Branching to find feasible solutions in Unmanned Air Vehicle Mission Planning

Cristian Ramirez-Atencia[1], Gema Bello-Orgaz[1],
Maria D. R-Moreno[2], and David Camacho[1]

[1] Departamento de Ingeniería Informática, Universidad Autónoma de Madrid,
C/Francisco Tomás y Valiente 11, 28049 Madrid, Spain
cristian.ramirez@inv.uam.es, {gema.bello,david.camacho}@uam.es
aida.ii.uam.es
[2] Departamento de Automática, Universidad de Alcalá,
Carretera Madrid Barcelona, km 33 600, 28871 Madrid, Spain
mdolores@aut.uah.es

Abstract. Mission Planning is a classical problem that has been traditionally studied in several cases from Robotics to Space missions. This kind of problems can be extremely difficult in real and dynamic scenarios. This paper provides a first analysis for mission planning to Unmanned Air Vehicles (UAVs), where sensors and other equipment of UAVs to perform a task are modelled based on Temporal Constraint Satisfaction Problems (TCSPs). In this model, a set of resources and temporal constraints are designed to represent the main characteristics (task time, fuel consumption, ...) of this kind of aircrafts. Using this simplified TCSP model, and a Branch and Bound (B&B) search algorithm, a set of feasible solutions will be found trying to minimize the fuel cost, flight time spent and the number of UAVs used in the mission. Finally, some experiments will be carried out to validate both the quality of the solutions found and the spent runtime to found them.

Keywords: unmanned aircraft systems, mission planning, temporal constraint satisfaction problems, branch and bound

1 Introduction

Unmanned Aircraft Systems (UAS) can take advantage of planning techniques where the application domain can be defined as the process of generating tactical goals for a team of Unmanned Air Vehicles (UAVs). Nowadays, these vehicles are controlled remotely from ground control stations by humans operators who use legacy mission planning systems.

Mission planning for UAS can be defined as the process of planning the locations to visit (waypoints) and the actions that the vehicle can perform (loading/dropping a load, taking videos/pictures, acquiring information), typically over a time period. These planning problems can be solved using different methods such as Mixed-Integer Lineal Programming (MILP) [14], Simulated Annealing [2], Auction algorithms [8], etc. Usually, these methods are the best way to find the optimal solutions but, as the number of restrictions increase, the complexity grows exponentially because it is a NP-hard problem.

In the literature there are some attempts to implement UAS that achieve mission planning and decision making using temporal action logic (TAL) for reasoning about actions and changes [3], Markov Decision Process (MDP) and dynamic programming algorithms [4], or hybrid partial-order forward-chaining (POFC)[7], among others. Other modern approaches formulate the mission planning problem as a Constraint Satisfaction Problem (CSP), where the tactic mission is modelled and solved using constraint satisfaction techniques.

This work deals with multiple UAVs that must perform one or more tasks in a set of waypoints and specific time windows. The solution plans obtained should fulfill all the constraints given by the different components and capabilities of the UAVs involved over the time periods given. Therefore a Temporal Constraint Satisfaction Problem (TCSP) representation is needed. The approach from [9] is used to model a mission planning problem using Gecode [13] to program the constraints. In this previous work Backtracking (BT) method is applied to find the complete space of solutions, but in many real-life applications it is necessary to find only a good solution, what can be achieved considering a Constraint Satisfaction Optimization Problem (CSOP). For this purpose, in this work a new optimization function has been designed to look for good solutions minimizing the fuel cost, the flight time and the number of UAVs needed. Finally, Branch and Bound (B&B) search is employed for solving this CSOP model.

The rest of the paper is structured as follows: section 2 shows the state of the art in CSPs. Section 3 describes how a Misison is defined in the UAV domain and the modelization of the problem as a TCSP. In Section 4, the objective functions that will be used in the experimental phase are explained in detail. Section 5 explains the experiments performed and the experimental results obtained. Finally, the last section presents the final analysis and conclusions of this work.

2 Constraint Satisfaction Problems

A mission can be described as a set of goals that are achieved by performing some tasks with a group of resources over a period of time. The whole problem can be summed up in finding the correct schedule of resource-task assignments that satisfies the proposed constraints, like a CSP [1]. In a CSP, the states are defined by the values of the variables and the goal test specifies the constraints that the values must obey.

