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PLANNING AIR TEAM MISSIONS WITH MULTIPLE OBJECTIVES

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Abstract

Planning an air mission for a team flying in hostile environments is a complex task since multiple goals need to be considered, e.g., performing the mission tasks and avoiding enemy fire. This work investigates how to model these goals to in such a way that the relevant dependencies are described and that the team perspective is taken into account. The models should be used in a mission planning system that suggests appropriate plans in accordance with the pilots' expectations and needs. Simulations are used for analyzing and illustrating how the pilots' preferences and trade-offs can be handled. Finally, four design considerations for mission support systems are identified and elaborated upon: team aspects, pilot preferences, model complexity and support approach. It is concluded that these perspectives are highly interrelated and should not be considered in isolation.

1 Introduction

Planning an air mission for a team flying in hostile environments is a complex task where multiple goals need to be considered. Schulte [1] identified three classes of goals for air missions: flight safety, mission accomplishment and combat survival. These goals are highly interrelated. When flying within hostile territory, it is often necessary to accept some risk in order to accomplish the mission goals. On the other hand, if an aircraft gets harmed, it will not be able to perform neither its current nor future missions. Sometimes it is better to exclude some tasks rather than expose the aircraft to the enemy's sensors and weapons during long periods of time.

Fighter pilots fly together in teams and collaborate when performing their missions. The technology for unmanned aerial vehicles is emerging and it has been anticipated that there will be teams with both manned and unmanned aircraft flying together in the future [2],[3]. Hence, the teams might be heterogeneous where the members have different resources and characteristics. Depending on the team structure, it could be desirable to distribute the risk exposure and workload evenly within the team or to leave the most dangerous tasks to the least vulnerable or valuable aircraft. A great challenge in developing such a mission planning system is that the system should suggest plans in accordance with the pilots' expectations and needs at both the individual and team level.

Mission planning can be regarded as a multi-objective optimization problem, where the aim is to simultaneously minimize/maximize several objectives, such as fuel consumption, risk exposure and mission effectiveness. Goals can also be expressed in terms of constraints, for instance that the aircraft should fly above ground or that the fuel consumption should not exceed the available amount of fuel. A common approach, which is used here, is to combine the objectives with a weighted sum [4]. A potential mission plan is evaluated with a fitness function of the form:

$$f^{plan} = \begin{cases} \sum_i w_i f_i\,, & \text{if } \sum_j c_j = 0 \\ -\sum_j c_j\,, & \text{if } \sum_j c_j > 0 \end{cases} \quad (1)$$

The objectives are described with fitness functions $0 \leq f_i \leq 1$, such that a good plan has a high fitness. w_i is the weight for objective i. The constraints are associated with violation cost functions, c_j:s, such that $c_j = 0$ in case the constraint j is fulfilled and $c_j > 0$ otherwise. The mission planner aims at finding the plan with the highest fitness, f^{plan} in equation (1).

The pilots' preferences regarding the goals can be included in several ways. First of all, a goal can be modeled as an objective, a constraint or both. The weights w_i are used to balance the objectives. However, it has been argued that decision makers often find it difficult to articulate their preferences in terms of weights [5]. It could therefore be suitable to use a single or few objectives and express all other goals as constraints. There is no need to articulate trade-off preferences between the constraints, since a valid plan must fulfill all the constraints.

1.1 Related Work

Multi-objective route planning for single aircraft in hostile environments has been studied extensively in the literature. The literature review presented in [6] concluded that most multi-objective route planners aimed at minimizing threat exposure and route length, but a few references included more goals such as altitude, flight dynamic constraints and mission effectiveness. A team of aircraft can perform more complex mission tasks than a single aircraft. The literature provides examples of work regarding collaborative area coverage [7], border patrol [8] and distribution of medical supplies [9]. However, these studies assumed that the missions were performed in areas without threats and there was no need for trade-offs between risk exposure and mission accomplishment.

There exist a few works that describe mission planning for teams within hostile environments. Besada-Portas et al. [10] studied route planning for multiple UAVs with multiple objectives including avoiding collisions between the UAVs and minimizing the risk of getting hit. Erlandsson [11] studied a reconnaissance mission where a team of aircraft should maximize the number of visited targets as well as minimize the risk exposure and the route length. There are also studies regarding coordinated attack missions where the mission plan must allow several aircraft to arrive simultaneously while still minimizing the threat exposure and the time in the air, see e.g., [12],[13],[14].

