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ASSESSING THE ROBUSTNESS OF UAV ASSIGNMENTS

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ABSTRACT

The deployment of unmanned aerial vehicles (UAV) is increasingly commonplace. UAVs support military forces by flying over dangerous zones mainly for surveillance missions. Route planning for UAVs is therefore a critical problem. With many side constraints such as visitation time requirements, mission priorities, and vehicle capabilities, route planning is a hard problem. Heuristic approaches have therefore been developed to construct near optimal routes. Given the hostile operating conditions, however, robustness of these plans is emerging as a more significant concern than optimality. This paper thus investigates the robustness of constructed UAV routes. To this end, a greedy assignment algorithm that takes into consideration physical constraints and operational risks is used to construct UAV tours. The sensitivity of these tours to various operational parameters such as mission threat level, weather risk, and crash rates as well as their interactions is assessed in a simulation study through a set of designed experiments.

1 INTRODUCTION

Introduced in 1950s, unmanned aerial vehicles (UAVs) were mostly used for surveillance missions during the early years of operation. With the rapid evolution of technology and the fast growth in demand, UAVs are replacing manned vehicles for an increasingly broad portfolio of missions. In particular, UAVs are deployed for intelligence gathering purposes with significant advantages over traditional aircraft. First, UAVs eliminate direct risk to human life. Second, UAVs are cost effective (in terms of operating and maintenance costs) compared to manned aerial vehicles. Finally, the vehicle is not bound by human limitations (Geer and Bolkcon 2005). For example, most of the fighter aircrafts are limited to a certain gravitational force or *g* level because of pilots' physical endurance. Furthermore, it is unimaginable for a fighter aircraft to fly continuously for 50 hours. However, *g* limits or endurance is not an issue for a UAV. Given these significant advantages, the need for the UAVs will most likely increase in a more rapid pace in the near future. It may even be safe to predict that nearly all the future combat systems would require the involvement of a large number of UAVs in every stage of combat, starting from the pre-combat intelligence to post-combat Battle Damage Assessment missions (Entous, Barnes, and Gorman 2012).

The growing reliance on UAVs necessitates their effective deployment to outstanding missions such as border patrols or search and tracking. As the list of missions or the Air Tasking Orders (ATO) are created prior to the operations, it is necessary for the UAVs to be assigned effectively to ensure that the mission goals are fulfilled. Different operational requirements of these missions along with the heterogeneous operating characteristics of the UAVs make the assignment of UAVs to pending missions a hard problem. Combinatorial in nature, route planning necessitates an approach that satisfies both operational, technical, and computational constraints. There exists a significant literature on UAV route construction that is anchored in the traveling salesman problem (TSP) and the vehicle routing problem (VRP). TSP requires visiting a set of customers once using one or more vehicles. VRP enriches this setting by adding vehicle capacities and customer requirements. Laporte et al. (2000) provides a comprehensive review of heuristic approaches to VRP.

The solution process is further complicated by the risks associated with the missions. Such risks range from aborting a take-off due to a malfunction on the vehicle to abandoning a mission due to poor weather conditions or from crashing during take-off to being shot down by hostile fire. As noted by Ahner et al. (2006), "military operations are dynamic complex set of events. The problems associated with military operations are naturally also dynamic and complex." It is therefore crucial to assess the robustness of the planned routes (i.e., UAV assignments to missions) through rigorous sensitivity analysis. In particular, Shetty et al. (2008) "*recommend developing a simulation-based approach and rigorous performance evaluation for validating this (or a variant) model and solution approach. Simulation can allow study of many more realistic battlefield considerations such as sensor networking, line of sight, and weather conditions that are too detailed to be considered in a single mathematical formulation. Design of experiment studies and analysis of variance can provide the military commander with significant and interacting factors, and provide practical insights.*"