There are many studied methods to search the space of solutions for CSPs, such as BT, Backjumping (BJ) or look-ahead techniques (i.e. Forward Checking (FC)). BT search method solves CSP by incrementally extending a partial solution that specifies consistent values for some of the variables, towards a complete solution, and by repeatedly choosing a value for another variable consistent with the values in the current partial solution.

In many real-life applications it is necessary to find a good solution, and not the complete space of possible solutions. CSOP consists of a standard CSP and an optimization function (objective function) that maps every solution (complete labelling of variables) to a numerical value measuring the quality of the solution.

There are several methods for solving CSOP such as Russian doll search [12], Bucket elimination [11], Genetic algorithms [5] and Swarm intelligence [6]. The most widely used algorithm for finding optimal solutions is called B&B [10]. This algorithm searches for solutions in a depth first manner and behaves like BT except that as soon as a value is assigned to the variable, the value of heuristic function for the labelling is computed. If this value exceeds the bound (initially set to minus or plus infinity given it is a minimization or maximization problem), then the sub-tree under the current partial labelling is pruned immediately. The efficiency of B&B is determined by two factors: the quality of the heuristic function and whether a good bound is found early.

A TCSP is a particular class of CSP where variables represent times (time points, time intervals or durations) and constraints represent sets of allowed temporal relations between them [15]. A UAS mission can be perfectly represented as a set of temporal constraints over the time the tasks in the mission start and end. Besides the temporal constraints, the problem has several constraints imposing the proficiency of the UAVs to perform the tasks.

3 UAV Mission Plan Model based on TCSPs

A UAV mission can be defined as a number n of tasks to accomplish for a team of UAVs. A task could be exploring a specific area or search for an object in a zone. One or more sensors belonging to a particular UAV, as can be seen in Table 1, may be required to perform a task. Each task must be performed in a specific geographic *area*, in a specific *time interval* and needs an amount of *payloads* to be accomplished.

Table 1: Different task actions considered

Id.	Action	Payload Needed
A1	Taking pictures of a zone	– Camera EO/IR
A2	Taking real-time pictures of a zone	– Camera EO/IR – Communications Equipment
A3	Tracking a zone	– Radar SAR

To perform a mission, there are a number m of UAVs, each one with some specific characteristics: *fuel* consumed, *maximum reachable speed*, *minimum cruise speed*, permission to go to *restricted areas*, and capacities or *payloads* (cameras, radars, communication equipments, . . .). Moreover, in each point in time, each UAV is positioned at some specific *coordinates* and is filled with an amount of *fuel*. The main goal to solve the problem is to assign each task with a UAV that is able to perform it, and a start time of the UAV departure to reach the task area in time.

In this approach, the problem domain is modelled as a TCSP where the main variables are the *tasks* and their values will be the *UAVs* that perform each task and their respective *departure times*. There are two additional variables, the *fuel cost* and *distance travelled* for each task, that can be deduced from tasks assignment and UAV characteristics. Further details of this model can be seen at [9], but the main constraints defined in this model are as follows:

- **Temporal** constraints assuring a UAV does not perform two tasks at the same time.
- **Speed** window constraints: the mean cruise speed of a UAV to perform a task is contained in specific speed window v_{max} and v_{min} of the UAV.
- **Payload** constraints: checks whether a UAV carries the corresponding payload to perform a task.
- **Altitude** window constraints: the UAV altitude window must be contained in the altitude window of the area of the performing task.
- **Zone permission** constraints: just UAVs with permissions in restricted areas shall perform tasks developed in restricted areas.
- **Fuel** constraints: the total fuel cost for a UAV in a mission must be smaller than its actual fuel.

4 Optimization Function Description

In order to apply a method for solving CSOP, a new optimization function has been designed. This new function is looking to optimize (minimize) 3 objectives:

- The total **fuel consumed**, i.e the sum of the fuel consumed by each UAV at performing the tasks of the mission.
- The **number of UAVs** used in the mission. A mission performed with a lower number of vehicles is usually better because the remaining vehicles can perform other missions at the same time.
- The total **flight time**, i.e. the sum of the flight time of each UAV at performing the tasks of the mission. We have computed it as the difference between the ending of the last task performed by the UAV and its departure time.

