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"Multi-Objective Coordinated Path Planning for a Team of UAVs in a Dynamic Environment"

Autonomy
Modeling and Simulation
Experimentation, Metrics and Analysis

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Multi-Objective Coordinated Path Planning for a Team of UAVs in a Dynamic Environment*

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ABSTRACT

UAVs are becoming ubiquitous due to their high-risk mission acceptance and ultra-long endurance capabilities. However, because a significant subset of UAVs have limited payload capacity and sensor ranges, teams of UAVs are often required to operate cooperatively in executing specific tasks (e.g., time-critical complex surveillance tasks requiring multiple UAVs) to ensure superior mission performance. In this paper, we model a coordinated path planning problem for a team of UAVs within a dynamic mission scenario that requires them to cooperatively execute time-critical mission tasks in the presence of manned aircraft. The problem is formulated as a multi-objective optimization problem and, more specifically, as a Mixed Integer Linear Programming problem. A major contribution of this paper lies in coordinating multiple UAVs to synchronize their arrival at locations requiring cooperative execution of mission tasks, while allowing for loitering en-route to avoid collisions and for maintaining a safe separation distance from manned aircraft or other obstacles. We solve this problem via a two-phase process. In phase I, we determine the path for each UAV by minimizing the cumulative mission risk; in phase II, we determine the arrival time of each UAV at every task location by following the path generated in phase I that minimizes the task latency to meet the specified deadlines.

Keywords: Mixed Integer Linear Programming, Path Planning

I. INTRODUCTION

A. Motivation

Unmanned Aerial Vehicles (UAVs) have been used to perform dull, dirty and dangerous missions for military and civilian operations as they provide a unique range of features such as ultra-long endurance and high-risk mission acceptance which cannot be reasonably performed by manned aircraft [1][4]. Examples of these complex missions include military surveillance and reconnaissance operations, de-mining operations and inspection of environments that are typically inaccessible to humans, such as active volcanic craters or nuclear power plants where high radiation levels are present [1][5][6]-[8]. Other applications include traffic monitoring and covert payload delivery, surveillance of drug traffickers, counter-piracy operations, anti-terrorism operations, etc. Most of these missions involve tasks that are time-critical requiring immediate attention as they may be dangerous or highly lucrative within a specific time window. In order to operate the UAVs to execute these time-critical tasks, a number of practical issues need to be considered [9][10]. These include: 1) *the limited sensor ranges and payload limitations of a significant subset of UAVs* result in the

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need to assign more than one UAV for a specific task. This requires that the cooperating UAVs must synchronize their arrivals at the required locations for executing the task subject to the specified constraints. For example, in a search and prosecution operation, UAVs may have to simultaneously attack the target with various resources of different capabilities. As the UAVs are capable of carrying only limited resources in small quantities, a group of UAVs needs to be assigned that satisfy the target resource requirement [11]. Assigning a team/multiple UAVs for a mission task will not only expedite the mission execution, but also reduce the possibility of mission failure [12][13]; 2) *the See and Avoid capability of a significant subset of UAVs* is not adequate when compared to an onboard pilot's ability to see and avoid other airspace users resulting in mid-air collisions with the manned vehicles [1][14][15]. Due to this limitation, these UAVs are currently restricted to operate in segregated regions in the airspace with substantial amount of human supervision required (e.g., multiple humans per UAV), which limits their operational flexibility [16][17]. Thus, seamless integration of flexible UAV operations within the existing airspace requires coherent and systematic coordination of UAVs with the manned/unmanned aerial vehicles.

Motivated by the need to coordinate multiple UAVs in a dynamic environment, an *a priori* path plan is necessary to maneuver the UAVs to execute the assigned tasks. In this paper, we consider a centralized, multi-objective, dynamic path planning problem wherein the UAVs are allowed to hover en route to realize a collision-free safe path. The objectives of the path planning are measured in terms of both reward and cost. By reward, we mean the benefit of accomplishing the mission, e.g., task performance, mission completion time; by cost, we mean the usage of UAV resources, e.g., power and fuel. The need to coordinate multiple UAVs temporally and/or spatially while avoiding collisions with static obstacles (e.g., mountainous terrain, high-rise buildings) and moving obstacles (e.g., manned aircraft and other UAVs) within the environment complicates the multi-objective path planning problem. When a UAV is assigned to a task requiring the cooperation of other UAVs, they must coordinate to synchronize their operations for executing the task to meet the specified deadline. Consequently, the delays in task execution are primarily due to synchronization and waiting for busy UAVs to become available. In order to reduce task latencies, the synchronization delay and waiting time should be minimized. Specifically, we seek to optimize variables such as when a UAV should be dispatched to the task location, how the UAVs traverse to the task location, and how much time the UAVs wait at various locations prior to task execution, and so on. Additional constraints to maintain safe separation distance among the UAVs and the (static and moving) obstacles are also considered.

B. Literature Review

Path planning problems constitute one of the most extensive areas of research due to their wide spectrum of applications in the real world, e.g., telecommunications, fire hazard analysis and transportation [18][19]. Generally, path planning addresses the problem of computing efficient routes by optimizing a cost function (e.g., traveling cost, risk along the path, etc.) for a given set of vehicles. The path planning problem within a single objective optimization framework is also known as the shortest path problem. A variation of the shortest path problem is the Multi-Objective Shortest Path problem (MOSP). For example, in the case of military route planning, it is crucial to consider time, distance, and the ability to camouflage on the path, simultaneously.

In the context of UAV path planning, it is important to consider several factors such as safety, time, energy consumption and uncertainty in the environment. Specifically, path planning for a large fleet of UAVs requires systematic coordination among all the vehicles for a safe mission operation [20]. Ter Mors [21] proposed context aware route planning, where a conflict-free shortest-time route plan is developed without ending up in a deadlock situation.

However, context aware route planning is computationally expensive in comparison with the traditional route planning techniques. Shanmugavel [6] describes cooperative path planning for a group of UAVs with simultaneous arrivals on the target by making all the paths equal in length. They produce flyable paths using Dubins paths with clothoid arcs by means of differential geometry. Extra constraints are added for producing safe paths to avoid collision with other UAVs and obstacles. The path planning problem is reduced to tuning of flyable paths by increasing the shorter paths equal to that of the reference path [6][7]. Bellingham [22][23] considers path planning of multiple UAVs in an uncertain environment by modeling the probability of UAV loss. The coordination plans are designed to optimally exploit the coupling effects of cooperation between UAVs to improve the survival probabilities. The algorithm uses straight-line paths to estimate the time-of flight and risk for each mission. The task allocation for UAVs is posed as a Mixed Integer Linear Program (MILP) [22][23].