The objective of this paper is therefore to investigate the robustness of the solutions for the route planning (i.e., mission assignment) problem for different types of UAVs and to determine those parameters (and their interactions) that affect mission success. To this end, we first deploy a time-oriented nearest neighbor heuristic (Solomon 1987) to solve the UAV route construction problem within a plausible computing time. We then construct a valid discrete event simulation model to test the robustness of the proposed solution under various operational risks. Finally, we investigate the sensitivity of system performance, defined as the ability to complete all assigned missions, to various operating parameters through carefully designed experiments. This analysis would help policymakers in planning the procurement and deployment of different UAVs with different operational capabilities as well as logistics specialists in constructing effective maintenance policies. The analysis would also help military planners in making the final go/no-go decision before flying a mission (for instance, given the prevailing weather conditions), and in identifying and analyzing out-of-the-ordinary occurrences such as unexpectedly high attrition rates after the missions.

The remainder of the paper is organized as follows. Section 2 introduces the modeling and analysis framework as well as the details of the experimental design. Section 3 discusses the results and, in particular, the effects of the input factors on performance. The last section summarizes the results and points out possible future work.

2 MODELING AND ANALYSIS FRAMEWORK

Mirroring the increasing deployment of UAVs in field operations, research on their scheduling and routing is also expanding rapidly. Given the inherent complexity of the problem, researchers have been proposing tour-building heuristics that are anchored on the VRP framework. More recently, such algorithms have been coupled with metaheuristics such as tabu search to obtain significant improvements in route planning. For example, Shetty et al. (2008) introduce an innovative approach for allocating targets to unmanned combat aerial vehicles and sequencing them to maximize service to targets based on their criticality. One should note, however, that these "*procedures are usually context dependent and require finely tuned parameters which may make their extension to other situations difficult*" (Laporte et al. 2000). While these approaches have been relatively successful in static tour building, a dynamic approach is needed to reflect the changing combat conditions (Ahner et al. 2006). There has been recent work in incorporating emerging targets or missions dynamically during mission execution. For example, Harder et al. (2004) describe a general architecture along with a Java implementation of heuristics for automating both route planning and modification. An alternative approach to route planning and modification is to use dynamic programming; however, this approach suffers from the curse of dimensionality. Flint et al. (2009) try to overcome this challenge through approximate dynamic programming and simulation. They also provide guidelines for modeling inherent randomness in such systems. Ahner et al. (2006) propose a heuristic approach that combines discrete-event simulation with optimization. Kamrani and Ayani (2007) propose a static simulation-aided path planning approach to discover and track a ground target. Corner and Lamont (2004) introduce a parallel simulation test bed to depict the swarm behavior of UAVs. Hamilton et al. (2007) emphasize the importance of building valid simulation models; they also propose a test bed for UAV simulations. A recent stream of research focuses on the cooperative behavior of a swarm of UAVs in mission execution (for example, Lian and Deshmukh (2006) and the references therein). Pohl and Lamont (2008) address the swarm routing problem by optimizing paths for both cost and risk.

There exist, however, a multitude of risks awaiting the UAVs, ranging from vehicle malfunction to hostile fire. It is therefore crucial to assess the robustness of the planned route through rigorous sensitivity analysis. This is indeed the focus of our work. More specifically, we first deploy a route building heuristic based on the framework of vehicle routing and scheduling problem with time windows (VRSPTW) for solving the assignment problem of different types of UAVs to missions with different attributes and constraints. We then assess the solution's robustness through designed simulation experiments. To this end, in the first (planning) phase, we create an Air Tasking Order (ATO) list for the following day's missions assuming the availability of a fixed number of resources (e.g., UAVs, sensor packages, maintenance workers, etc.). We then solve the assignment problem to find a solution that deploys the vehicles effectively. In the second phase, we simulate the execution of the assigned missions to assess the robustness of the routes in the presence of uncertainty and disruptions. We then investigate the sensitivity of performance metrics to various operational parameters. We should note that the unpublished dissertation of Nannini (2006) is the closest work to our paper. While Nannini investigates various scheduling policies, he stops short of investigating operational parameters that impact the success of the proposed UAV schedules.

