chose to formulate the scheduling problem as an optimization, as shown in Eq. 1.

$$
\begin{aligned}
\min_{x} \quad & J(x,\theta) & \\
s.t. \quad & f(x,\theta) & \leq g(x,\theta) \\
& x \in \chi &
\end{aligned}
\tag{1}
$$

Eq. 1 is a very general representation of the scheduling problem and in fact could represent any optimization problem. Again, for the purposes of this paper, scheduling is defined as creating a temporal plan that assigns tasks among a team of UVs and determines when the tasks will be completed. We placed no restrictions on the type of objective function, *J*, used by the algorithm, which may or may have not taken into account the decision variables, may or may not have been linear, may or may not have been convex, and could simply have been 1 and thus a Constraint Satisfaction Problem (CSP) as opposed to an optimization. We also placed no restrictions on the constraints applied to the problem as well. For example, one paper[10] attempted to maximize the total score accumulated given that each task has a specific value. The decision variables, x_{ij}, were binary in the set {0,1} where x_{ij} =1 if agent i is assigned to task j. The optimization was subject to constraints including the maximum number of tasks that one vehicle could perform, a minimum number of tasks that needed to be assigned, and that the schedule was "conflict-free," where each task is assigned to no more than one UV. In a different paper,[38] the objective function, J, was to minimize the cumulative flight time of all UVs. The decision variables were once again, x_{ij}, which are binary in the set {0,1} where x_{ij} =1 if agent i is assigned to task j. The constraints in the problem formulation included a conflict-free assignment and timing constraints on each task.

Once a paper was found that fits the general category, we attempted to collect data on certain characteristics of the algorithm and to classify the algorithm into broad categories. Simple data such as the year of the paper and the primary institution of the authors was collected. The paper was classified as either originating from academia or industry based on the institution of the authors. Academia was defined as any university or academic research institution, while industry was defined as any private company or research organization outside of academia, including any of the research laboratories of the armed forces or the National Aeronautics and Space Administration (NASA).

While previous methods of classifying the characteristics of algorithms have been developed for logistics[39] and computer science,[40, 41] the problem of real-time, human-computer collaborative scheduling of multiple UVs in a dynamic and uncertain environment required a new classification method. Our methods drew from those previous classification techniques while extending the state of the art.

We began by examining the method chosen by each paper for solving the combinatorial optimization problem. Typical methods of solving the optimization included enumeration, the simplex method, dynamic programming, branch and bound, and greedy algorithms. Meta-heuristic methods were often inspired by biological processes and included Genetic Algorithms, Simulated Annealing, Tabu Search, Particle Swarm Optimization, and Ant-Colony Algorithms, among others. Market-based auction algorithms were often applied to solve a variety of scheduling problems. Also, Dynamic Vehicle Routing (DVR) methods using Voronoi partitions were identified as a potential solution method that could guarantee a certain level of performance without the need to replan constantly in a dynamic environment. DVR methods produce policies or decision rules, as opposed to specific task assignments, typically by optimizing the expected value of performance.

Finally, a variety of other algorithm characteristics were analyzed. What guarantees did the algorithm make about the optimality of the solution? Did the algorithm take into account uncertainty in the environment, uncertainty in the inputs or constraints used by the algorithm, or the potential movement of targets? Was the solution method centralized or decentralized? Can the algorithm handle heterogeneous UVs or only homogeneous UVs?

Obviously, many of these designations are subjective and dependent on the authors' written descriptions of their algorithms. While others have performed computational comparisons of the performance of these different algorithms,[42, 43] the point of this paper is to glean some insights on what researchers and practitioners are focusing on when designing new multiple UV scheduling algorithms, and to analyze the implications for human-computer collaborative scheduling.