Even though these studies considered multiple objectives for the team, they did not focus on the problem of capturing the pilots' preferences regarding the relative importance of the objectives. Furthermore, the balance between individual goals and team goals were not discussed nor how to incorporate the members' resources and characteristics, such as vulnerability and value.

1.2 Structure of Paper

This work studies how to model and combine the typical goals for a team of aircraft performing a reconnaissance scenario within hostile environments. Section 2 describes how the goals are modeled both in terms of objectives and constraints. Different ways of incorporating the team perspective within each goal are also analyzed. Section 3 presents simulations with a mission planner and illustrates the consequences of different choices of objectives and constraints in order to reflect different kinds of pilot preferences. Section 4 discusses four design considerations for the development of future mission planners that have been identified in this study. Finally, conclusions and suggestions for future work are presented in Section 5.

2 Mission Goals, Objectives and Constraints

This work considers a reconnaissance scenario where a team of N_{mem} aircraft should gather information about N_{tar} interesting objects (targets) located within an area protected by enemy ground-based air defense systems. A mission plan is described as routes with waypoints for all members in the team. This section discusses how three typical goals can be expressed in terms of objectives with fitness functions, f_i, and constraints with violation cost functions, c_j, in this kind of missions.

2.1 Route Length, *R*

Route length is associated both with how much fuel the team members will consume as well as the amount of time they will spend in the air and be exposed to the enemy's air defense systems. It is therefore desirable with short routes. For team member k, the route length fitness is defined as:

$$f_R^k = \frac{N_{tar} - \min({R^k}/{R_{nom}}, N_{tar})}{N_{tar} - 1},$$

where R^k is the route length for aircraft k and R_{nom} is a normalization factor. Here, it is assumed that the start position and destination differ and R_{nom} is selected as the length of the straight path between these two points. $f_R^k = 1$ if the member takes the shortest path between start and destination and if $R^k \geq N_{tar} \cdot R_{nom}$, the fitness is $f_R^k = 0$.

The members' individual fitnesses can be combined in different ways in order to calculate the route length fitness for the entire team. In case the total route length should be minimized, the fitness function could be:

$$f_R^{sum} = \sum_{k=1}^{N_{mem}} \omega_R^k \cdot f_R^k$$

where ω_R^k is the weight for member k. In homogenous team, the route fitness should be equally important for all members, i.e., $\omega_R^k = 1/N_{mem}$. However, in a heterogeneous team, the importance of short route lengths might differ between the members depending on the size of their fuel tanks.

A potential disadvantage with f_R^{sum} is that the routes might differ much in length and that one member has to fly a much longer route than the others. One way to balance the route lengths more evenly in the team is to focus on the worst fitness in the team, i.e.,

$$f_R^{worst} = \min_k f_R^k$$

Instead of minimizing the route length, it could be sufficient to keep the route length below a threshold value, i.e., $R^k \leq R_{max}^k$, where R_{max}^k is typically associated with the available fuel amount for member k. The violation cost for aircraft k is then:

$$c_R^k = \max\left(\frac{R^k - R_{max}^k}{R_{nom}}, 0\right).$$

It is also possible to define a constraint on the sum of route lengths, if suitable for the mission.

2.2 Survivability, *S*

Combat survival implies that each aircraft within the team should be able to return from the mission without getting hit by enemy fire. The survivability, i.e., the probability that an aircraft can fly a route unharmed, is calculated individually for each aircraft with the model proposed in [15]. The model captures that the enemy's sensor and weapon systems communicate with each other and that the risk of getting hit depends on the probability that the enemy has previously detected the aircraft. The model is based on a continuous-time Markov model with the states: Undetected, Detected, Tracked, Engaged and Hit, see Fig. 1.