2.1 The Route Planning Problem

Our approach to route planning is based on the time-oriented nearest neighbor heuristic, which was originally proposed to solve VRSPTW (Solomon 1987). Before describing our heuristic, let us recall the key characteristics of the problem. First, a UAV can be assigned to more than one mission. However, a UAV can only be assigned to a limited number of missions since there are constraints for both the missions and the UAVs. The most important constraint on the missions is their target opportunity window (TOW). The missions must therefore start and finish within that time window. For the UAVs, the most important constraint is their endurance. The UAVs will fly only for a specific number of hours due to fuel availability. Within these constraints, one might consider various objective functions. For example, one may wish to maximize the number of assigned missions. Alternatively, it may be more important to use the limited resources to complete critical missions rather than completing a larger number, but not necessarily critical, missions. To reinforce this perspective, we assign to each mission in the ATO list bonus points or mission values that reflect its criticality. Ahner et al. (2006) also use mission values in determining mission assignments. Our objective can then be reformulated as assigning missions to the squadron of UAVs to maximize the total bonus points earned by the proposed schedule.

Given the combinatorial nature of the problem, it is impossible to enumerate and compare the scores of all the possible assignments when the number of missions and/or the number of UAVs are large. Instead, we construct the routes on the fly in a greedy but myopic fashion, which is similar to the time-oriented nearest neighbor heuristic. We start with the earliest mission on the ATO list. We check a series of constraints to determine whether a UAV can be assigned to that mission. These constraints include:

- The maximum operational range of the UAV has to be longer than the distance between the location of the mission and the squadron base.
- The UAV has to perform the mission within the given time period. It has to be in the mission area after TOW start time and has to accomplish the mission before TOW end time.
- The UAV has to be able to return to base after executing the mission.
- The UAV has to have reserve fuel for another 60 minutes after returning to base. This reserve fuel is required for emergencies (e.g., if a runway is closed, the UAV has to divert to an alternate airfield).

If a UAV satisfies all these constraints, the first mission on the ATO list is added to the mission list of that UAV, the location of the UAV is updated to reflect the mission location along with the remaining fuel of the UAV, and the current time is recalculated.

Based on the updated time, the location and the remaining fuel of the UAV, the algorithm checks whether the UAV can accomplish the second mission on the ATO list. If the UAV satisfies the above constraints, the second mission becomes a feasible candidate that can be added to the mission list of the UAV. Since the algorithm aims at finding the next feasible mission that earns the largest bonus (i.e., the largest sum of mission values), it keeps evaluating the feasibility of all subsequent missions, which can be accomplished with higher bonus points. For example, if the UAV can be assigned to the second, fifth, and ninth missions after accomplishing the first mission, only the mission with the highest bonus points is added to the mission list of the UAV. After determining the next mission with the highest bonus, the location and the remaining endurance of the UAV as well as the current time are updated.

This process is repeated until all the missions on the ATO list are evaluated. At the end of this process, a feasible flight schedule (route) with the highest total bonus points is constructed. The total bonus that the UAV can earn by accomplishing these missions is calculated by adding the bonus points of each mission in the UAV's route. The process is repeated as long as there are both unassigned missions on the ATO list and available UAVs. Figure 1 depicts an example, where there are two possible routes, one starting from M1 and the other from M9. The total bonus earned for the first route is equal to 200 while the second route earns 195 points. The algorithm therefore selects the first route and assigns M1, M5, and M6 to the UAV. More specifically, the tree is searched in a breadth-first fashion.

Since there are two different types of UAVs in our study (namely Heron and Gnat), the same process is repeated for the other type of UAV. Therefore, at the end of a full run of the route planning phase, there will be two lists: one containing the missions with the most points for Herons and one containing the missions with the most points for Gnats. Finally, the algorithm selects the UAV and the route combination that has the highest bonus points. The assignment process terminates when either all the missions in the ATO list are exhausted or there are no more UAVs left to be scheduled.