III. Results

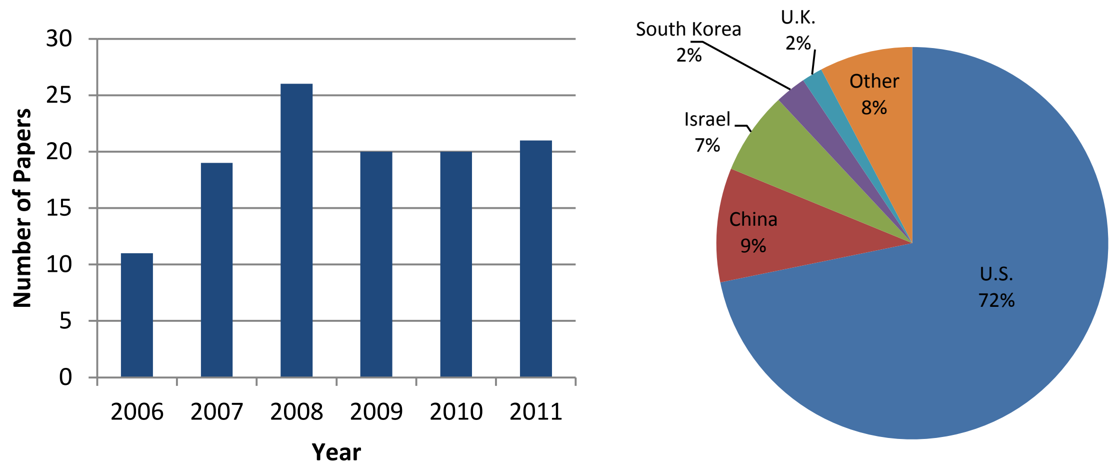
Based on the previously mentioned criteria, 117 papers[*] published between 2006 and 2011 were identified as describing the development of a scheduling algorithm for assigning tasks to multiple UVs in real-time. Thirty-nine different conferences and journals were represented in the survey, with the majority of the contributions from: AIAA Guidance, Navigation, and Control Conferences, AIAA Infotech@Aerospace Conferences, American Control Conferences, IEEE Conferences on Decision and Control, AIAA Journal of Aerospace Computing, Information, and Communication, AIAA Journal of Guidance, Control, and Dynamics, IEEE Transactions on Control Systems Technology, and IEEE Transactions on Automation Science and Engineering. While it is likely that some papers were missed, a large enough sample has been collected to analyze general trends in the development of scheduling algorithms for multiple UVs.

A. Institutions Researching Scheduling Algorithms

Fig. 3a shows the distribution of these papers over the past 5 years. Approximately 20 papers per year were found on the topic at hand. Fig. 3b shows the distribution of the papers based on the geographic location of the

[*] The references for all papers included in the survey can be found here: http://web.mit.edu/aeroastro/labs/halab/algorithmsurvey.shtml

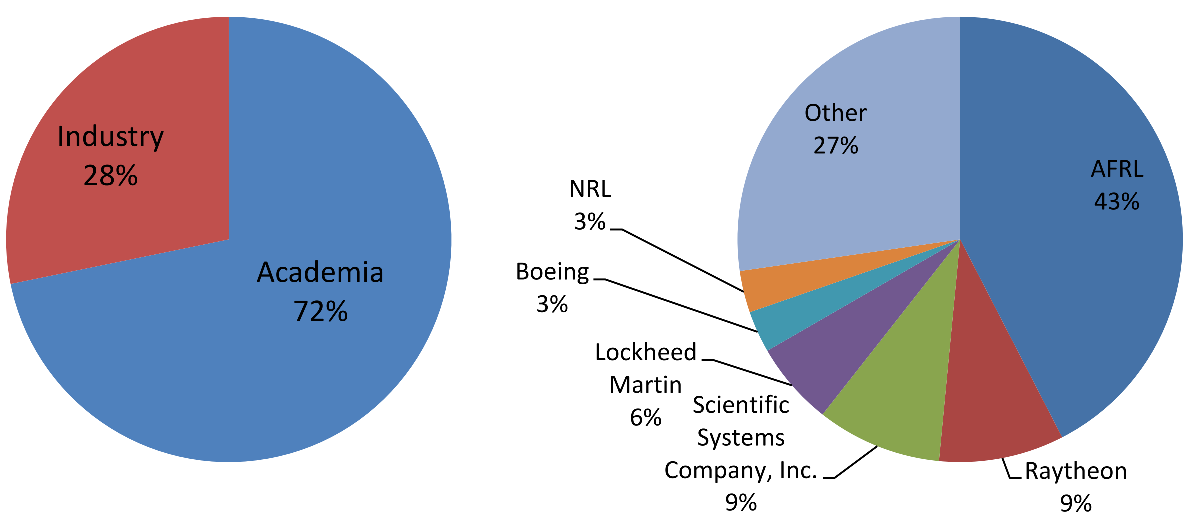
primary author's institution. Seventy-two percent of the papers were published by United States based institutions, followed by Chinese and Israeli institutions.