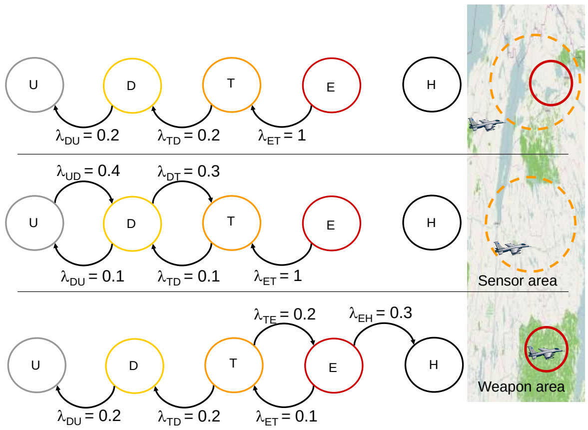

Fig. 1. The survivability model with the states Undetected, Detected, Tracked, Engaged and Hit (denoted by their initial letter). The arrows show the possible state transitions when the aircraft is within a weapon area (bottom), a sensor area (middle) or outside all areas (top). λ_{ij} describes the probability per time unit that the process will transit to state j given that it is in state i. For more details regarding the model, see [15].

The survivability for member k at a a time point on the route, t_S^k, is the probability that the process is not in the state Hit at that time, i.e.,

$$S(t_S^k) = 1 - p_{Hit}(t_S^k).$$

The survivability fitness for aircraft k is the probability that it is unharmed at the time it reaches its destination, t_D^k , i.e.,

$$f_S^k = S(t_D^k).$$

Similarly to route length, the survivability fitness for the entire team can be calculated either as the sum, $f_S^{sum} = \sum \omega_S^k \cdot f_S^k$, or as the worst survivability in the team, $f_S^{worst} = \min f_S^k$. The violation cost function for team member k is:

$$c_S^k = \max(S_{min}^k - f_S^k, 0),$$

where S_{min}^k is the minimum acceptable survivability for aircraft k.

2.3 Mission Effectiveness, *M*

The team should perform a reconnaissance mission within the hostile area. In order for a member to investigate a target, the aircraft must first reach the target unharmed. The mission effectiveness is therefore related to the survivability. The probability that at least one aircraft reaches target m unharmed, M_m, can be calculated as (see further [11]):

$$M_m = 1 - \prod_{k=1}^{N_{mem}} \left(1 - S(t_m^k)\right),$$

where t_m^k is the time point when aircraft k visits target m and $S(t_m^k) \equiv 0$ if the aircraft does not visit m. Let τ_m denote the utility of reaching target m. The mission effectiveness fitness for the entire team is:

$$f_M = \frac{1}{\sum \tau_m} \sum_{m=1}^{N_{tar}} \tau_m \cdot M_m.$$

There is no point in flying the mission unless at least some of the targets will be visited. It might therefore be necessary to formulate a constraint regarding the minimum acceptable mission effectiveness, M_{min}. The corresponding violation cost function is:

$$c_M = \max(M_{min} - f_M, 0).$$

In case there is a desire to divide the workload within the team, there should also be individual constraints regarding the expected target score for each member. A member with a too low expected target score is not contributing enough to the mission and should either be removed from the team or be assigned more targets. On the other hand, a member that is assigned many targets might get tired and will not be able to perform as good as expected. The constraint therefore has two threshold values, M_{min}^k and M_{max}^k. The violation cost is:

$$c_M^k = \max(M_{min}^k - f_M^k, f_M^k - M_{max}^k, 0),$$

where $f_M^k = \sum_m \tau_m \cdot S(t_m^k)$.

3 Mission Planning Simulations

Simulations with a mission planner have been performed to investigate the consequences of expressing the goals in terms of objectives and constraints. The scenario has a homogenous team of two aircraft that together should visit eight targets protected by enemy sensors and weapons, see Fig. 2. The mission effectiveness fitness, f_M, is calculated with $\tau_m = 1/8$ i.e., all targets are equally valuable. The survivability fitness, f_S^{sum}, and route length fitness, f_R^{sum}, are used with $\omega = 1/2$ for both members. The numerical values of the transition intensities, λ_{ij}, are depicted in Fig. 1. In the simulations, the objective weights, w_i in equation (1), have been alternated to favor the different objectives. Furthermore, two different sets of constraint values have been used, see Tab.1.

Tab. 1. Two sets of constraint values (loose and hard) that are used in the simulations

	S_{min}^k	R_{max}^k	M_{min}
Loose	0.5	$4 \cdot R_{nom}$	$0.5 \cdot 8 = 4$
Hard	0.7	$3 \cdot R_{nom}$	$0.7 \cdot 8 = 5.6$

3.1 Mission Planner

The mission planner uses particle swarm optimization (PSO), which is a population-based algorithm for solving optimization problems [16]. A number of simulated particles interact in order to find a good solution. It is used here since it does not require derivative information and has previously been used for route planning with good results, see e.g., [18],[19],[20].