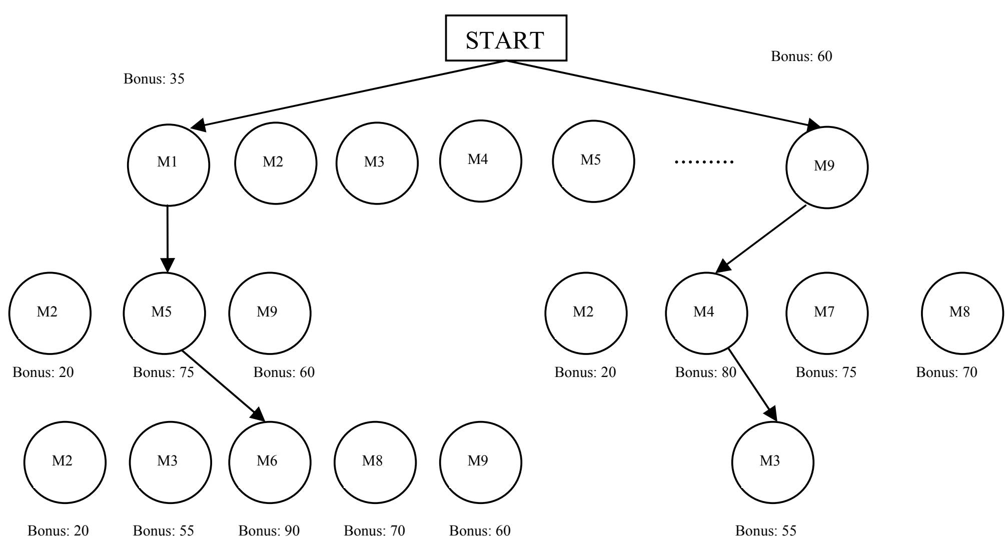

Figure 1: Time Oriented Nearest Neighbor algorithm for the Mission Assignment Problem

2.2 Simulation Model Description

Once a route for the UAVs is created (typically one day prior to the execution phase), the robustness of the flight schedules is assessed through a simulation model that takes into account various operational risks. The simulation model, implemented in Simkit (Buss 2001), is depicted in Figure 2.

The execution phase starts with the first UAV's *preflight inspection*. If the UAV fails the inspection, all the missions in its mission list are aborted (to be subsequently re-assigned) while the UAV is immediately sent to *maintenance*. If the UAV passes inspection, a *launch* event is scheduled. There is a small probability that the UAV would *crash* at take-off. If a crash occurs, all the missions on that UAV's ATO list have to be aborted and reassigned. If the launch is successful, an *ingress* event is scheduled to depict the travel time to the mission area. Due to a technical malfunction, it is possible to have an *air abort*. If this is not the case, the UAV *performs its mission*. At *mission end*, the UAV may travel to its next mission, may *loiter* in a safe area while waiting for the TOW of the next mission or may simply *return to base*. At the base, following a successful *landing*, the UAV proceeds to *maintenance*. There is a small but positive probability that the UAV may *crash* at landing. In that case, all remaining missions are aborted to be subsequently re-assigned. The execution phase ends when the last UAV *lands* at the base and its *maintenance* is complete. Since the missions can start within a 24-hour period, the execution phase may take more than 24 hours, including the time for the last UAV to return to base and the time for its maintenance to be completed.