(a) Number of Papers per Year **(b) Geographic breakdown of sources**

Figure 3. Year and geographic location breakdown of relevant papers.

Seventy-two percent of the papers analyzed were from academia, as shown in Fig. 4a. As expected, based on the choice to use primarily peer-reviewed conference papers and journal articles, the majority of the papers were from academia. Access to industry information was often limited due to algorithms being declared proprietary or even classified. Of the 33 papers published by authors working in industry, 43% of them were published by the Air Force Research Laboratory (AFRL), as shown in Fig. 4b.



(a) Industry/Academia papers **(b) Breakdown of industry sources**

Figure 4. Percentage of relevant papers from academia and industry/government sources.

B. Guarantees of Optimality

Next, we investigated the guarantees of optimality made by the solution method of the scheduling algorithm. Since we analyzed real-time UV scheduling algorithms in uncertain, dynamic environments, the authors were likely planning in situations with unbounded indeterminacy,[41] where the set of possible preconditions or effects either is unknown or is too large to be enumerated completely. Depending on the problem formulation chosen by the authors, the problem could have been NP-hard, meaning that the algorithm cannot find an optimal solution in polynomial time.[41] Finally, the objective function may be non-convex, meaning that certain algorithms may become stuck in local minima. In many of these cases, where either the environment is stochastic or the search space is large, it is unlikely that an optimal plan can be found or will remain optimal throughout the mission. In addition, the definition of "optimal" in uncertain, dynamic, command and control environments may be difficult to quantify and represent in a single, static objective function. Thus, we assume that the algorithm must continuously replan to adjust to the environment.

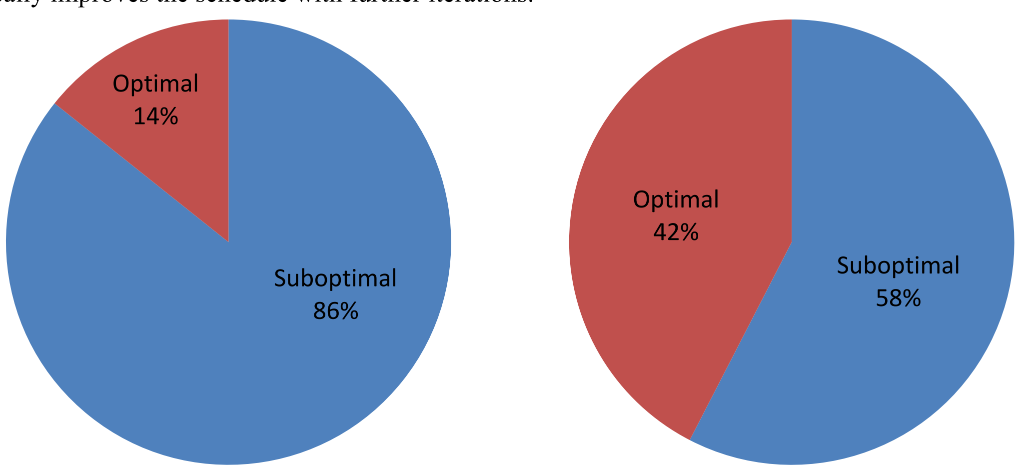
In classifying the guarantees of optimality made by scheduling algorithms for multiple UVs, we investigated whether or not the algorithm could generate a schedule that was guaranteed to be optimal based on the given objective function and data at that time. Examples include branch and bound and dynamic programming. As explained above, due to the size of the solution space, many of these algorithms may not scale in polynomial time with greater numbers of UVs and tasks.