Kuwata [24] investigates the coordination and control of fleets of UAVs in a dynamic environment which includes task assignment, graph-based coarse path planning and detailed trajectory optimization using Receding Horizon Control (RHC). MILP has been applied for task allocation and trajectory design to encode logical constraints and discrete decisions. The combined use of MILP and RHC provides a good estimate of the cost-to-go and greatly reduces the computational effort required to design the complete trajectory, but discrepancies in the assumptions made in the two models can lead to infeasible solutions [24]. Tin [5] proposed an algorithm to coordinate a team of UAVs to search in an unknown environment, while balancing the need to track moving targets. The Receding Horizon Mixed-Integer Linear Programming (RH-MILP) control hierarchy has been used to handle uncertainty and properly react to rapid changes in the environment [5]. In this paper, our work goes beyond previous research on UAV path planning by incorporating multiple objectives of minimizing the cumulative traveling cost and minimizing the total task latency, as well as accounting for realistic constraints (e.g., synchronization constraints, stopping en-route, etc.).

C. Organization of the paper

The remaining paper is organized as follows: section II introduces the problem and formulates it as an MILP problem. Section III describes a decomposition method to solve the problem. Experimental results are provided in section IV. Finally, the paper concludes with a summary of key findings and future research directions in section V.

II. PROBLEM DESCRIPTION AND FORMULATION

A. Problem Description

Consider a scenario where a group of $\kappa = \{1,...,K\}$ UAVs are scheduled to execute a set of $\ell = \{1,...,L\}$ tasks which are geographically distributed over a two-dimensional grid map. Let $k \in \{1,\ldots,K\}$ be the UAV index and $l \in \{1,\ldots,L\}$ be the task index. The grid map also includes: 1) static obstacles including no fly zones, high-rise buildings, mountainous terrain, etc.; 2) dynamic obstacles, e.g., manned aerial vehicles moving over different paths over the grid map. Each task l on the grid map is characterized by its geographic location $loc(l)$, UAV requirements Ψ_l^{asgn}, start time t_l^{start}, processing time $t_l^{process}$, and deadline $t_l^{deadline}$. Each UAV, specified by its capability (e.g., velocity), departs from a start cell (base) towards a destination cell while executing a series of assigned tasks during its transit. The UAVs experience an associated time-varying risk denoted by r_{ijkt}, which accumulates as UAV k travels from cell $i \in \mathrm{I} = \{1,...,N\}$ to cell $j \in J = \{1,...,N\}$ at time epoch $t \in \mathrm{T} = \{1,...,T\}$. Here, N represents the total number of cells on the grid map. Each cell on the grid can accommodate only one vehicle at a time (i.e., one UAV or one manned aircraft) except for the start cell, end cell and the task cells which are capable of accommodating multiple vehicles at the same time. UAVs assigned to tasks requiring the cooperation of other UAVs are to be synchronized at specific task locations. We assume that the processing of a task cannot begin until all the required UAVs have arrived at the scene. As a result, delay in task execution occurs primarily due to synchronization and waiting for busy UAVs to become available. Also, while coordinating the UAVs, a safe separation distance should be maintained with respect to the manned vehicles to avoid any risk of mid-air collisions. The overall objective here is to efficiently maneuver a group of UAVs within a dynamic grid map by minimizing task latencies and cumulative risk along the path while satisfying the deadlines of time-critical tasks. The problem formulation and the constraints are discussed next.

B. Problem Formulation

We model the path planning problem as a multi-objective mixed integer linear programming (MILP) problem of minimizing the following:

a) *Cumulative Path Risk*: A time-dependent cost, denoted by r_{ijkt}, is defined as the path risk experienced by UAV k in moving from cell i to cell j at time epoch t, which includes the traveling cost (e.g., distance, time) and the usage cost of UAV (fuel consumption, UAV's exposure to the environment). We assume that a UAV can navigate from its current cell to one of the neighboring cells in each time epoch and therefore the time-varying cost function is defined as:

$$\begin{gathered}\mathrm{Obj}_1 : \min_{x_{ijkt}} \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{(i,j)\in\Omega} r_{ijkt} x_{ijkt} \\ x_{ijkt} = \begin{cases} 1, & \text{if UAV } k \text{ moves from cell } i \text{ to cell } j \text{ at time } t \\ 0, & \text{otherwise} \end{cases}\end{gathered} \tag{1}$$

Here x_{ijkt} is a binary decision variable; t denotes the discrete time epoch; $(i, j) \in \Omega$ denotes the path that links cell i and cell j, where neither cell is occupied by static obstacles nor manned vehicles.

b) *Task Latencies*: A particular task l is delayed if it cannot meet the specified deadline denoted by $t_l^{deadline}$. We assume that the amount of time required for task l to be processed $t_l^{process}$ is a known parameter. The time delay in processing task l is defined as:

$$t_l^{latency} = \max(0, t_l^{start} + t_l^{process} - t_l^{deadline}) \tag{2}$$

Here t_l^{start} is the start time of task l. The associated cost function to be minimized is defined as:

$$\mathrm{Obj}_2 : \min \sum_{l=1}^{L} t_l^{latency} \tag{3}$$

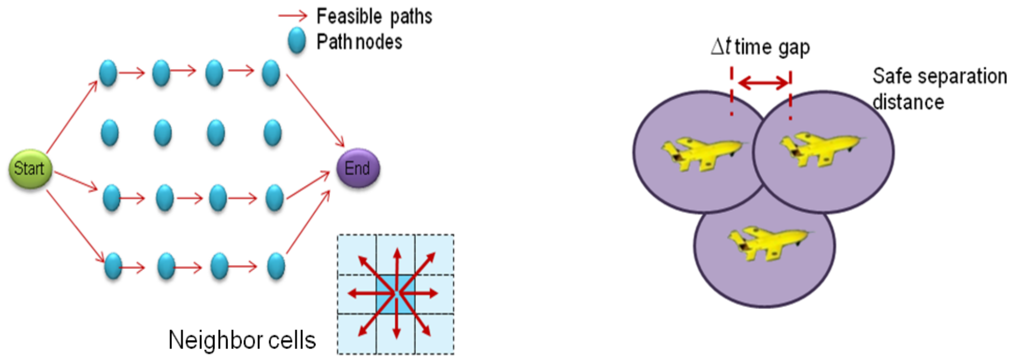

Figure 1: UAV Mission Planning Constraints (a) Network Flow constraints (b) Safe separation distance