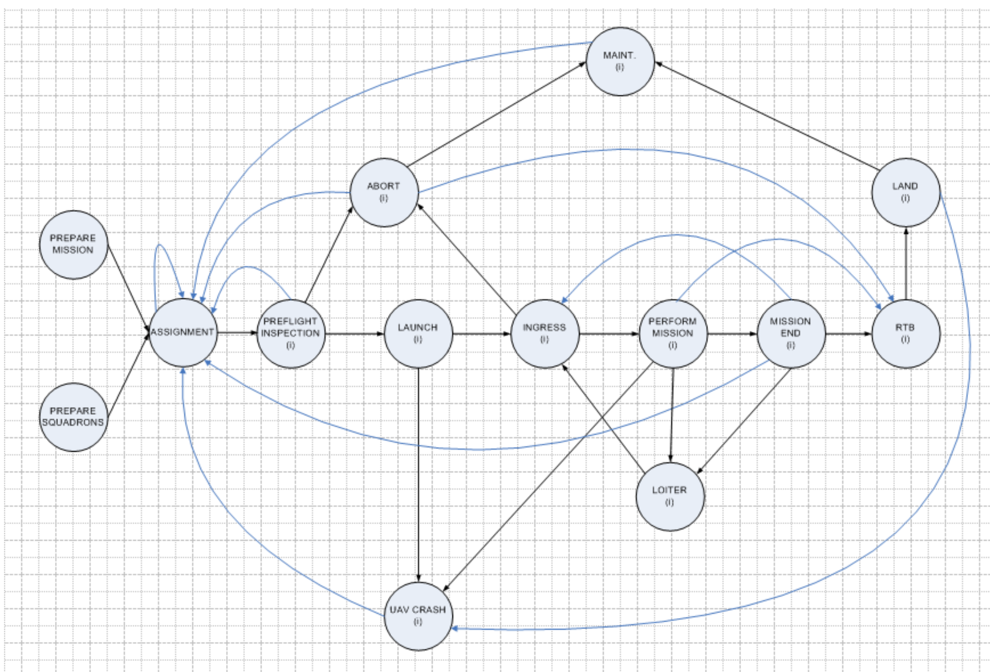

Figure 2: Event graph model implementation in Simkit

The input factors of the model that reflect the operational parameters are depicted in Table 1. Table 2 shows the performance measures, which focus on mission effectiveness, and efficient use of aircraft and maintenance resources.

2.3 Design of Experiments

Valid modeling must be coupled with efficient experimental design for effective analysis of robustness through simulation. There are many experimental design methods in literature. For most methods, however, the required experimental effort grows significantly with the number of factors. In this paper, we adopt Nearly Orthogonal Latin Hypercube (NOLH) designs, which are space-filling designs that provide increased efficiency and flexibility (Cioppa and Lucas 2007). As depicted in Table 1, for our 12 input factors, we use 129 design points in our NOLH design to collect a sufficient amount of data that would enable accurate sensitivity analysis of the simulation experiments. Note that 100 independent replications have been conducted at each design point.

Table 1: Input Parameters

Coordinates of the UAV squadrons
Coordinates of the mission area
Total number of UAVs: 6 – 14
Total number of missions: 20 – 50
Mission duration: triangular(30, 120, 480) minutes
Ground abort rates: 0.03 – 0.2
Air abort rates: 0.01 – 0.10
Crash rates: 0.01 – 0.09
Total no of maintenance servers: 1 – 3
Malfunction maintenance time: triangular(15, 60, 120) minutes
Mission area threat level: uniform(0,1)
Mission area weather risk: 0 – 1

Table 2: Performance Measures

Average number of accomplished missions
Average number of crashed Gnats and Herons
Average number of aborted Gnats and Herons
Total number of assigned UAVs
Mean delay time in the maintenance queue

3 RESULTS AND OUTPUT ANALYSIS

This section summarizes the results obtained from our simulation experiments. We first focus on the main factors for each performance measure and then analyze in detail their interactions.

3.1 Main Factors

We use regression analysis to explain the relationship between the input factors and the performance measures. To ensure the validity of the analysis, we first observe that the residual-by-predicted plot exhibits a random distribution of points. Once the absence of a discernible pattern is established, we compute the R^2 value to see how much of the variance in the data is explained by the model. Finally, by using the sorted parameter estimates, we analyze the effect of each factor on the performance measures. For the regression models, we also form 95% confidence intervals.

3.1.1 Average Number of Total Accomplished Missions

The factor with the highest impact on accomplished missions is the total number of missions. As the total number of missions increases, the total number of accomplished missions increases as well. Area threat level has a negative effect on the accomplished missions. As the initial number of UAVs increases, the total number of accomplished missions increases. The increase in mission durations of the UAVs leads to a decrease in the total number of accomplished missions since the UAVs can only be assigned to fewer missions. There is a slight difference between the effects of different types of

UAVs; this is due to a modeling convention, whereby we tend to select a Heron if the bonus points collected for the missions is the same for both aircrafts. In addition, air abort rates of both UAVs and the crash rate of Herons have a negative effect on the number of accomplished missions. The regression model yields an R^2 value of 0.93.