The broad category of suboptimal algorithms consists of a number of different methods of solving the optimization problem. A heuristic may be used to guide the algorithm's search for a solution that approaches optimality. Often times, these methods utilize a finite number of steps to solve the problem, where the quality of the solution can be improved upon with increased iterations or larger bundle sizes[24]. Examples include receding horizon methods or iterative bundling methods. These methods are typically more useful on larger problems because they can predictably achieve near-optimal results with faster computational times than other algorithms.

Another commonly used solution method for combinatorial optimization problems is the meta-heuristic algorithm. These algorithms solve the problem by iteratively trying to improve the solution based on a given objective function, typically through pseudo-random changes to the solution. Examples include genetic algorithms or simulated annealing. No guarantees of optimality are made, but with proper tuning, meta-heuristics can achieve near-optimal results.[44]

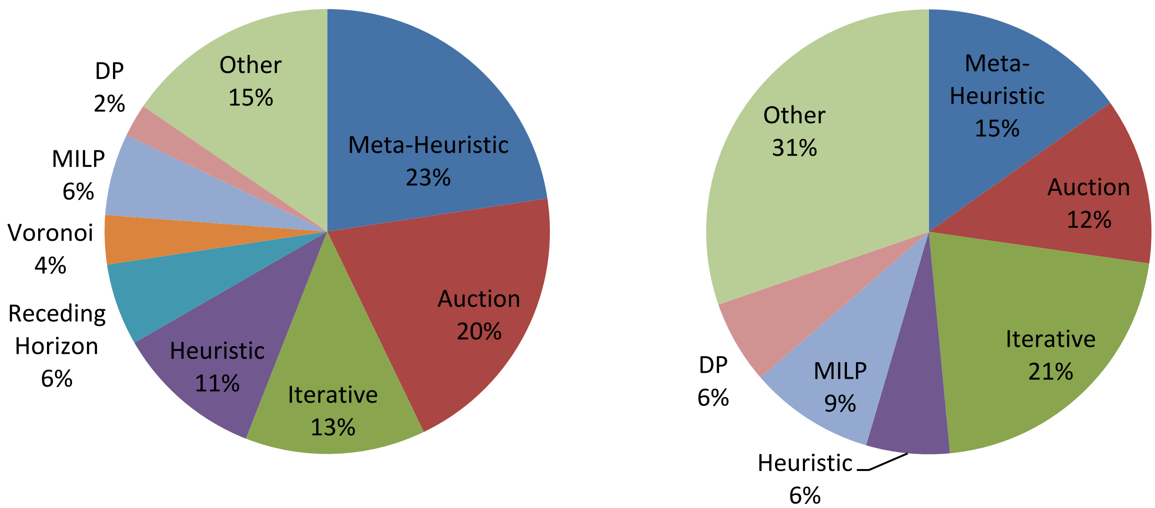
Auction algorithms were generally classified as sub-optimal, depending on the information provided in the paper. These decentralized market-based approaches, where each vehicle bids on tasks to perform, can scale in polynomial time with increasing numbers of vehicles and tasks, and have been shown to perform within 93% of the optimal solution.[10] Finally, DVR methods using Voronoi partitions were classified as a sub-optimal solution method that could produce policies which guarantee a certain level of performance without the need to replan constantly in a dynamic environment.

Figs. 5a and 5b show the guarantees of local optimality made by algorithms developed in academia and industry. Forty-two percent of industry-developed algorithms guaranteed that their schedules would be optimal based on the given objective function and data. Whereas in academia, only 14% of the algorithms used a solution method that explicitly guaranteed optimality. As shown in Figs. 6a and 6b, the most widely used solution methods in academia are meta-heuristic and auction-based algorithms. It is clear that academia has settled on these methods as the best balance of performance and computational speed. In industry, however, the most widely used solution methods are "iterative" approaches, which include branch and bound and any solution method other than meta-heuristics that monotonically improves the schedule with further iterations.



(a) Academia **(b) Industry**

Figure 5. Comparison of whether academia and industry algorithms guarantee local optimality.



(a) Academia **(b) Industry**

Figure 6. Comparison of solution methods chosen by academia and industry.