The dual-objective optimization is solved subject to path constraints, arrival and departure times, task execution and collision avoidance constraints to guarantee that the UAVs follow a flyable and safe path. The constraints are formalized as follows:

a) *Network Flow Constraints*: The network flow constraints, shown in Figure 1(a), ensure that every UAV departs from a start base (i=1) and arrives at the end base (i=N); these are formalized in equations 4(a) and 4(b). *Here, it is assumed that the start and end base are capable of accommodating multiple vehicles at any time epoch*. The constraints 4(c) and 4(d) eliminate the possibility of a UAV entering the mission scenario without exiting and vice versa. Constraint 4(d) also allows a UAV to stay at a specific cell until a risk-free path is available. Therefore, for any time epoch $\tilde{T}$, strictly less than T, the number of incoming UAVs is greater than the number of departing UAVs.

$$
\begin{aligned}
&\sum_{t=1}^{T}\sum_{i\in Q(1,t)} x_{1ikt} = 1, \forall k && (a)\\
&\sum_{t=1}^{T}\sum_{i\in P(N,t)} x_{iNkt} = 1, \forall k && (b)\\
&\sum_{t=1}^{T}\sum_{j\in Q(i,t)} x_{ijkt} - \sum_{t=1}^{T}\sum_{j\in P(i,t)} x_{jikt} = 0, \ \forall k, \forall i \neq 1 \,\&\, i \neq N && (c)\\
&\sum_{t=1}^{\tilde{T}}\sum_{j\in Q(i,t)} x_{ijkt} \leq \sum_{t=1}^{\tilde{T}}\sum_{j\in P(i,t)} x_{jikt}, \forall k, \forall i \neq 1, \forall \tilde{T} < T && (d)
\end{aligned}
\qquad (4)
$$

In (4), $P(i,t)$ and $Q(i,t)$ denote the set of available predecessor and successor cells of cell i at time t, respectively.

b) *Arrival and Departure Constraints*: In order to keep track of the execution status of a task, we introduce the variables t_{ki}^{arrive} and t_{ki}^{depart} to denote the exact time when UAV k arrives and departs cell i. The relationship between the departure and arrival time can be formalized as follows:

$$
\begin{aligned}
& t_{k1}^{arrive} = 0, \forall k && (a) \\
& t_{ki}^{depart} + t_{k}^{travel} x_{ijkt} \le t_{kj}^{arrive} + M(1 - x_{ijkt}), \forall k, \forall i, \forall j \ne 1, \forall t && (b) \\
& t_{ki}^{depart} \ge t_{ki}^{arrive}, \ \forall i \notin \{loc(l)\}, \forall k && (c) \\
& t_{ki}^{depart} \ge t_{ki}^{arrive}, \ \forall i \in \{loc(l)\}, \forall k \notin \Psi_{l}^{a\mathrm{sgn}} && (d)
\end{aligned}
\qquad (5)
$$

Equation 5(a) ensures that all the UAVs are at the base location at $t = 0$. The time of arrival of a UAV at any cell j has to be greater than the sum of the departure time t_{ki}^{depart} from cell i and travel time t_{k}^{travel} to the next successor cell; this is guaranteed by 5(b) which avoids cyclic paths [12]. Here, M is an arbitrarily large number greater than time horizon T, such that if $x_{ijkt} = 1$ (i.e., UAV k travels from cell i to cell j), then the arrival time is the sum of the departure time and travel time. Otherwise, $t_{ki}^{depart} \le M$. The constraint 5(c) ensures that the departure times of all the UAVs are greater than their arrival times at every cell except at task locations. For the cells where tasks are located $i \in \{loc(l)\}$, all UAVs not involved in the task $k \notin \Psi_{l}^{asgn}$, will have departure times greater than their arrival times.

c) *Task Execution Constraints*: UAVs operating together to execute a particular task need to be synchronized at their assigned task locations. This couples the routes of two or more vehicles. Depending on the mission scenario, vehicle routes may be synchronized temporally or spatially [18]. Here, we consider spatial synchronization as each task requires a specific set of UAVs in order to process it. The processing of a task cannot begin until all the required UAVs arrive at the specified task location. At every task location, the departure time of the UAVs involved in processing the task should be greater than the sum of the task start and processing times. The constraint 6(a) ensures that the assigned UAVs execute the task completely before navigating to the next cell. The constraint 6(b) guarantees that a task cannot start until all the required UAVs have arrived at the scenario. The constraint 6(c) puts a limit on the maximum number of UAVs required by a task l, denoted by q_l

$$
\begin{aligned}
& t_{kloc(l)}^{depart} \ge t_{l}^{start} + t_{l}^{process}, \ \forall l, \forall k \in \Psi_{l}^{a\mathrm{sgn}} && (a) \\
& t_{l}^{start} = \max_{k \in \Psi_{l}^{a\mathrm{sgn}}} t_{kloc(l)}^{arrive}, \forall l && (b) \\
& \sum_{j \in P(loc(l),t)} \sum_{k=1}^{K} x_{jloc(l)kt} \le q_l, \ \forall l, \forall t && (c)
\end{aligned}
\qquad (6)
$$

d) *Collision Avoidance Constraints*: A safe path requires the UAVs to stay outside the no-fly zones and avoid colliding with static and dynamic obstacles, such as mountainous terrain, high-rise buildings and manned aircraft. Additionally, it is important to avoid collision among the UAVs as they arrive at the task locations at the same time. A collision occurs if: i) two or more UAVs arrive at the same cell location (excluding the start cell, end cell and the task locations) at the same time during their transit; ii) during transit a UAV arrives at a manned aircraft location at the same time or a UAV arrives at a static obstacle location; iii) multiple UAVs attempt to reach a required task location simultaneously. Collision during transit is avoided by allowing the UAV to wait at the specific cell location i.e., allowing for lingering en-route until it is safe to move to the next cell location. To avoid collision in situations when multiple UAVs arrive at the same cell location, it is imperative to ensure a safe separation distance between every pair of UAVs at each time step by considering the difference in time of arrival between every vehicle at each task location, as shown in Figure 1(b). We incorporate this *non-convex* constraint using binary variables and a large number M as follows [24]:

$$\begin{aligned} & t_{k'i}^{arrive} - t_{ki}^{depart} \geq \Delta t - M\alpha_{kk'i} \ \forall i,k,k' \neq k && (a) \\ & t_{ki}^{arrive} - t_{k'i}^{depart} \geq \Delta t - M(1-\alpha_{kk'i}) \ \forall i,k,k' \neq k && (b) \\ & \alpha_{kk'i} \in \{0,1\}, \forall i,k,k' \neq k \end{aligned} \tag{7}$$

where Δt denotes the time a UAV needs to travel a predefined safe distance; $\alpha_{kk'i}$ denotes a binary variable which takes on the value 1 when k arrives after k' departs from location i, and 0 otherwise. This multi-objective MILP problem is difficult to solve due to the large number of constraints and the dynamic obstacles considered here. Moreover, MILP problem is recognized as NP-hard and therefore difficult to solve. In the next section, we propose a decomposition method to solve the cooperative path planning and task execution problem.

