Communication Role Allocation for Joint Air Operations in a Network-Centric Environment

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Abstract

Joint Air Operations (JAO) are traditionally orchestrated using static vehicle roles assigned from command and control. With recent advances in information and communication technology and the increased need for a dynamic and flexible response, vehicles are expected to assume multiple roles over the course of a mission. In addition, this level of flexibility requires the capability for a vehicle to determine when to facilitate network communication. In this study, we develop an efficient mathematical model that can be used to dynamically assign vehicles to roles including the role of communication in a threat-filled environment. We compute rewards for role assignment based on the marginal benefit to the system and the risk to the individual vehicle. These rewards are utilized within an efficient network optimization formulation to allocate vehicle roles.

Key words:

Dynamic Vehicle-Role Assignment, Network-Centric Environment, Network Optimization, and Joint Air Operations.

1. Introduction

Joint Air Operations (JAO) involve joint air capabilities and forces in support of a military operation. Currently in JAO, vehicles are assigned predefined tasks through the Air Tasking Order (ATO) from the centralized command and control. The tasks are based on the needs of the mission and the limits of the vehicle capabilities. This results in a set of vehicles with static roles during an operation, such as communication, surveillance and reconnaissance (ISR), and strike. With recent advances in information and communication technology and the increasing need for flexibility and responsiveness in JAO, vehicles are expected to perform multiple tasks and roles depending on situation needs and circumstances. Various infrastructures based on centralized control and decentralized execution are currently being investigated by the Air Force. However, these network-centric operations require communication connectivity in the battlespace that has not previously been investigated. In this paper, we present a task allocation model that can be used to reassign vehicles their roles as ISR or strike vehicles in a threat-filled environment, while also assigning vehicles to facilitate communication in the battlespace.

In the event the command and control decides to reallocate vehicle roles based on new information or reallocation needs during a battle, we reallocate the roles and tasks of vehicles utilizing a network optimization algorithm that considers communication benefits and area threats. We define the reallocation events as the following:

(i) An unsuccessful or successful confirmation of a target,
(ii) A strike on a confirmed target,
(iii) Verification of an unsuccessful or successful strike on a target, and
(iv) The loss of a vehicle.

Upon the occurrence of one of the above events or by command decision, we reassign the tasks of the vehicles by determining the marginal benefit to the system of the vehicle performing that task, e.g., strike target i or confirm a target j, while approximating the threat to the vehicle based on the distance to the target in a Voronoi graph and the proximity of the integrated air defense sites (IADs) over that path. We also incorporate the value of information by discounting these values based on the amount of time elapsed since full communication network connectivity existed between the vehicles. This connectivity is only achieved by assigning a vehicle the role of a communications hub. As a result, we can explicitly determine the trade-off for the value of assigning a vehicle the role of communication in lieu of the other roles. At this point, we only require (and allow) a single vehicle to be assigned as a communications hub. This builds a foundation on which future work can incorporate connecting sets of disconnected networks through multiple hub allocations.

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The scope of our problem is related to the weapon-to-target assignment problem and vehicle task allocation. The weapon-to-target assignment problem deals with allocating weapons to targets in either a static or dynamic environment and has been studied extensively with surveys in [7], [14], and [23]. These classic target assignment models consider static and dynamic assignment, but they neglect multiple roles for vehicles and communication. Task allocation is primarily discussed in the cooperative control of unmanned air vehicle (UAV) literature; see [5, 6, 16, 17, 20, and 21]. It includes assigning vehicles to various tasks such as attacking targets, classifying targets, and verifying a strike on targets with battle damage assessment (BDA).