3.1.2 Average Number of Crashed Herons

Increased threat levels in an operational area leads to larger number of crashed Herons. Another important factor is the initial number of Herons. Average number of crashed Herons increases, as the total number of Herons increases since each Heron has a non-zero probability of crashing or being shot down. Mission duration of Herons and Gnats are also important factors that affect the average number of crashed Herons. A decrease in mission duration of Herons results in an increase in the average number of crashed Herons. This might seem counter-intuitive at first. However, a decrease in mission duration for Herons leads to an increased number of mission assignments for Herons. Since every mission has its specific risk level, more missions translate into higher risk. Another factor is the total number of missions. As the total number of missions increases, the average number of crashed Herons also increases. Mission duration of Gnats also affects the mean number of crashed Herons. If the mission duration of Gnats increases, Gnats will be capable of accomplishing fewer missions, increasing our reliance on Herons. Finally, a larger number of launched Herons will result in more crashes. It is obvious that crash rate of Herons has a direct effect on the average number of crashed Herons. Initial number of Gnats has a negative effect on the average number of crashed Herons. As the initial number of Gnats decreases, the mean number of crashed Herons increases. This is because if there are fewer Gnats, more Herons will be assigned to missions, which may lead to an increase in the average number of crashed Herons. The last factor that affects the average number of crashed Herons is the air abort rate of Gnats. As the air abort rate of Gnats increases, the average number of crashed Herons increases. Since we have a limited number of Gnats in our setting, if Gnats abort in the air frequently, there will be a shortage of Gnats. Herons will therefore be called upon to carry out those missions, which once again may lead to a higher number of crashed Herons. The regression model yields an R^2 value of 0.915.

3.1.3 Average Number of Aborted Herons

Ground and air abort rates of Herons and the initial number of Herons directly affect the average number of aborted Herons. It is obvious that, as the value of these parameters increases, the average number of aborted Herons also increases. As the mission duration of Herons or the initial number of Gnats decrease, the average number of aborted Herons increases. When the mission duration of Herons decreases, Herons will be able to accomplish more missions in one sortie. More missions in one sortie implies increased probability of aborting for UAVs. When the initial number of Gnats decreases, more Herons will be assigned to missions, which will increase the probability of Heron aborts. Finally, the average number of Herons that are aborted increases as the total number of missions and mission durations of Gnats increase since Herons will be required to carry out a larger number of missions.

3.1.4 Mean Wait Time in Maintenance Server for Heron

A linear model for the total maintenance wait time for Herons turned out to be unsatisfactory; however, fitting a quadratic model increased the R^2 value from 0.59 to 0.91.

While the quadratic model seems to perform better than the linear one, they were both unable to capture the exponential increase in waiting time that is typical of a congestion phenomenon. Since the variability in the arrival or in the service processes cannot be reduced, the wait time is directly driven by capacity utilization. That is, if the total number of UAVs increases while the number of maintenance servers remains constant or if the number of maintenance servers is reduced while the number of UAVs requiring service remains constant, we observe an exponential increase in the expected waiting times of the UAVs at the maintenance shop.

3.2 Key Interactions

There are different approaches for analyzing interactions such as multiple regression analysis, stepwise regression analysis or partition trees (Schlotzhauer 2007). With a large number of factors, we find it more intuitive to conduct a stepwise regression analysis by first eliminating insignificant factors and interactions, and then building the regression model with the remaining significant ones.

3.2.1 Average Number of Total Accomplished Missions

A quadratic model that includes 21 two-way interactions has increased the R^2 value to 0.99. We observe that, as the total number of Gnats increases from three to seven, the number of accomplished missions also increases for both settings with three and seven Herons. However, there is a slight difference between the two settings. If there are three Herons, the number of accomplished missions will increase to around 20. On the other hand, if there are seven Herons, the number of accomplished missions increases to around 25.