Our model uses weights to map these three objectives into a single cost function, as the similar approach WCOP [16]. This function is computed as the sum of percentage values of these three objectives, as shown in Equation 1. In this sense, in the experimental phase, a comparative assessment of weights for finding feasible solutions of the problem is carried out. To solve the UAVs missions modelled is employed B&B search for minimization implemented by Gecode.

$$f_{cost}(i) = K_F \frac{Fuel(i)}{\max_j Fuel(j)} + K_U \frac{N^\circ UAVs(i)}{\max_j N^\circ UAVs(j)} + K_T \frac{FlightTime(i)}{\max_j FlightTime(j)}$$

$$K_F, K_U, K_T \in [0,1], \qquad K_F + K_U + K_T = 1 \qquad (1)$$

5 Experimental Results

5.1 Mission Scenario Description

In this paper, a scenario (from the previously described model) with a group of 9 UAVs to perform a mission of 10 tasks is used for the experimental phase. Each task of the mission collides in time with its two previous tasks, i.e. task 10 collides with tasks 9 and 8; task 9, with tasks 8 and 7, and so on (see Figure 1).

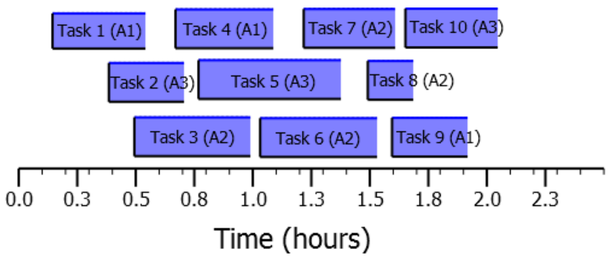

Fig. 1: Scenario perspective with dependency of each task with the two previous tasks.

Each task is assigned an action, which type identifier from Table 1 is shown in Figure 1 after each task. The mission described is performed in approximately two hours and involves varied actions in different areas. Each of the 9 UAVs available has different types of payloads for performing the tasks. In this approach, we consider the topology specified in Figure 2.

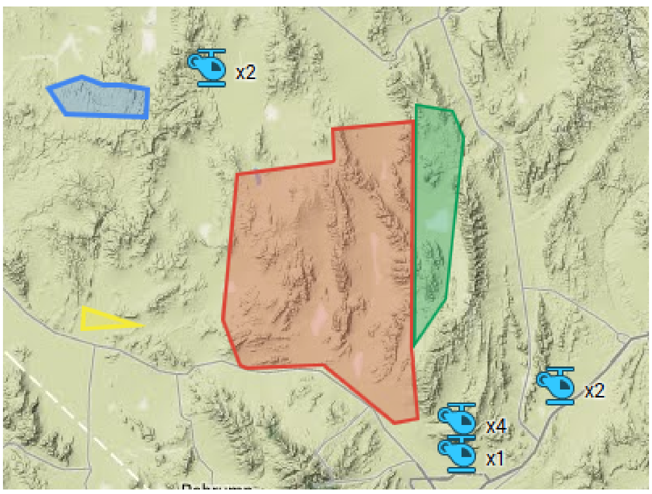

Fig. 2: Topology of the scenario where missions are performed. Coloured areas represent the areas where tasks are performed. Helicopters represent the airports where UAVs are situated at the beginning of the mission.

5.2 Results

Firstly, an analysis of the optimal solution found considering as cost function each one of the objectives individually is carried out. It can be seen in Table 2.

Table 2: Objective values and runtime spent in the search of the optimal solution using cost functions considering individually each objective.

Cost function	Flight Time	No. of UAVs	Fuel	Runtime
100% Fuel	22h 8min 13s	4	269.561L	4min 9s
100% No. of UAVs	23h 22min 23s	4	282.003L	8.87s
100% Flight Time	18h 0min 8s	8	284.875L	7min 32s

It can be appreciated when considering cost function 100% Flight Time that, besides the high runtime needed, the optimal solution found has a high number of UAVs and fuel consumption. This could be due to shorter flight times are obtained using UAVs that reach higher speeds but consuming more fuel. Considering this aspect, in this simple approach we have decided to only consider fuel consumption and No. of UAVs for the comparative assessment of optimization function weights, see Table 3.

Table 3: Objective values and runtime spent in the search of the optimal solution using cost functions considering fuel and number of UAVs with different percentages.