Each particle has a position that represents a possible solution, which in this case is a plan consisting of 2D-waypoint routes for the members in the team. Let $\bar{x}_i$ be a vector with the position of particle i, which has the velocity $\bar{v}_i$ and previous best position $\bar{p}_i$. The global best position of the entire swarm is denoted $\bar{p}_g$. In each iteration, all particles' positions are updated according to:

$$\bar{v}_i \leftarrow \omega \cdot \bar{v}_i + \varphi_1 \cdot \bar{U}_1 \otimes (\bar{p}_i - \bar{x}_i) + \varphi_2 \cdot \bar{U}_2 \otimes (\bar{p}_g - \bar{x}_i),$$

$$\bar{x}_i \leftarrow \bar{x}_i + \bar{v}_i.$$

$\bar{U}_1$ and $\bar{U}_2$ are two vectors with uniformly distributed numbers in the interval [0,1] with the same dimension as $\bar{x}_i$. $\otimes$ denotes component-wise multiplication. In this work, $\omega = 0.7298$ and $\varphi_1 = \varphi_2 = 1.49618$, which corresponds to the canonical version of PSO, see [17]. The particle's new position is evaluated with fitness of the plan, f^{plan} in equation (1), that combines all objectives and constraints. If f^{plan} for the new position is higher than for the particle's previous best position, $\bar{p}_i$ is updated with the new position. The global best position is updated in the same way, when applicable.

3.2 Maximize Survivability

In the first simulation, the objective weights in equation (1) was set to $w_S = 1$ and $w_R = w_M = 0$, implying that the mission planner should maximize the survivability. Fig. 2 shows the routes for the team suggested by the mission planner for the two sets of constraints. The mission planner suggests routes with 100% survivability for both aircraft in both cases. The set with looser constraints states that $f_M \geq M_{min} = 4$, which the black plan fulfills, since 5 targets are visited. In the case with the harder constraints, 6 targets are visited and the constraint $f_M \geq M_{min} = 5.6$ is fulfilled.

The routes could be both smoother and shorter without worsening the survivability. However, the route constraints are fulfilled and the mission planner has no incentives of shortening the routes further.

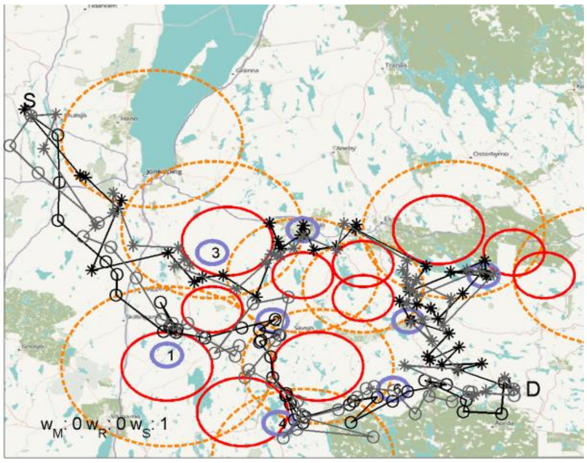

Fig. 2. The scenario includes 8 targets (circles with numbers) that are protected by the enemy's sensors (dashed circles) and weapons (solid circles). The team of aircraft should fly from the start position (S) to the destination (D). The mission planner should maximize the survivability objective. The suggested routes for the looser constraints (black routes) and harder constraints (grey routes) are depicted.

The survivability model only takes into account the known enemy sensor and weapon areas and therefore considers all of these routes as safe. In practice, information regarding enemy positions is uncertain and incomplete. Flying within hostile environments longer than necessary is therefore unsuitable. There are different ways to address this behavior. The survivability model could be extended to take this aspect into account. Another way is to acknowledge that even though the main objective is survivability, route length is also important and let $w_R > 0$. One could also use a lexicographical approach, where the objectives are ranked. The mission planner first aims to optimize the highest ranked objective. Thereafter it continues to optimize the second objective with the constraint that the fitness of the highest ranked objective may not decrease, see further [4]. In this scenario, there are many possible routes with 100% survivability and the mission planner should be able to find shorter routes without worsening the survivability.

3.3 Maximize Mission Effectiveness

Fig. 3 shows the routes for the team suggested by the mission planner when it should maximize the mission effectiveness.