The vast majority of academia-developed algorithms allowed for near-optimal solutions in favor of acceptable computational times. The different objectives of industry and academia are reflected in these results, where academia may have been more interested in solving large-scale futuristic problems, while industry was looking for small-scale problem solving, with reliable, repeatable solutions that take into account realistic operating conditions. These objectives are reflected in the written comments by industry authors. For example, one industry author, who advocates for auction-based algorithms, admits that:

> "while in theoretical and academic models, where one can assume infinite bandwidth and negligible latency, global information exchange and even auctions perform well, systems in the production world must acknowledge and mitigate the cost of sharing information between nodes."[45]

Another industry paper requires their scheduling algorithms to be "fault tolerant" and "take into account real world constraints" while stating that "there is an acceptable algorithm processing delay time…of 5-15 seconds."[46] Finally, another industry paper states that they formulated their problem as a MILP and:

> "solved to optimality using commercial or open-source optimization software. To guarantee a solution in real time, if the optimal solution is not found within a specified time (e.g. 1 minute), the current best, yet feasible solution is used. This procedure has produced good results for the types of scenarios the…system was designed to execute."[47]

For human-computer collaborative scheduling, the computational speed of suboptimal algorithms is appealing because it allows the human operator to view automation-generated schedules quickly. "What-if" testing by modifying the plan slightly to see the results can also be conducted if the algorithm is fast enough. Of course, certain solution methods such as linear programming also enable sensitivity analysis of the effect of changes to the problem on the quality of the solution as well. The scalability of meta-heuristic and auction algorithms is also appealing as human operators begin to supervise greater numbers of UVs.

An open question, however, is how human operators react to the unpredictability of working with these types of algorithms, where the algorithm's behavior is non-deterministic. A number of recently developed meta-heuristic algorithms, such as Particle Swarm Optimization or Cross-entropy optimization, may have potential performance benefits, but it is unclear how human operators would react while collaborating with these new advanced algorithms. A prime concern for any human operator collaborating with a scheduling algorithm is gaining a sufficient understanding of how the algorithm created the solution.[48] Increasing automation transparency may be difficult with the use of meta-heuristic and auction algorithms, whereas deterministic solvers such as greedy algorithms often emulate the method by which humans would choose to solve the problem.[49] Would a human operator collaborating with an "inferior," but understandable algorithm perform better than a human operator collaborating with a more "advanced" but less predictable and more opaque algorithm?

Finally, one of the largest issues with the adoption of stochastic algorithms for UV scheduling may be regulatory[50] – how does one certify that an algorithm with no guarantee of repeatability is safe or ready for deployment in safety critical missions? This crucial question will need to be answered by both the military and the Federal Aviation Administration (FAA) if the benefits of stochastic algorithms are to ever be realized in real-world operations.

C. Algorithm Structure and Types of UVs

Scheduling algorithms for multiple UVs can also be classified as either centralized or decentralized implementations.[40] Centralized scheduling algorithms typically have a central node that collects information from all of the UVs and attempts to create a globally optimal schedule which is then communicated to all of the UVs. The drawbacks to a centralized scheduling algorithm are the high communication bandwidth necessary to collect global information, the increased computational resources necessary to plan for the entire team of UVs, and the vulnerability of the system to single node failures. Decentralized algorithms, which have become popular recently, allow each UV to compute its locally optimal plan while attempting to achieve conflict-free schedules, where each task will be serviced by the minimum number of vehicles necessary to accomplish the task. Decentralized algorithms can potentially respond to changes in the environment more quickly, scale to larger numbers of UVs while taking advantage of each UV's added computational power, and are potentially more robust to communications failures.[9, 34] However, it can be difficult to reach a conflict-free schedule without needing a large amount of communication between the vehicles. In addition, the behavior of the UVs is emergent and sometimes difficult to predict in advance. Finally, decentralized algorithms cannot always guarantee optimal schedules.