Our model is an extension of the network optimization methods for task assignment and is related to the model by Schumacher et al. [20, 21]. Schumacher et al.'s model is a network flow optimization model that assigns tasks to each aircraft. They efficiently solve this problem with a specialized integer programming model. However, we note that their work does not account for threats in the vicinity or the value of communication and connectivity. Darrah et al. [6] and Schumacher et al. [19] also provide a mixed integer linear programming formulation for the assignment of multiple tasks over time. Their work explicitly deals with departure times and task timing for UAVs. In this study, we do not explicitly deal with the timing issue because we are assigning manned aircraft to tasks unlike UAVs. Again, their model does not account for area threats or lack of complete vehicle communication.

Several papers have investigated methods for routing UAVs in a threat-filled search space including [4], [10], and [15]; however, we focus on the methodology for assessing path threats in [4] because of its computational efficiency. Beard et al. [4] develop a model for the cooperative control problem of dynamically assigning targets to aircraft while accounting for threats. They develop heuristic objective values derived to balance the objectives of minimizing the path length to a target; minimizing the group threat exposure; maximizing the number of vehicles assigned to a target; and maximizing the number of targets visited. Using the paradigms of satisficing [10] and social welfare, a target assignment problem is solved. The determined allocations are updated dynamically as new threats appear. However, their model ignores connectivity, lacks a communication element, and lacks the optimization component of the network-based models.

We are not aware of any research dealing with the explicit allocation of a communications role to a vehicle. However, Beard and McLain [3] present a model of cooperative search using UAVs where the communication among the team of vehicles is maintained by a hard constraint on proximity of the vehicles. Flint et al. [9] incorporate the communication of UAVs in a stochastic model of cooperative autonomous search. In a discrete-time stochastic dynamic programming model, the authors model the limits of communication by only allowing the vehicles to communicate every b time steps in an N step model, where b is a given communication batch delay relaying the location and heading information about each vehicle. Mitchell et al. [12] investigate the impact of communication delays using a UAV control simulation with a task allocation model given in [21]. This is primarily a performance comparison and the problem of allocating a vehicle to facilitate communication is not addressed. In this paper, we combine these models to create a network optimization-based algorithm accounting for threats and explicitly allocate the task of facilitating communication.

We first present a network optimization formulation for the static allocation of the target confirmation, strike, and BDA tasks in the presence of threats. We discuss how this model can be used to dynamically assign tasks to vehicles. In the subsequent section, we expand the model to include the communication task assignment.

2. Mathematical Model

2.1. Confirm, Destroy, and Verify

We begin with N simultaneously deployed vehicles with indices $i = 1, 2, \ldots, N$. In the theater of operations, we assume the location of the T geographically dispersed targets, $t = 1, 2, \ldots, T$, are known. During various stages of the operation the status of each target will be either *unconfirmed*, *confirmed*, *unverified-destroyed*, or *verified-destroyed*. All targets begin as unconfirmed and are only adjusted to confirmed after a successful sensor sweep by a vehicle verifies a target's viability. After target confirmation, a target is available for a strike. After a strike on a target, its status is changed to unverified-destroyed. This status is not changed until another sensor sweep by a vehicle verifies the destruction of the target. If the sensor verifies its destruction, its status is changed to verified-destroyed. Otherwise, it verifies that the target is still viable and changes its status back to confirmed. Confirming a target and verifying its destruction, also known as BDA, are ISR activities. Each target is assigned a value, V_i, representing its importance or priority in the mission. Although we assume that the assigned target values are given, these values (or weights) can be determined using several well-known procedures including SMART or SMARTER [2, 8], SWING [22], or analytical hierarchy process [18]. Similarly, these values could be derived from priorities using the current Air Force practice of developing a Joint Integrate Prioritized Target List. We also assume the target area is populated with I known IAD sites. At discrete decision epochs, the vehicles are assigned roles associated with targets. A vehicle will be assigned to either confirmation of a target (confirm), strike a confirmed target (strike), or verify the destruction of a target (BDA). The vehicle's tasks are then defined by a role, {confirm, strike, BDA}, and an associated target, $t = 1, \ldots, T$. We assume that a vehicle can only be assigned a single task and each task can only be performed by a single vehicle. This can be relaxed if there are tasks that can be performed simultaneously, e.g., communication and ISR; however, we leave this extension as part of future research. Although there are other relevant tasks that can be assigned to vehicles, for this initial model we restrict ourselves to these narrowly defined roles.