Cost function	Flight Time	No. of UAVs	Fuel	Runtime
100% Fuel	22h 8min 13s	4	269.561L	4min 9s
90% Fuel + 10% No. of UAVs	22h 8min 13s	4	269.561L	3min 22s
80% Fuel + 20% No. of UAVs	22h 8min 13s	4	269.561L	2min 7s
70% Fuel + 30% No. of UAVs	22h 8min 13s	4	269.561L	1min 39s
60% Fuel + 40% No. of UAVs	22h 8min 13s	4	269.561L	1min 23s
50% Fuel + 50% No. of UAVs	22h 8min 13s	4	269.561L	54.67s
40% Fuel + 60% No. of UAVs	22h 8min 13s	4	269.561L	46.03s
30% Fuel + 70% No. of UAVs	22h 8min 13s	4	269.561L	35.02s
20% Fuel + 80% No. of UAVs	22h 8min 13s	4	269.561L	33.99s
10% Fuel + 90% No. of UAVs	22h 8min 13s	4	269.561L	34.13s
100% No. of UAVs	23h 22min 23s	4	282.003L	8.87s

Analysing results shown in Table 3, it can be appreciated that only considering the fuel consumption in a low percentage, an optimal solution both for the fuel and number of UAVs minimization is reached. Additionally, it takes a better runtime than only considering fuel consumption. For this reason, it can be considered that a cost function of 10% fuel + 90% No. of UAVs is pretty good for searching feasible solutions of the kind of problem solved.

Finally, the runtime spent in the search of feasible solutions and the runtime spent in the search of the entire space of solutions using BT are compared in Figure 3. The time difference observed is very high, as expected. Concretely the BT runtime is higher than B&B in an order of $3 \cdot 10^5$.

6 Conclusions and Discussion

In this paper, we try to search feasible solutions for a UAV Mission Planning model based on TCSP. The presented approach defines missions as a set of

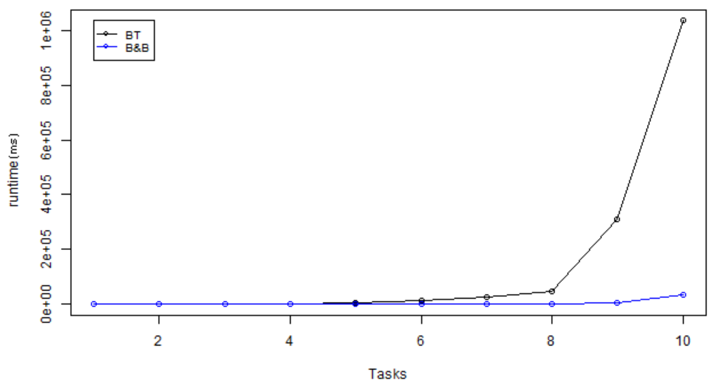

Fig. 3: Runtime spent in the search of the space of solutions with BT and the optimal solution with B&B using the cost function 10% fuel + 90% No. of UAVs.

tasks to be performed by several UAVs with some capabilities. The problem is modelled using: (1) temporal constraints to assure that each UAV only performs one task at a time; (2) logical constraints such as the maximum and minimum altitude reachable or restricted zone permissions, and (3) resource constraints, such as the sensors and equipment needed or the fuel consumption.

Concretely, we have designed an optimization function to minimize three objectives: the fuel consumption, the number of UAVs used in the mission and the total flight time of all the UAVs. From the obtained results, we have observed that the flight time does not help in the optimization of the rest of the objectives; so we have considered to put it aside.

Studying the solutions found by several cost functions with different weights for fuel and number of UAVs, we have observed how the runtime spent in the search decrease as the percentage of fuel decreases. Moreover, we show the solutions obtained by these cost functions inside the POF of fuel versus No. of UAVs, observing that for the cost function 10% fuel + 90% number of UAVs we obtain both the optimal solutions obtained with 100% fuel and 100% No. of UAVs, which together with its low runtime makes this cost function pretty good for finding feasible solutions in a reasonable time.

It is important to remark that the results obtained are highly dependant on the proposed scenarios and on the topology of the areas the missions are developed in. So further works should consider different scenarios and topologies, so a more general conclusion would be obtained. Furthermore, we will use a Multiobjective model, such as the Multiobjective Evolutionary Algorithms (MOEAs), and SPEA2 or NSGA-II algorithms; to find the Pareto Optimal Frontier.

As future lines of work, these results need to be compared against other optimization algorithms (such as Tabu Search and Genetic Algorithms, among others) to observe which one is better in terms of optimality of the solutions and runtime spent. Using these new algorithms, new heuristics to reduce the complexity of the problem and adapting our current model, we expect to be able to simulate problems near to real scenarios.

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