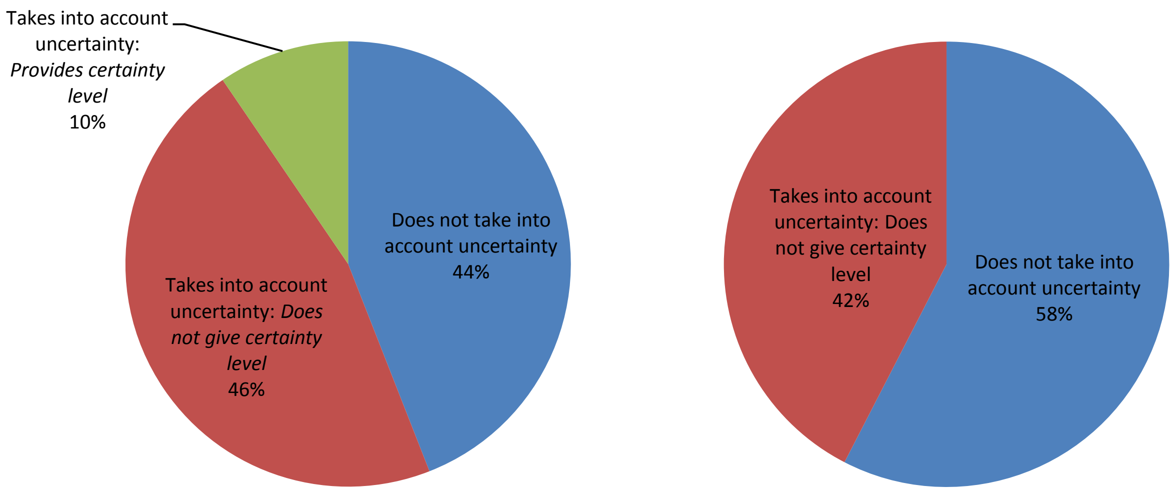
No differences were found between academia and industry in terms of whether algorithms were centralized or decentralized. In both cases, 61% of the papers utilized centralized algorithms. As expected, since decentralized algorithms are a more recent development and are more difficult to implement, centralized algorithms remain prevalent in the literature.

It has been shown that human operators are capable of collaborating with decentralized algorithms for scheduling multiple UVs.[4, 29, 31] The addition of a human operator creating tasks and issuing commands to the UVs necessitates a "central" node to which all of the UVs are connected to provide the human operator with global Situational Awareness (SA). It remains an open question whether decentralized algorithms maintain their theoretical advantages over centralized algorithms when used by a human operator due to the need for a centrally connected node.[51] Initial results indicate that under high task-load, decentralized systems may be robust enough to prevent the human operator from becoming cognitively overloaded while experiencing only mild performance decrements.[52]

The ability of a scheduling algorithm to handle heterogeneous UVs, defined here as vehicles of different types, speeds, or capabilities, was also analyzed in the survey. It was found that 49% of academia-produced scheduling algorithms could perform scheduling for heterogeneous UVs, while 67% of industry-developed algorithms could handle heterogeneous UVs. This may reflect the fact that academia is more likely to use the simplifying assumption of homogenous vehicles, while industry understands that there is a strong desire for coordination between UVs in the air, ground, and sea.[53] The impact of controlling heterogeneous UVs on operator workload has been studied,[54] showing that the added complexity of heterogeneous UVs leads to higher operator workload. Collaboration between humans and more suitable scheduling algorithms for heterogeneous UV control could aid in mitigating the workload increase and merits further research.

D. Taking into Account Uncertainty

Finally, we compared whether algorithms in the survey took into account uncertainty. If the problem formulation assumed a deterministic, static environment with perfect information accuracy, then the algorithm was classified as not taking into account uncertainty. On the other hand, if the problem formulation a) took into account a dynamic environment with potential disturbances or changes, b) could handle uncertain constraints, c) or utilized probabilistic transitions between states, then the algorithm was classified as taking into account uncertainty. While the definition of uncertainty is not agreed upon within the community, it was decided that these three forms of uncertainty would be used for classification purposes. As shown in Figs. 7a and 7b, 56% of algorithms developed in academia took into account sources of uncertainty while only 42% of industry-developed algorithms made the realistic assumption of imperfect information and a dynamic environment.



(a) Academia **(b) Industry**

Figure 7. Comparison of whether academia and industry algorithms take into account uncertainty.