III. SOLUTION APPROACH

The MILP problem formulated above is multi-objective, which includes minimizing the path risk with respect to x_{ijkt}, and minimizing the task latencies with respect to t_{ki}^{arrive}. We propose a two-phase algorithm that decomposes the problem into two sub-problems and solve them iteratively. In phase I, we determine the path of each UAV by minimizing the cumulative risk given the expected arrival time at each cell location; in phase II, we determine the arrival time of each UAV at each cell location by following the path generated in phase I. An initial setup for x_{ijkt} can be solved by solely minimizing the risk associated with a path as follows:

$$\begin{aligned} & \min_{x_{ijkt}} \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{(i,j)\in\Omega} r_{ijkt}x_{ijkt} \\ & s.t. \sum_{t=1}^{T}\sum_{i\in Q(1,t)} x_{1ikt} = 1, \forall k && (a) \\ & \sum_{t=1}^{T}\sum_{i\in P(N,t)} x_{iNkt} = 1, \forall k && (b) \\ & \sum_{t=1}^{T}\sum_{j\in Q(i,t)} x_{ijkt} - \sum_{t=1}^{T}\sum_{j\in P(i,t)} x_{jikt} = 0, \ \forall k, \forall i \neq 1 \ \& \ i \neq N && (c) \\ & \sum_{t=1}^{\tilde{T}}\sum_{j\in Q(i,t)} x_{ijkt} \leq \sum_{t=1}^{\tilde{T}}\sum_{j\in P(i,t)} x_{jikt}, \forall k, \forall i \neq 1, \forall \tilde{T} < T && (d) \\ & \sum_{j\in P(loc(l),t)}\sum_{k=1}^{K} x_{jloc(l)kt} \leq q_l, \ \forall l, \forall t && (e) \\ & x_{ijkt} \in \{0,1\}, \forall i,j,k,t \end{aligned} \tag{8}$$

where 8(a-d) correspond to network flow constraints and 8(e) refers to task execution constraints. We applied IBM's mixed integer linear programming solver (CPLEX) [26] to solve the above problem. In phase II, we determine the arrival time of each UAV at each cell location by following the path generated in phase I, i.e. given x_{ijkt}^{*}, as follows:

$$\min_{t_{k1}^{arrive}, t_{ki}^{depart}} \sum_{l=1}^{L} \max(0, t_l^{start} + t_l^{process} - t_l^{deadline})$$

$$\begin{aligned}
s.t.\ & t_{k1}^{arrive} = 0, \forall k && (a) \\
& t_{ki}^{depart} + t_k^{travel} x_{ijkt}^{*} \le t_{kj}^{arrive} + M(1 - x_{ijkt}^{*}), \forall k, \forall i, \forall j \ne 1, \forall t && (b) \\
& t_{ki}^{depart} \ge t_{ki}^{arrive},\ \forall i \notin \{loc(l)\}, \forall k && (c) \\
& t_{ki}^{depart} \ge t_{ki}^{arrive},\ \forall i \in \{loc(l)\}, \forall k \notin \Psi_l^{\text{asgn}} && (d) \\
& t_{kloc(l)}^{depart} \ge t_l^{start} + t_l^{process},\ \forall l, k \in \Psi_l^{\text{asgn}} && (e) \\
& t_l^{start} \ge t_{kloc(l)}^{arrive}, \forall l, k \in \Psi_l^{\text{asgn}} && (f) \\
& t_{k'i}^{arrive} - t_{ki}^{depart} \ge \Delta t - M\alpha_{kk'i}\ \ \forall i \notin \{loc(l), 1, N\}, k, k' \ne k && (g) \\
& t_{ki}^{arrive} - t_{k'i}^{depart} \ge \Delta t - M\left(1 - \alpha_{kk'i}\right)\ \forall i \notin \{loc(l), 1, N\}, k, k' \ne k && (h) \\
& \alpha_{kk'i} \in \{0,1\}, \forall i, k, k' \ne k \\
& t_{ki}^{arrive} \ge 0, \forall i, k \\
& t_{ki}^{arrive} \in \Sigma,\ t_l^{start} \in \mathbb{R},, \forall i, k
\end{aligned} \tag{9}$$

where 9(a-d) are the arrival and departure constraints as in section II, 9(e-f) correspond to the task execution constraints, 9(g-h) are the collision avoidance constraints, and Σ denotes the set of time epochs that will not violate the manned vehicles' paths, all of which can be computed offline. Once optimal decision variables $t_{kj}^{arrive*}$ and $t_{ki}^{depart*}$ are obtained, we solve a modified phase I sub-problem as:

$$\min_{x_{ijkt}} \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{(i,j)\in\Omega} r_{ijkt} x_{ijkt}$$

$$\begin{aligned}
s.t.\ & \sum_{t=1}^{T} \sum_{i \in Q(1,t)} x_{1ikt} = 1, \forall k && (a) \\
& \sum_{t=1}^{T} \sum_{i \in P(N,t)} x_{iNkt} = 1, \forall k && (b) \\
& \sum_{t=1}^{T} \sum_{j \in Q(i,t)} x_{ijkt} - \sum_{t=1}^{T} \sum_{j \in P(i,t)} x_{jikt} = 0,\ \ \forall k, \forall i \ne 1 \,\&\, i \ne N && (c) \\
& \sum_{t=1}^{\tilde{T}} \sum_{j \in Q(i,t)} x_{ijkt} \le \sum_{t=1}^{\tilde{T}} \sum_{j \in P(i,t)} x_{jikt}, \forall k, \forall i \ne 1, \forall \tilde{T} < T && (d) \\
& \sum_{j \in P(loc(l),t)} \sum_{k=1}^{K} x_{jloc(l)kt} \le q_l,\ \ \forall l, \forall t && (e) \\
& t_{ki}^{depart*} + t_k^{travel} x_{ijkt} \le t_{kj}^{arrive*} + M(1 - x_{ijkt}), \forall k, \forall t, \forall i, \forall j \ne 1 && (f) \\
& \sum_{t_{ki}^{depart*}}^{T} \sum_{j \in Q(i,t)} x_{ijkt} > 0,\ \forall k,\ \ \forall i \ne N && (g) \\
& \sum_{t=1}^{t_{kj}^{arrive*}} \sum_{i \in P(i,t)} x_{ijkt} > 0,\ \forall k,\ \ \forall j \ne 1 && (h) \\
& x_{ijkt} \in \{0,1\}, \forall i, j, k, t
\end{aligned} \tag{10}$$

where 10(f-h) are added to ensure that: 1) if $t_{ki}^{depart*} \geq t_{kj}^{arrive*}$, $x_{ijkt}^{*} = 0$; 2) UAV k has to leave cell i after time $t_{ki}^{depart*}$; 3) UAV k has to arrive at cell j before time $t_{kj}^{arrive*}$. This iterative process in (9) and (10) is continued until the decision variables do not change from one iteration to the next.

