Solving UAV Mission Planning based on Temporal Constraint Satisfaction Problem using Genetic Algorithms

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Abstract. The problem of Mission Planning for a large number of Unmanned Air Vehicles (UAV) consists of a set of locations to visit in different time windows, and the actions that the vehicle can perform based on its features such as the payload, speed or fuel capacity. We study how this problem can be formulated as a Temporal Constraint Satisfaction Problem (TCSP). This problem contains several constraints assuring UAVs are assigned to tasks they have enough characteristics to perform, and soft-constraints for optimizing the time and fuel spent in the process. Our goal is to implement this model and then try to solve it using Genetic Algorithms (GAs). For this purpose, we will carry out a mission simulation containing \(m\) UAVs with different sensors and characteristics located in different waypoints, and \(n\) requested tasks varying mission priorities. The GA will match the model constraints and use a multi-objective function in order to minimize the cost.

Keywords: unmanned aircraft systems, mission planning, genetic algorithms, temporal constraint satisfaction problems

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 vehicles can perform (loading/dropping a load, taking videos/pictures, etc.), typically over a time period. These planning problems can be solved using different methods to find
optimal solutions but, as the number of restrictions increases, the complexity grows exponentially because it is a NP-hard problem. Some modern approaches formulate mission planning 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. In previous works [5], we model a mission planning problem using Gecode[8] to program the constraints and find the complete space of solutions using Backtracking (BT). But as in many real-life applications it is necessary to find only a good solution, in recent works [6] we consider a Constraint Satisfaction Optimization Problem (CSOP) with an optimization function to minimize the fuel cost, the flight time and the number of UAVs needed; and Branch and Bound (B&B) search was employed for solving this CSOP model.

The main goal of this work is to present a Genetic Algorithm (GA) approach to solve our CSOP model and maximize the number of solutions found using a multi-objective fitness function. GAs have been traditionally used in a large number of different domains, mainly related to optimization problems. They have demonstrated to be robust and able to find satisfactory solutions in highly multidimensional problems with complex relationship between the variables. This is an initial approach and the GA method is still work in progress, so the features described in this paper could be changed in future works.

This paper is structured as follows: section 2 describes how a Mission is defined in the UAV domain and the modelization of the problem as a TCSP. Section 3 explains the process that will be developed to create a GA-based solver for the model. Finally, last section presents analysis and discussions of this work.

2 UAV Mission Plan Model based on TCSPs

UAV missions consists of a number $n$ of tasks performed by a team of UAVs. A task could be exploring a specific area or search for an object in a zone. Each task consist of an action that must be performed in a specific geographic area, in a specific time interval and needs an amount of payloads to be accomplished.

On the other hand, a mission has a number $m$ of available UAVs for its development. Each UAV has some specific characteristics: fuel consumption rate, cruise speed, maximum and minimum altitude reachable, permission to go to restricted areas, and capacities or payloads (cameras, radars, . . .). 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
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There are some additional variables, as the departure time, fuel cost and distance travelled for each task, that can be deduced from tasks assignment and UAV characteristics. The main constraints defined in this model are as follows:

1. Temporal constraints assuring a UAV does not perform two tasks at the same time. Let $t_i$ be the time when task $i$ is completed, and $\tau_i$ the duration of the task. Besides, let $t_{d_i}$ be the departure time of the UAV $k$ that is assigned to task $i$. We also define the distance travelled by $k$ to reach the area of $i$ in time, $d_{k\to i}$, and the cruise speed of the UAV, $v_k$, which is fixed.

For each task, the flight time is computed as:

$$flightTime_i = \frac{d_{k\to i}}{v_k} + \tau_j$$

(1)

So let $k$ be a UAV that executes two tasks $i$ and $j$, where $i$ takes place before $j$, then $t_i$ must precede the departure time $t_{d_j}$:

$$t_i \leq t_{d_j} = t_j - flightTime_i$$

(2)