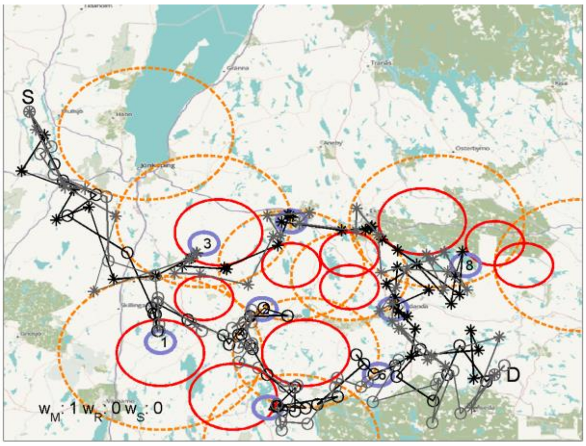

Fig. 3. The team plan when the mission planner should maximize the mission effectiveness and fulfill the constraints.

The plans are similar for the two sets of constraints. All targets are visited and the times spent within the weapon areas are short. In the beginning of the routes, both members avoid the enemy's sensors as much as possible in order to reduce the risk that the enemy will detect the aircraft and fire weapons when they must enter the weapon areas. This behavior results in high survivabilities for both aircraft and high mission effectiveness. This scenario clearly shows the dependency between mission effectiveness and survivability and that maximizing the mission effectiveness is suitable also from the survivability perspective. However, the survivability is lower than in the previous case where the targets inside weapon areas were excluded from the mission.

Similar to the case with maximizing the survivability, the routes are long and could be shortened without affecting the other objectives. It was earlier discussed that short route lengths are suitable from the survivability perspective. One can also argue that short routes are desirable from the mission effectiveness perspective, since the members then have time for improvisations and corrections, for instance revisiting a target in case the first fly over was not successful.

3.4 Minimize Route Length

Fig. 4 shows the routes in the team mission plan when the mission planner should minimize route length.

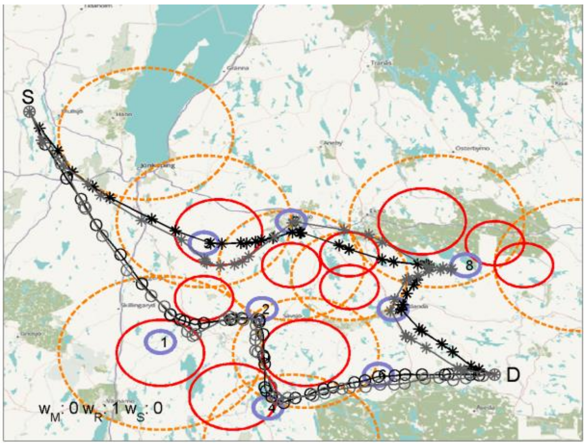

Fig. 4. The team plan when the mission planner should minimize the route length and fulfill the constraints.

The routes are significantly straighter than in the previous simulations. The case with the harder constraints results in detours around the weapon areas, which result in a fairly high mission effectiveness and survivability especially for the member with circular waypoints. Target 1, which is located within a weapon area close to the start position, is avoided in both cases. Excluding this target enables the aircraft to visit its other targets with a fairly high survivability. The mission planner can thereafter afford to take shortcuts through the weapon area in the end and still fulfill the constraints.

3.5 Equal Weights for all Objectives

The mission planner was also run with equal weights for all objectives, see Fig. 5. The plans corresponding to the two sets of constraints are very similar. All targets are visited and the times within weapon areas are short resulting in high survivabilities. The mission effectiveness and survivability is slightly worse than in Fig. 3 where the mission planner maximized mission effectiveness. However, the routes are significantly shorter. Hence, the mission planner balances the three objectives in this case, since they are considered equally important.

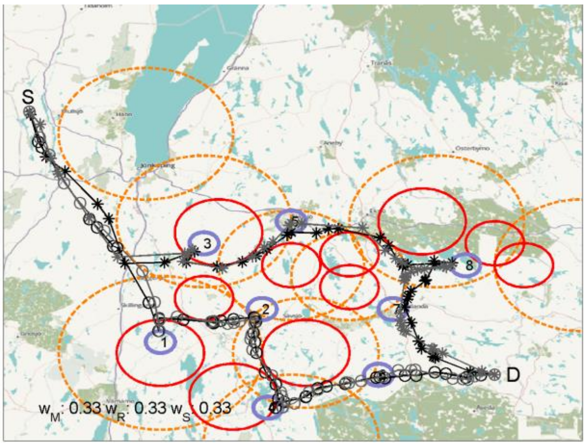

Fig. 5. The team plan when the mission planner should minimize the sum of the objectives as well as fulfill the constraints.