IV. EXPERIMENTAL RESULTS

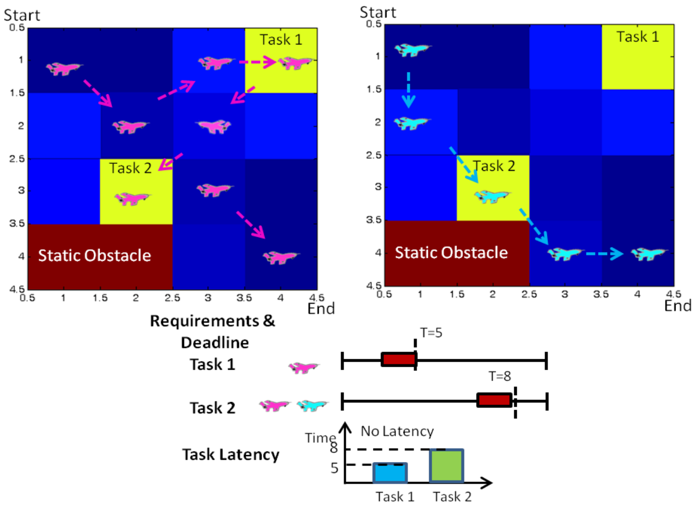

Figure 2: UAV Path Planning Results with static obstacles (*Scenario I* (*a*))

Given a set of tasks and their locations over a dynamic risk map with static and dynamic obstacles (such as buildings in urban area, mountains, manned vehicles, etc.), we modeled the path planning problem as a time-dependent multi-objective MILP problem of minimizing: a) the path risk and b) the cumulative task latencies. We consider the following constraints: 1) each UAV must start from the start cell (UAV start base) and return to an end cell (UAV destination base); 2) UAVs can only move to one of the neighboring cells at any time epoch; 3) collision avoidance constraints are considered by maintaining a safe separation distance while the UAV travels from one task location to another. At task locations where multiple UAVs are required to execute the task, a time gap (Δt) between the arrival of each UAV is maintained to avoid collision among the UAVs; 4) UAVs can visit non-obstacle sites at any time; 5) execution of a task cannot start until all the UAVs required for that particular task have arrived at the task location. The proposed UAV path planning model is evaluated using a number of experimental scenarios. The experimental scenarios investigated here are illustrated in the context of time-critical or time-relaxed (meaning deadlines can be missed with penalties) mission tasks as discussed below.

Due to the dynamic nature of the scenario and the constraints considered here, the resulting MILP problem is enormously large. In order to solve such a complex and large scale problem, we decomposed it into two sub-problems corresponding to each objective as described in the previous section. In phase I, we determine the path of each UAV by minimizing the cumulative risk (e.g., the distance of UAV from the static and moving obstacles) given the expected arrival time at each cell location. In phase II, we determine the arrival time of each UAV at each cell location by following the path generated in phase I. We solve these two sub-problems iteratively until no further improvements can be made.

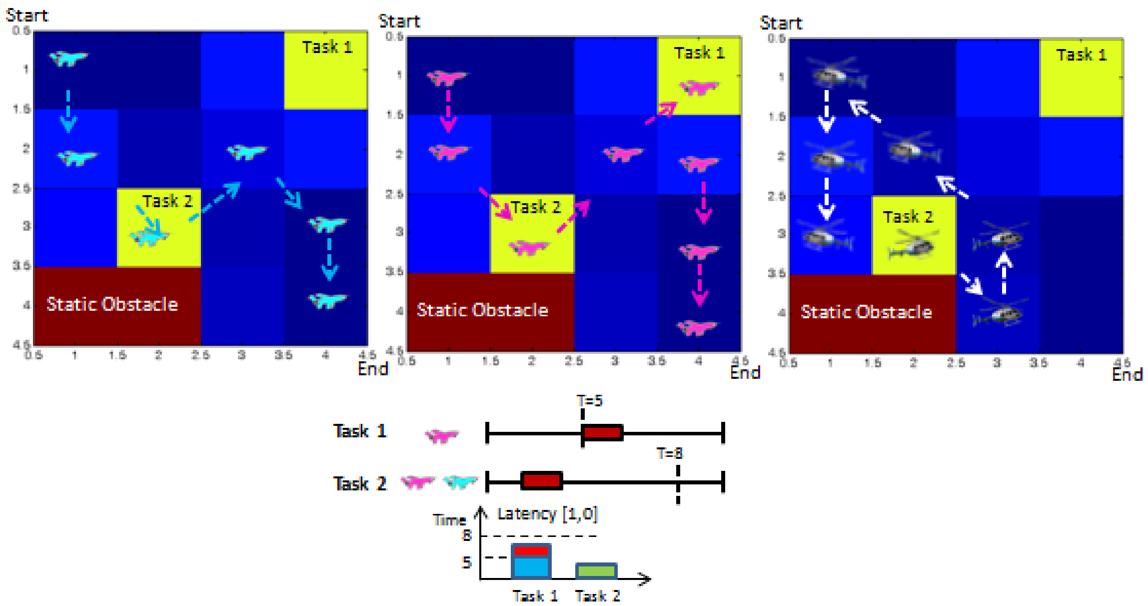

Figure 3: UAV Path Planning Results with One Manned Aircraft (*Scenario I* (*b*))

Scenario I: We consider a 4x4 grid map with two tasks at different geographic locations and these tasks are to be completed before the specified deadlines. The task locations and the required UAVs are shown in Figure 2. We simulate three different scenarios where we analyze how the tasks are executed under different static and dynamic obstacles within a confined mission area. In *scenario I*(*a*), only static obstacles are considered and Task 1 requires only one UAV to complete the task, while Task 2 requires the cooperation of two UAVs. The simulation results, as shown in Figure 2, indicate that both the tasks are completed before their respective deadlines, which is commensurate with our intuition as there are no moving obstacles to obstruct the path of the UAVs.