At each reallocation event or decision we assign a feasible task to each vehicle. To determine the task allocations for each vehicle, we utilize a framework that is an extension of the classic assignment problem [11, 13]. This formulation has the advantage that although it is a binary integer program it can be solved in polynomial time. We define $x_{cnf}(i, t) = 1$ if vehicle i is allocated to confirm target t and 0 otherwise. We similarly define $x_{str}(i, t)$ and $x_{bda}(i, t)$. Additionally, we define $r_{cnf}(i, t)$, $r_{str}(i, t)$ and $r_{bda}(i, t)$ as the rewards for assigning the ith vehicle to the tth target for the various roles. These definitions result in the following binary integer program,

$$NC = \max_{x} \sum_{i,t} r_{cnf}(i,t)x_{cnf}(i,t) + r_{str}(i,t)x_{str}(i,t) + r_{bda}(i,t)x_{bda}(i,t) \quad (1a)$$

subject to

$$\sum_{t=1}^{T} x_{cnf}(i,t) + x_{str}(i,t) + x_{bda}(i,t) \le 1, \text{ for } i = 1,\ldots,N, \quad (1b)$$

$$\sum_{i=1}^{N} x_{cnf}(i,t) \le 1, \text{ for } t = 1,\ldots,T, \quad (1c)$$

$$\sum_{i=1}^{N} x_{str}(i,t) \le 1, \text{ for } t = 1,\ldots,T, \quad (1d)$$

$$\sum_{i=1}^{N} x_{bda}(i,t) \le 1, \text{ for } t = 1,\ldots,T, \quad (1e)$$

$$x_{cnf}(i,t), x_{str}(i,t), x_{bda}(i,t) \in \{0,1\}. \text{ for } i = 1,\ldots,N \text{ and } t = 1,\ldots,T. \quad (1f)$$

The set of constraints 1b restrict each vehicle to be assigned to at most one task. The confirmation role for each target t is restricted to at most one vehicle through the set of constraints 1c. The constraints 1d and 1e are defined similarly for strike and BDA roles. Central to this formulation is the definition of the rewards for assigning a vehicle to a task. Given the current statuses of the targets, if an assignment is infeasible due to precedence constraints, e.g. a vehicle cannot strike a target until it is confirmed, we assign an appropriately low weight to remove its selection when there are feasible alternatives. We next discuss the elements and derivations of the rewards.

When assigning a vehicle to a target we must account for both the benefit to the mission and the threat to the vehicle. For a given vehicle-target assignment, we measure the threat based on a set of preferred paths through a Voronoi graph [1] considering threats and distance. Given the set of IAD sites, we determine the Voronoi network presented in Figure 1.