We observe another interesting result for the interaction between air abort rate of Herons and the number of Heron maintenance servers. When the number of maintenance servers is limited to one, the number of accomplished missions for both air abort rates of 0.1 and 0.01 are indistinguishable. This observation implies that, in this setting, the maintenance server is a severe bottleneck. Nevertheless, as the number of maintenance servers increases to three, the air abort rate of Herons makes a difference on the number of accomplished missions. For an abort rate 0.1 (representing a higher load on the maintenance server), the number of accomplished missions decreases while, for 0.01 (representing a lower load on the maintenance server), the number of accomplished missions increases.

3.2.2 Average Number of Crashed Herons

A regression model with 37 inputs (main effects and two-way interactions) increased the R^2 value to 0.98. When we analyze the interaction between the ground abort rate of Herons and the total number of Herons, we can see that when the initial number of Herons is low, the ground abort rate of Herons does not have an impact on the number of crashed Herons. As the total number of Herons is increased, the ground abort rate starts to make a difference. If the ground abort rate is higher, the number of crashed Herons decreases. This is intuitive because, as the ground aborts increase, this causes fewer Herons to take off for missions –hence, fewer casualties occur. This can be readily seen in the event graph model in Figure 2.

Another important interaction is observed between the total number of Herons and that of missions. When there is a small number of missions, we observe a small difference in the number of crashed Herons. For three Herons, the average number of casualties is around one while, for seven Herons, the average number of casualties is around 1.5. However, as the number of missions increases, the number of Herons has a higher impact on the number of casualties.

The third interaction is between the total number of Herons and the air abort rate of Herons. When the initial number of Herons is high, the air abort rate of Herons has no effect on the number of crashed Herons. However, for a low initial number of Herons, as the air abort rate increases, the number of casualties decreases because higher air abort rates imply that fewer Herons continue their missions.

The last interaction affecting the number of crashed Herons is between the total number of Herons and the mission area threat level. Normally, area threat level is the most important factor on the number of casualties. Nevertheless, its effect also changes with the initial number of Herons. While there is less threat, the initial number of Herons does not have as big an impact as in the higher threat levels. In the high threat situation, as the initial number of Herons increases, the number of crashed Herons increases rapidly.

3.2.3 Average Number of Aborted Herons

The addition of 22 two-way interactions has pushed the R^2 value to 0.98. Let us specifically focus on four key interactions. First, consider the interaction of ground abort rate of Herons and the total number of Herons. When there is a low number of Herons, the ground abort rate does not have as big an impact as when there is a high number of Herons. As the number of Herons increases, low abort rates do not necessarily affect the number of total aborts, while higher abort rates increase the total number of aborts more sharply.

There is a similar observation for the interaction between the initial number of Herons and the air abort rate of Herons. For smaller air abort rates, the number of aborted Herons is nearly the same for low and high initial number of Herons. As the air abort rate increases, a significant difference emerges between the numbers of initial Herons on the aborted ones. For low rates, the number of aborted Herons is around one for both situations. As the air abort rate increases, the number of aborted herons for two situations appears to increase differently. However, the increase in ratio remains nearly the same.

Another important interaction is observed for air abort rate and mission durations for Herons. For low air abort rates, the number of aborted Herons is the same for low and high mission durations. Low mission durations leads to more total aborts as the air abort rate increases. This is because aborts occur while the UAVs ingress from one mission area to another. The shorter times that the UAV spends on a mission area implies that it spends more time to ingress, hence more vulnerable to abort.

Finally, consider the interaction between the crash rate and the ground abort rate of Herons. For low ground abort rates, the crash rate does not make a big difference on the total number of aborts. However, as the abort rate increases, the crash rate and the number of total aborts change inversely. As more Herons crash, there are fewer Herons susceptible to be aborted during mission.

3.2.4 Mean Wait Time in Maintenance Server for Heron

As indicated earlier, neither linear nor quadratic regression models satisfactorily captured the exponential explosion in congestion systems such as the maintenance shop. We therefore used a partition tree (Schlotzhauer 2007) to confirm our intuition on the important factors affecting the waiting time of Herons in the maintenance queue. Figure 3 depicts the partition tree for three splits, showing the most important factors affecting the total maintenance waiting times for Herons.