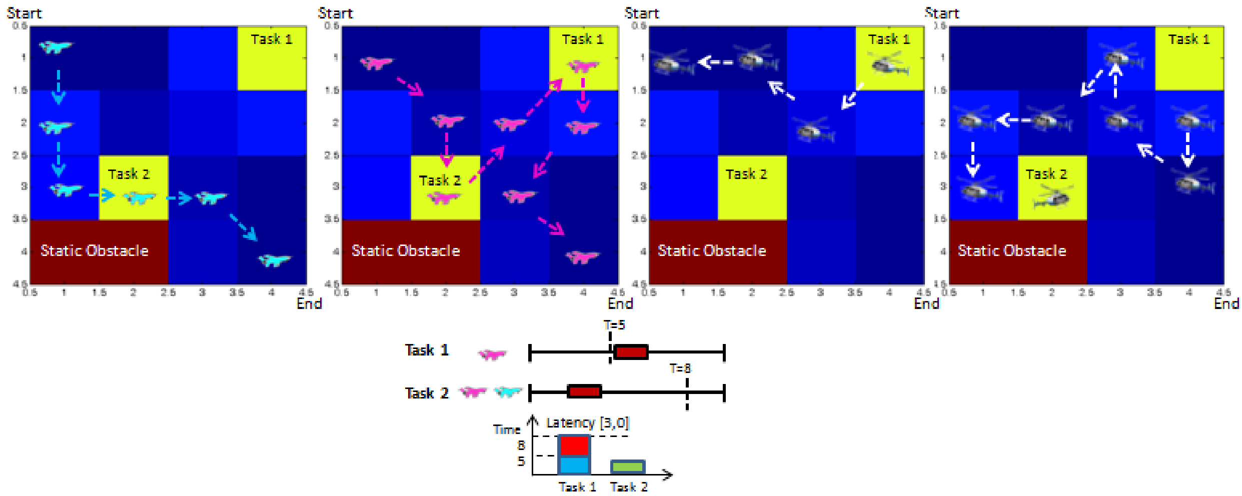

Figure 4: UAV Path Planning Results with Two Manned Aircraft (*Scenario I* (*c*))

In *scenario I*(*b*), we introduce a manned aircraft and analyze the delay in task execution. Figure 3 illustrates the results where Task 2 is processed well in advance of the deadline, while Task 1 gets delayed by one time unit. This happens because the UAVs always follow a least risk path (light blue boxes) during their transit to the task locations. Also a collision with the manned aircraft is anticipated if Task 1 is processed first. Thus, even though Task 1 is not executed before the deadline, the UAVs navigate safely, maintaining a safe separation distance at the synchronization location and also during transit.

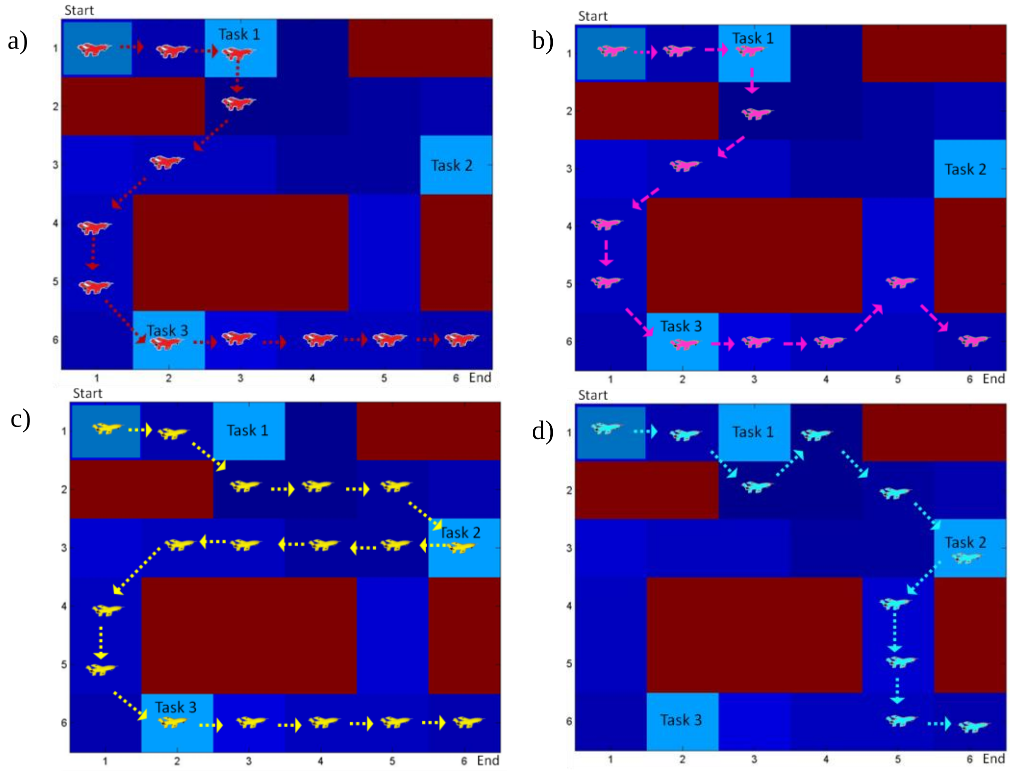

Figure 5: UAV Mission Planning Results a) Red UAV b) Pink UAV b) Yellow UAV, and d) Blue UAV

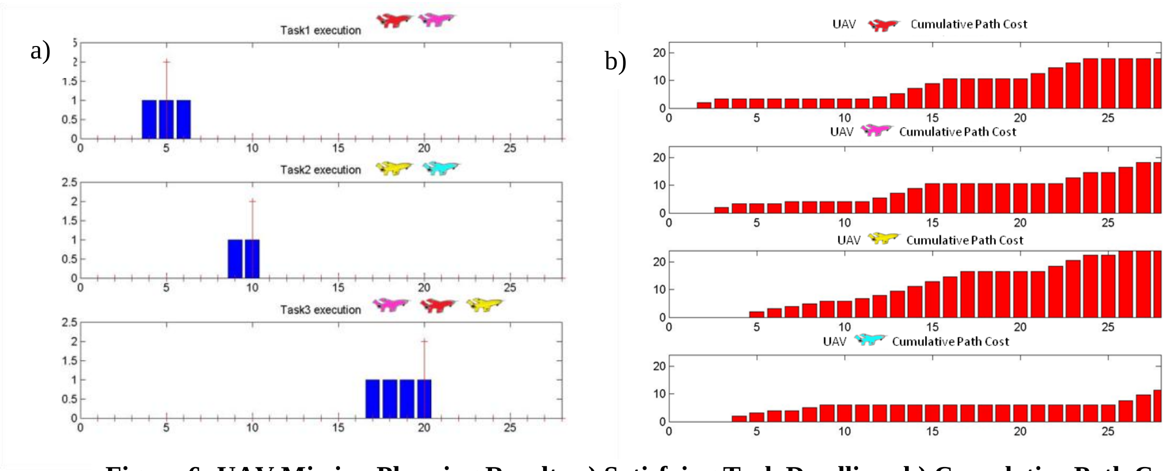

Figure 6: UAV Mission Planning Results a) Satisfying Task Deadlines b) Cumulative Path Cost

In *scenario I*(*c*), an additional manned aircraft is introduced which results in further delay in processing Task 1, as shown in Figure 4. Thus, we see that the delay in task execution increases as we increase the number of manned vehicles; however, as the tasks are not time-critical, we focus more on the maneuver of the UAVs, while guaranteeing the completion of tasks.