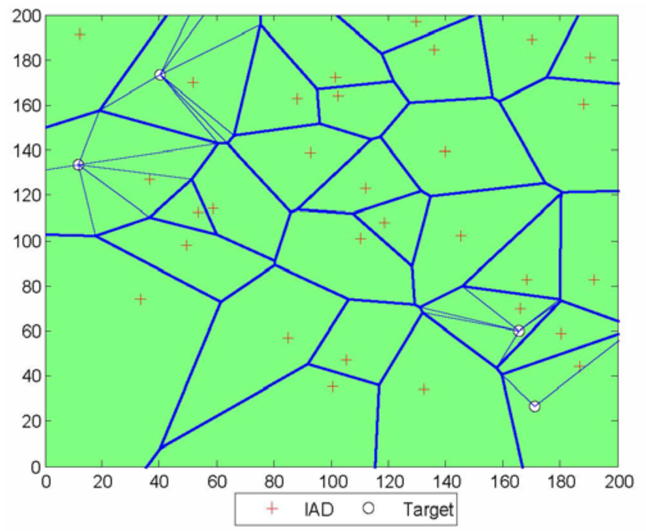

Figure 1: Voronoi graph with 30 IADs and four targets

This network provides a set of feasible paths through the IADs that maximizes the distance from individual IADs. We then connect the targets to this network by finding the closest vertices creating a connected network with a set of nodes V and arcs A. Although pilots will select their own paths to minimize exposure, these path approximations are used for computationally efficient target assignment valuation. As in Beard et al. [4], an efficient measure of the threat along an arc a of this network is computed based on its proximity to the set of IADs. For an arc $a \in A$ of length d_a, we use three points along the arc ($d_a/6$, $3d_a/6$, $5d_a/6$) to estimate the threat over that link. Using the distance from IAD b to the point 1/6 of the length along arc a, defined as $d_{1/6,a,b}$, and the similarly defined $d_{3/6,a,b}$ and $d_{5/6,a,b}$, we compute a cumulative threat measure over arc a,

$$threat_a = \frac{d_a}{3} \sum_{b=1}^{I} \left(\frac{1}{d_{1/6,a,b}^4} + \frac{1}{d_{3/6,a,b}^4} + \frac{1}{d_{5/6,a,b}^4} \right) \quad (2)$$

We seek a task assignment that accounts for the distance travelled and the threat over that path for a given vehicle to task assignment. We therefore find the closest node to the vehicle based on the vehicle's current location and determine a "shortest path" to a target using a weighted average of the length of each arc and the above threat measure for that arc, $m_a = \gamma d_a + (1-\gamma) threat_a$, where $\gamma \ge 0$. The weight γ will be determined by the decision-maker's preference to balance a vehicle's proximity to a target and the threat over that path. We define $c(i, t)$ as the shortest path for vehicle i to travel to target t using the m_a values as arc lengths. We incorporate this into the reward for assigning vehicle i to target t as subsequently described.

To determine a reward for various assignments, we must first define several parameters. We assume a vehicle confirms a target in its sensor range in a region with a given probability. Although the actual probability of confirmation is based on several factors, such as the sensor footprint and angle to the target, we simplify this by defining the probability that a vehicle confirms a target as a fixed p_c. After a target is confirmed, a vehicle can be assigned to strike the target. For a strike, we utilize a single probability p_s as the probability that a vehicle destroys a target. Once a target has been attacked a vehicle can be assigned for BDA. We assume that there is no error in a vehicle's BDA. Although each of these parameters could be vehicle and target specific, for clarity of presentation, we assume they are homogeneous. Similar to Schumacher et al. [21], we define the benefits for vehicle to task allocation:

$r_{cnf}(i,t)$ = The expected reward from confirming target t and subsequently destroying target t with vehicle i – the threat/distance of vehicle i traveling to target t,
$= \alpha^m p_c p_d V_t - \beta c(i,t)$.

$r_{str}(i,t)$ = The expected reward for striking confirmed target i with vehicle t – the threat/distance of vehicle i traveling to target t,
$= \alpha^m p_d V_t - \beta c(i,t)$.

$r_{bda}(i,t)$ = The expected reward for verifying the post-strike status of target t by vehicle i – the threat/distance of vehicle i traveling to target t,
$= \alpha^m (1 - p_d) V_t - \beta c(i,t)$,

where m is the amount of time elapsed since a communication network was in place and α is a discount factor, $0 \le \alpha \le 1$ to account for the lack of communication network connectivity. The β is a scaling factor to relate the path threat values and the expected rewards.

Each time a reallocation event occurs or by a command decision, the roles and tasks of the available aircraft will be reevaluated using the above optimization problem. Through the use of penalty parameters, assignment preferences can be included in the model. For example, if role consistency is preferred for a subset of aircraft, the previous role can be tracked and the reward function for changing roles can be reduced. In this way, the role will only change when there is a significant expected advantage for the system. Similar methods, can be used to reduce possible cycling between roles for aircraft. However, these will be mission specific and will not be discussed in detail here. Using the above allocation optimization problem, the roles and assigned targets will not be static, but could vary with each reallocation decision. However, the above model neglects to incorporate the every increasing role of communication networks in today's military missions. In the next section we address the issue of assigning the role of communication to an aircraft during a mission.