4 Design Considerations

The modeling of objectives and constraints in Section 2 as well as the simulations with the mission planner in Section 3 have highlighted that designing a multi-objective mission planner is not a trivial task. During this work, four design considerations have been identified that should be taken into account in such a process: team aspects, model complexity, pilot preferences and support approach. These issues are highly interrelated as illustrated in Fig. 6. This section summarizes and elaborates them further.

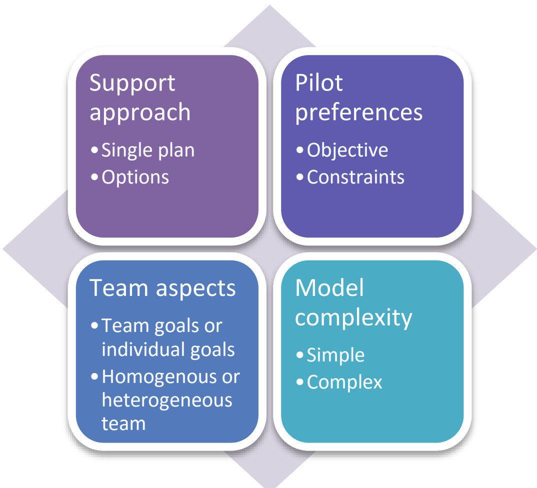

Fig. 6. Four highly interrelated design considerations have been identified for creating a multi-objective mission planning tool.

4.1 Team Aspects

The mission goals can either be regarded as team goals or individual goals for each member. Constraints can easily be formulated both on a team level and on an individual level. For instance, the constraints used in the simulations in Section 3 stated the minimum acceptable mission effectiveness for the entire team, but acceptable survivability and route length for each member. Objectives need to either be expressed on a team level, as mission effectiveness, or to be aggregated into a common fitness function. As discussed in Section 2, to sum the individual fitness contributions will optimize the total use of the resources, but might result in an unbalanced distribution where one member has to take all the risk and fly long routes. The objectives should then be complemented with suitable constraints to ensure that the situation is bearable for all members. In order to spread the risk and workload within the team, the lowest fitness within the team could be maximized. However, the routes might then be suboptimal, since the mission planner only focuses on the team member within the worst situation.

In a heterogeneous team, for example a team with both manned and unmanned aircraft, the team members' different characteristics and resources should be taken into account. The survivability model could include the vulnerability of a member, for instance that the risk of getting detected is lower for an aircraft with low visibility. The target areas in the mission effectiveness model should depend on the members' sensor ranges, since an aircraft with a good sensor can depict the target from a longer distance. The constraint values can easily be individualized for each member. The survivability threshold should reflect how valuable the member is and the route length threshold should be set in accordance with the member's fuel supply.

4.2 Model Complexity

The goals need to be modeled and expressed as objectives and/or constraints. The literature review in [6] concluded that the typical goals for route planning in hostile environments have been modeled in a number of different ways. The goal models used in this work capture the fact that a member must be unharmed when performing its mission task. In this sense, the models are more complex than many other models suggested in the literature. However, it can still be argued that the model is too simplified since it does not include the relations between available fuel and the opportunity to evade missiles or improvise to perform the mission task.

The main advantage with complex models is that they capture relevant dependencies, which should enable the mission planner to suggest suitable plans. For instance, the simulations showed that when the mission planner aimed at maximizing the mission effectiveness it suggested plans with high survivability, see Fig. 3. Assessing these dependencies between the objectives might be difficult for the human operator. Including them in the model has the potential to ensure that the plans are good and might even enable the mission planner to find plans that a human operator would not detect.

There are also disadvantages with complex models. The complexity can make the models difficult to comprehend and hard to update when needed. Furthermore, complex models often require more computational power resulting in a slower mission planner. Therefore, the models should not be more complex than necessary.