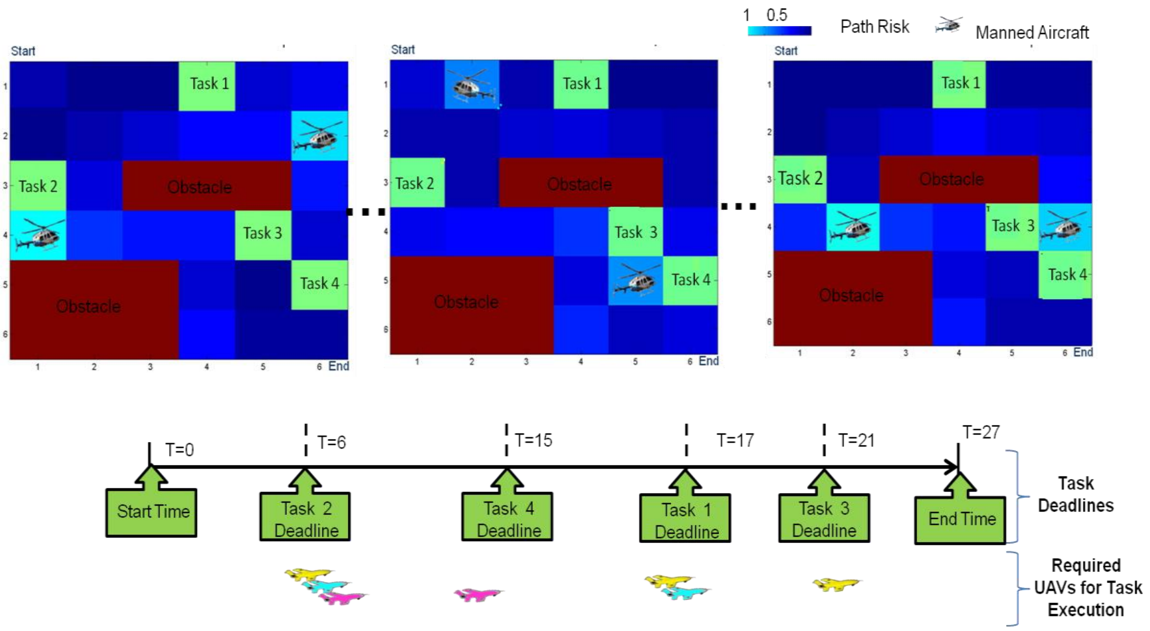

Figure 7: UAV Mission Planning Scenario

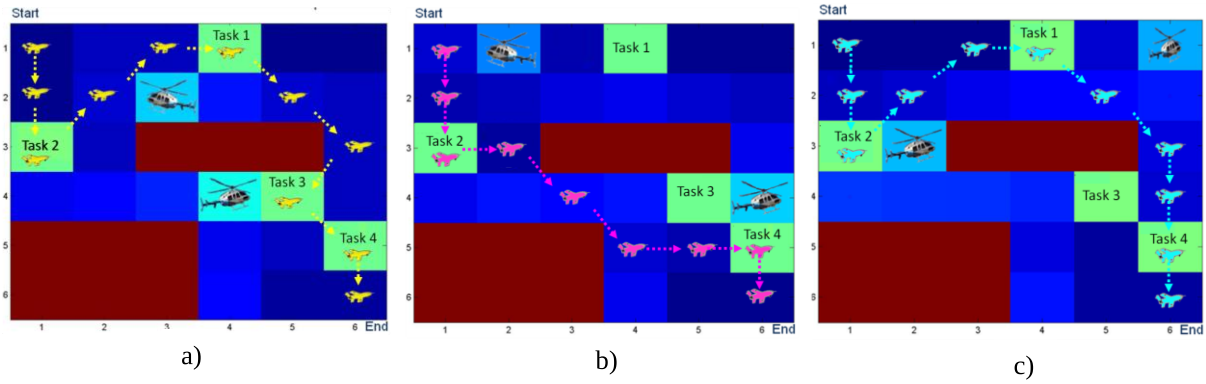

Figure 8: UAV Mission Planning Results (a) Path for Yellow UAV (b) Path for Pink UAV (c) Path for Blue UAV

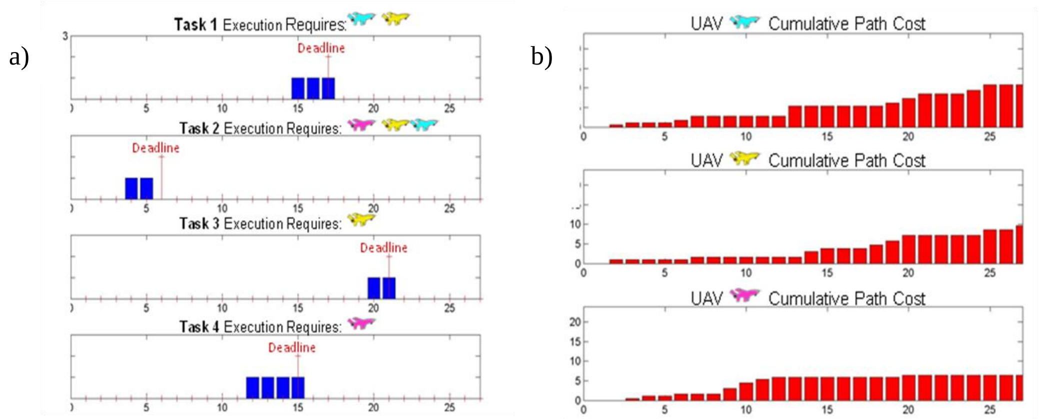

Figure 9: UAV Mission Planning Results (a) Task Deadline Criteria Met (b) Cumulative Path Cost