In addition, 10% of academic papers not only took into account uncertainty but provided a calculation of the certainty or robustness of the schedule developed. The movement to perform robust scheduling under uncertainty is a fairly recent development for multi-UV scheduling, but has been emphasized in manufacturing and operations research for many years.[55] In academic publications, however, the methods for quantifying uncertainty usually made substantial assumptions about the problem or environment. For example, while the length of time to complete a task may not have been known with certainty, the authors may have assumed that the task length had a known distribution. For academic purposes, this is useful, but industry practitioners may feel that quantifying uncertainty is too fraught with assumptions and therefore choose not to take into account uncertainty.

With regards to human-computer collaborative scheduling, understanding whether algorithms take into account these forms of uncertainty is essential because overly simplistic problem formulations can lead to human operators placing too much trust in algorithm-developed schedules or to operator frustration due to poor algorithm performance in real-world situations. Also, providing operators with certainty estimates could be beneficial in developing appropriate trust between the human operator and scheduling algorithm. Caution must be taken when providing human operators with probability estimates, however, as humans are notoriously poor at understanding variance and probability.[56, 57] Further research into the most appropriate way to display certainty during real-time collaborative scheduling is required.

IV. Conclusion

A survey of 117 publications within the past five years in academia and industry on multiple UV scheduling algorithms has been conducted. The purpose of the survey was to determine the types and frequency of scheduling algorithms that are currently in use and to classify the characteristics and capabilities of these algorithms. Results show that academia generally favors scheduling algorithms that are slightly sub-optimal, but have much faster computational times and scale better to larger problems. Academics have found that meta-heuristic and auction-based algorithms provide the best balance of performance and computational speed. In industry, however, the most widely used solution methods are either locally optimal methods such as branch and bound or other "iterative" approaches that monotonically improve the schedule with further iterations. Industry practitioners generally work with smaller numbers of vehicles and tasks, thus potentially slower, but reliably optimal algorithms are adequate for the mission. These algorithms are likely also easier to certify for systems that must operate with real vehicles.

We found little difference in the prevalence of decentralized vs. centralized implementations between academia and industry. More centralized algorithms have been developed overall, but interest has increased recently in decentralized algorithms for their potential ability to scale to larger problems, reduce communication bandwidth, and maintain robustness to single node failure. Results showed that industry had developed a higher percentage of algorithms that could schedule tasks for heterogeneous UVs, likely because of the intense focus in industry on cooperation between UVs with different speeds or coordinating air, land, and sea UV operations. Finally, academia had developed more algorithms that take into account uncertainty, especially algorithms designed for generating robust schedules and providing estimates of the certainty of the schedule. Taking into account uncertainty is essential for successful operations in dynamic environments with new tasks emerging, changing weather, and potential UV failures. While we recognize that academic researchers and industry practitioners have different objectives, understanding the strengths and the needs of each community can be valuable for guiding future work on this important topic.

The limitations of this kind of algorithm survey should be noted. As shown in Fig. 4, industry sources were underrepresented due to less available publications. Access to industry information was often limited due to algorithms being declared proprietary or even classified. Also, the frequency of publications about an algorithm may not necessarily be an accurate measure of how widely used an algorithm is. Despite these limitations, however, the data gathered through this method can still provide useful information on the types of algorithms in use for multiple UV scheduling.

The implications of these results for real-time human-computer collaborative scheduling of multiple UVs are three-fold. First, while decentralized, near-optimal algorithms have obvious performance benefits, the emergent behavior of the algorithm is a significant concern when pairing a human operator with a scheduling algorithm. Research should be conducted into how well human operators can understand the method by which the algorithm reached its solution and whether they are able to develop the appropriate level of trust in the algorithm. Second, in a human-computer collaborative scheduling system, a central node is necessary for the human operator to maintain SA and issue commands to the UVs. It remains an open question whether decentralized algorithms maintain their proposed advantages over centralized algorithms when used by a human operator due to the need for a centrally connected node. While decentralized systems may be capable of continuing a mission even with a communication interruption, the need for consistent updates to the human operator and the need for approval for major schedule changes from the operator may negate some of the proposed advantages of decentralized algorithms. Third, providing operators with robust schedules and certainty estimates could be beneficial to both system performance and developing appropriate trust between the human operator and scheduling algorithm. Further research is necessary into the most appropriate way to display certainty levels during collaborative scheduling to enable the human operator to use the certainty estimates effectively to make decisions under time pressure.

Acknowledgments

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