4.3 Pilot Preferences

The pilots have several ways of expressing their preferences regarding the mission goals. First of all, the pilots should select the objectives that should be optimized and assign weights to them. Preferences regarding team aspects can be included, such as a desire to balance workload and risk within the team. It is also possible to include individual preferences, for instance prioritize high survivability for the most valuable members, see Section 4.1. The importance of expressing preferences is highly connected with the goal models' complexity discussed in Section 4.2. In one extreme, only a single model is used that captures all important dependencies between the objectives and there is no need for the pilot to assign weights at all. The connection between mission effectiveness and survivability is an example of how the goal model can combine several objectives. In the other extreme, several simple models are used and the objectives are modeled independently. In this case, the pilots must assign several weights for describing trade-offs.

The pilots can also express the goals with constraints. These are handled independently, i.e., there is no need for trade-offs between the constraints. It is easy to include as many constraints as wanted, for instance individual constraints for each team member. However, the mission planner has no incentives to improve the plan more than the threshold, even though this would be possible. This resulted in unnecessarily long routes in the simulations where the route length was only included as a constraint, see e.g., Fig. 2. On the other hand, if the constraints thresholds are set too ambitious, there might not be any feasible plan that fulfills all constraints. It could therefore be suitable to express a goal with both constraints and include it as an objective in the fitness function.

It should be noted that weighted sums of objectives is not the only way to handle multi-objective optimization problems and that several other approaches have been suggested in the literature, for a survey see [4]. An example is lexicographical approaches which ranks the objectives and optimize one at the time, see Section 3.2, or physical programming where the pilots should specifies several thresholds for each objective, e.g., tolerable, desirable and unacceptable thresholds [5].

4.4 Support Approach

A mission planning system can present its results in different ways. It can either suggest a single plan or suggest several options for the operator to choose between. In multi-objective optimization, these approaches are referred to as a priori articulation of preferences approaches and a posteriori articulation of preferences approaches respectively [4]. Presenting a single plan is suitable when the pilots do not have much time for planning. To ensure that the mission planner presents a suitable plan, the goals must be modeled in an accurate way and the pilots must be able to express their preferences in terms of objectives and constraints.

Another opportunity is to design a system that presents several possible solutions. This approach is feasible when the models are too simple to capture all important aspects of the goals. Instead of forcing the pilots to specify abstract weights, the system can calculate plans for different possible weights and thereafter let the pilots select the best plan. Presenting several possible plans would support the pilots' option awareness, which Pfaff et al. define as "perception and comprehension of the relative desirability of available options" [21]. It has been argued that by enhancing the pilots' team option awareness, they will be able to use their resources more efficiently and better balance their different objectives during flight [22]. However, this approach requires that the mission planning system can present the options in a suitable way for the pilots to make well-informed decisions.

5 Conclusions and Suggestions for Future Work

Mission planning for a team of military aircraft is complicated due to the fact that multiple conflicting and dependent goals need to be considered. Typically, the aim is to maximize the probability of accomplishing the mission tasks without exposing the aircraft to unnecessary risks or waste scarce resources. This study has investigated how to design a multi-objective mission planner for a team of aircraft performing a reconnaissance mission within hostile environments. The typical mission goals were modeled and included team aspects, such as dividing workload and risk within the team as well as considering the individuals' characteristics in heterogeneous teams. Simulations with a mission planner showed that the suggested goal models captured the dependency between high mission effectiveness and high survivability.

This study has also investigated the consequences of expressing the goals in terms of objectives and constraints in order to include the pilots' preferences. When the objectives need to be balanced, the pilots can express trade-offs with weights. However, when combining several objectives it might be difficult to assign the weights appropriately. Constraints have the advantage that they are handled independently, but the mission planner has no incentives to improve the result above the constraint threshold.

Finally, four design considerations for multi-objective mission support systems were identified and elaborated upon; team aspects, model complexity, pilot preferences and support approach. It was concluded that these perspectives are highly interrelated and should not be considered in isolation. The goal models should include relevant team aspects and support the pilots' needs to articulate their preferences. A mission planner that only presents a single plan requires intricate models that capture important dependencies. On the other hand, a mission planner that suggests several plans can use simpler models and will also support the pilots' team option awareness.

For future work, it is interesting to conduct studies with pilots to investigate how they plan their missions with the tools available today and how they would want to plan their missions in the future. It is also of interest to identify which objectives they consider when planning their missions as well as how they handle trade-offs between these objectives.

Acknowledgement

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