Table 1: UAV Path Planning Results

Time Horizon	Yellow UAV	Blue UAV	Pink UAV	Manned Vehicle 1	Manned Vehicle 2	Mission Events
0	(1,1)	(1,1)	(1,1)	(1,4)	(6,2)	All UAVs at initial location
1	(1,2)	(1,1)	(1,1)	(1,4)	(6,2)	
2	(1,3)	(1,2)	(1,1)	(2,3)	(6,1)	
3	(1,3)	(1,3)	(1,2)	(3,4)	(5,2)	
4	(1,3)	(1,3)	(1,3)	(3,4)	(4,1)	Execution of Task 2 by Yellow, Blue & Pink UAV starts
5	(1,3)	(1,3)	(1,3)	(4,4)	(3,2)	
6	(1,3)	(2,2)	(2,3)	(5,4)	(2,1)	Task 2 Completed (Required deadline met)
7	(2,2)	(3,1)	(2,3)	(5,5)	(2,1)	
8	(2,2)	(3,1)	(2,3)	(6,4)	(2,1)	
9	(2,2)	(3,1)	(3,4)	(6,4)	(2,1)	
10	(2,2)	(3,1)	(4,5)	(6,3)	(2,1)	Execution of Task 4 by Pink UAV starts
11	(2,2)	(3,1)	(5,5)	(5,2)	(2,1)	
12	(2,2)	(3,1)	(6,5)	(4,1)	(2,1)	
13	(2,2)	(4,1)	(6,5)	(3,1)	(2,1)	Execution of Task 1 by Yellow & Blue UAV starts
14	(3,1)	(4,1)	(6,5)	(3,2)	(1,1)	Task 4 Completed (Required deadline met)
15	(4,1)	(4,1)	(6,5)	(2,1)	(1,2)	
16	(4,1)	(4,1)	(6,5)	(2,2)	(1,3)	Task 1 Completed (Required deadline met)
17	(4,1)	(4,1)	(6,5)	(1,3)	(1,4)	
18	(5,2)	(4,1)	(6,5)	(2,3)	(2,4)	Execution of Task 3 by Yellow UAV starts
19	(6,3)	(5,2)	(6,5)	(2,4)	(3,4)	
20	(5,4)	(6,3)	(6,6)	(2,4)	(4,5)	Task 3 Completed (Required deadline met)
21	(5,4)	(6,4)	(6,6)	(2,4)	(4,5)	
22	(5,4)	(6,4)	(6,6)	(2,4)	(4,5)	
23	(5,4)	(6,4)	(6,6)	(2,4)	(4,6)	
24	(5,4)	(6,5)	(6,6)	(2,4)	(4,6)	
25	(6,5)	(6,6)	(6,6)	(2,4)	(5,5)	
26	(6,5)	(6,6)	(6,6)	(2,4)	(6,4)	
27	(6,6)	(6,6)	(6,6)	(2,4)	(6,4)	All UAVs at destination base

Scenario II: In this scenario, we have four UAVs executing three time-critical tasks within a static obstacle environment. Figure 5 shows the detailed trajectories of all four UAVs at different time epochs. The task latencies and the cumulative path costs are shown in Figure 6 (a) and (b), respectively. Task 1 is slightly delayed due to travel time required by the UAV to reach its task location, while the remaining tasks are completed prior to the deadline.

Scenario III: In this scenario, a set of three UAVs are required to execute four different tasks on a 6×6 grid map. We included two manned vehicles moving along different paths as dynamic obstacles to be avoided by the UAVs. Figure 7 shows the task deadlines and the assigned UAVs to execute the four tasks. Figure 8 shows the experimental results, where the detailed trajectories of the three UAVs are shown. Table 1 displays the locations of the UAVs and the manned vehicles at each time epoch. From the values in the table, we can infer that the manned and unmanned vehicles are safely separated. Key features of this experimental result are: 1) the blue and yellow UAVs are aware that one of the manned vehicles will travel through Task 1's location and therefore decide to execute the task after the manned vehicle has left the area in order to avoid a collision; 2) After executing Task 2, the pink UAV waits for a low risk path and then travels directly to Task 4's location to execute it, while the other UAVs move to their next location; 3) Task 1 is executed cooperatively by blue and yellow UAVs, and thereafter the blue UAV allows the yellow UAV to leave first so that it can finish the next assigned task (Task 3). Figure 9(a) depicts how the execution of each task progresses and meets the specified deadlines. The cumulative path costs of all UAVs at each time epoch are shown in Figure 9(b).

Thus, all of these simulation results indicate that, based on the context of whether the mission tasks are time-critical or relaxed, the objective can be either meeting the strict task deadlines or opting for a safe collision free path (i.e. no penalty for delay) with the objective of completing the assigned tasks. The proposed iterative process provides a feasible solution without creating a deadlock situation due to the wait time allowed for the UAVs and realistic constraints considered in our problem.

Future advances in aviation technologies and military deployment envision merging unmanned systems from air, ground, and sea domains into teams of unmanned and manned systems. Coordinated and conflict-free path planning will be a major challenge in the case of manned-unmanned teaming. Recently with the development of automatic dependent surveillance-broadcast (ADS-B) [27], it is possible to relay the manned aircraft's altitude and location information to other aircraft in its vicinity. Although ADS-B would facilitate collision avoidance, efficient and reliable communication under bandwidth constraints is necessary for UAVs operating in jamming mission environments.

V. CONCLUSION AND FUTURE WORK

In this paper we presented a multi-objective UAV path planning problem for coordinated task execution within a dynamic environment including: 1) a mathematical formulation of the path planning problem; 2) a two-phase algorithm to solve the resulting MILP problem. Our decomposition method solves the multi-objective UAV path planning problem subject to a number of realistic planning constraints. We constructed our solution that iteratively solves a series of MILP problems and checks for the convergence of UAV routes, while ensuring no path conflicts occurred within the specified constraints. We used IBM's mixed integer linear programming solver (CPLEX) to solve each MILP problem for generating the sequence of cells to be visited by each UAV and the corresponding arrival and departure times.

Further research concerns include online implementation of the algorithm for context-driven task execution and mission planning. Motivated by the need for adapting the path planning to highly dynamic and uncertain mission environments, we would like to extend the current research along the following directions: 1) evaluate and compare the general MILP algorithms (e.g., branch and bound) in terms of mission effectiveness and computation cost; 2) explore and compare approximation techniques such as ant colony systems and genetic algorithms and incorporate them into the current two-phase multi-objective MILP approach; 3) extend the current two phase algorithm to generate the Pareto-optimal solutions for multi-objective problems; 4) revise the current planning structure to a distributed setting where each UAV decides its own route and communicates with others as needed to avoid collisions while guaranteeing collaborative task execution; 5) explore 3D path planning including the vertical deconfliction problem; and 6) incorporate environmental uncertainty into the current planning process, such as when manned vehicles change paths, thus requiring agile planning under uncertainty.

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