2.2. The Role of Communication

In addition the tasks of target confirmation, target strike, or BDA, we also allow the assignment of a vehicle to the role of communication. This vehicle will facilitate communication between all vehicles ensuring that $m = 0$ in the ensuing assignment optimization problem. We evaluate this by solving an assignment problem similar to above, but requiring that a vehicle be assigned a communications role. We then compare this solution to the optimal objective value of the assignment without communication, WC, to determine which is greater. The role of communication does not have an associated target, so it can also be defined as a task. We define $x_{comm}(i) = 1$ if vehicle i is designated as the communications vehicle and zero otherwise.

$$FC = \max_x \sum_{i,t} r_{cnf}(i,t)x_{cnf}(i,t) + r_{str}(i,t)x_{str}(i,t) + r_{bda}(i,t)x_{bda}(i,t) \quad (3a)$$

subject to

$$\sum_{t=1}^{T} x_{cnf}(i,t) + x_{str}(i,t) + x_{bda}(i,t) + x_{comm}(i) \le 1, \text{ for } i = 1,...,N, \quad (3b)$$

$$\sum_{i=1}^{N} x_{cnf}(i,t) \le 1, \text{ for } t = 1,...,T, \quad (3c)$$

$$\sum_{i=1}^{N} x_{str}(i,t) \le 1, \text{ for } t = 1,...,T, \quad (3d)$$

$$\sum_{i=1}^{N} x_{bda}(i,t) \le 1, \text{ for } t = 1,...,T, \quad (3e)$$

$$\sum_{i=1}^{N} x_{comm}(i) = 1, \text{ for } t = 1,...,T, \quad (3f)$$

$$x_{cnf}(i,t), x_{str}(i,t), x_{bda}(i,t), x_{comm}(i,t) \in \{0,1\}. \text{ for } i = 1,...,N \text{ and } t = 1,...,T. \quad (3g)$$

where,

$$r_{cnf}(i,t) = p_c p_d V_t - \beta c(i,t),$$
$$r_{str}(i,t) = p_d V_t - \beta c(i,t),$$
$$r_{bda}(i,t) = (1 - p_d) V_t - \beta c(i,t).$$

Constraint 3f ensures that exactly one vehicle is assigned the communication role. After solving the above problem, we have an objective value under full communication, FC, and can determine a task assignment. If $NC > FC$, we assign the vehicles to tasks according to the assignment that attains NC, i.e., there is no communications vehicle. If $FC \le NC$, we assign the vehicles to tasks according the assignment that attains FC and a vehicle will be assigned to the communications role. This optimization is computed dynamically when a reallocation event occurs or command deems it necessary to revaluate the current roles of the vehicles.

3. Conclusion

The existing vehicle-target assignment models either lack flexibility or the capability to consider the value of connectivity in a networked environment. In contrast, our model can be used in a dynamic manner, since the outcome of previous engagements and current position impact the future assignments; flexible, since it allows multiple roles over time for vehicles; and incorporates communication, since it takes into account the value of connectivity and communication. This model can be used to analytically determine when a vehicle should adjust its role during a battle in response to changes in the environment or information received in command and control. Given a suitable military test environment, the model parameters can be refined to create a robust decision support tool. In addition, the model can be used to gain tactical insight into when vehicle roles should be reassessed and determine rules of thumb for making these allocations.

Future work will expand this model to allow the simultaneous assignment of roles. In addition, further enhancements will partition the battlespace to only solve localized versions of the problem and then combine these results into a large-scale role allocation solution. This large-scale problem will address the issues of multiple vehicles creating a connected communication network.

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