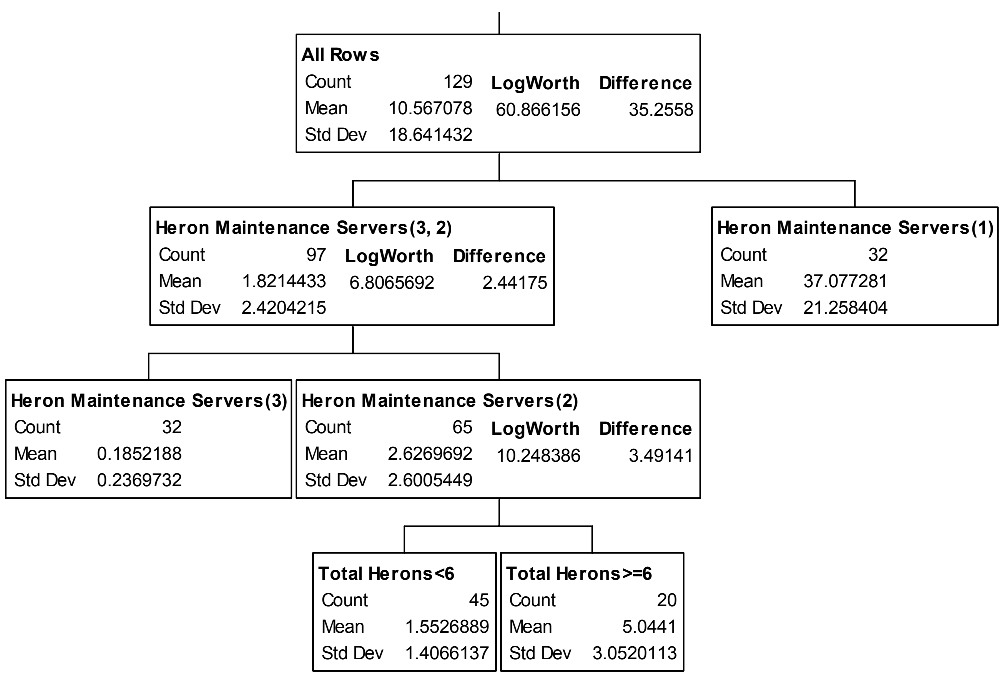

Figure 3: Partition tree for maintenance waiting time of Herons

In the first split, we can see a large difference between the mean wait times on the right and the left branches of the tree. The most important factor influencing the wait time is the number of maintenance servers –hence, maintenance shop capacity. If we have two or three servers, the wait time drops to 1.82 minutes and the standard deviation is 2.42 minutes. If we have only one server, then the mean wait time is 37.07 minutes and the standard deviation is 21.26 minutes.

In the third split, we can see that if we have two servers, the important factor is whether we have six or more Herons –hence, the load on the system. If we have less than six Herons while having two maintenance servers, the mean wait time is 1.55 minutes and the standard deviation is 1.4 minutes. If we have more than six Herons then the mean wait time jumps up to 5.04 minutes with a standard deviation of 3.05 minutes.

4 CONCLUSIONS

In this paper, we have deployed a greedy, but myopic, approach for assigning UAVs to a list of missions that must be executed on the following day. The assignment takes into consideration the capabilities of the aircraft as well as the geographical requirements and inherent risks of the missions. The main objective of our study, however, was to assess the robustness of the proposed schedule in the presence of unexpected hostilities. We also investigated the sensitivity of the assignments to various operating parameters through a rigorous experimental design. This analysis would help policymakers in planning the procurement and deployment of different UAVs with different operational capabilities as well as logistics specialists in constructing effective maintenance policies.

There are many more constraints in actual operations where UAVs are deployed. The number of ground control stations, their abilities to control UAVs or the personnel constraints may have an influence on the success of each mission; hence, these issues can be incorporated into the model to analyze their impact. Logistics is another important issue for all military operations; for example, the lack of a part in the logistics flow would create maintenance issues and could affect the whole operation's success. Therefore, ground logistics capabilities represent another important area of investigation.

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