To compute the distance, we need to know where the UAV is located before the start of the task. Therefore, we have created a $n \times m$ matrix of tasks to UAVs position, named $pos$, where $pos_{k,i}$ denotes the position of vehicle $k$ at the start of task $i$. With this matrix, we can compute every distance between two points using the Haversine formula with the latitude and longitude

$$d_{2D} = 2r_{EARTH} \arcsin \sqrt{\sin^2\left(\frac{\text{lat}_2 - \text{lat}_1}{2}\right) + \cos(\text{lat}_1) \cos(\text{lat}_2) \sin^2\left(\frac{\text{long}_2 - \text{long}_1}{2}\right)}$$

(3)

and then the Euclidean distance with the altitude

$$d_{3D} = \sqrt{d^2 + (alt_2 - alt_1)^2}.$$  

(4)

Therefore, if the distance from the UAV position is computed as the distance to the area of the task (i.e. to its entry point), we conclude that:

$$d_{k\to i} = i.area\_distance(pos_{k,i})$$

(5)
2. Speed window constraints: the mean speed necessary to perform the task \( i \), \( \bar{v}_i \), must be contained in the speed window \( v_{k,\text{max}} \) and \( v_{k,\text{min}} \) by:

\[
v_{k,\text{min}} \leq \bar{v}_i \leq v_{k,\text{max}}
\]  

(6)

3. Payload constraints: another constraint is whether a UAV carries the corresponding payload to perform a task. Let \( P_k \) denote the payloads available for UAV \( k \) and \( P_i \) the payloads needed for the task \( i \) (performed by \( k \)), then:

\[
P_i \subseteq P_k,
\]  

(7)

4. Altitude window constraints: a UAV \( k \), with an altitude window \( k_{h_{\text{max}}} \) and \( k_{h_{\text{min}}} \), performing a task \( i \) developed in an area with an altitude window \( h_{\text{max}} \) and \( h_{\text{min}} \), must obey:

\[
k_{h_{\text{max}}} \geq i_{\text{area}}h_{\text{max}}
\]  

(8)

\[
k_{h_{\text{min}}} \leq i_{\text{area}}h_{\text{min}}
\]  

(9)

5. Zone permission constraints: another constraint is the implication that a restricted area has in the tasks to perform. Just UAVs with permissions in those areas shall perform the tasks.

6. Fuel constraints: finally, we must constraint the fuel cost for each UAV. The fuel cost for a UAV \( k \) performing a task \( i \) is

\[
f_i = k_{\text{fuelConsumeRate}} \cdot (d_{k\rightarrow i} + \tau_i \bar{v}_i)
\]  

(10)

So the following inequality must be obeyed:

\[
\sum_{i \in T_k} f_i \leq k_{\text{fuel}}
\]  

(11)

3 Genetic Algorithms Approach

GAs are stochastic methods inspired by natural evolution and genetics. The complexity of the algorithm depends on the codification and the operations used to reproduce, cross, mutate and select the different individuals of the population.

In the related literature, there are many approaches to solve CSPs using GAs. Jashmi [4] modelled TCSPs and solved them with evolutionary algorithms. The proposal described in [1] develops a hybrid GA-CSP for solving resource constrained project scheduling (RCPS). There exist other approaches that hybridize GAs with constraint techniques [2], and several approaches that solve Multi-objective CSOP problem with GAs [9] [7].

Given the big amount of solutions that the problem can generate and the huge amount of constraints involved in the search of solutions, we have decided to use a GA to solve the TCSP modelled Mission Planning problem. In this approach, we will develop a hybrid GA-CSP, where the constraints of the problem will be applied as penalty functions in the evaluation phase of the GA.
An individual of the GA will be formed by a gene string $T_1 T_2 T_3 ... T_n$, i.e. its chromosome. Each gene of the chromosome is associated with a variable of our CSP model, i.e. the tasks, and an individual represents a solution, i.e. the UAVs assigned. This representation is shown in Figure 2.

The initial population can be randomly generated, or computed using a simple algorithm for CSP, e.g. BT searching for $k$ solutions. The second option is slower, but it assures that the initial population is composed of feasible solutions. Evaluation is computed in terms of a fitness function composed by two check steps. First, for the given solution, it handles that all constraints are fulfilled. If not, it acts as a penalty function, returning a negative number indicating the number of unfulfilled constraints. If all constraints are fulfilled, the fitness function works as a multi-objective function for the parameters of the model:

- The total fuel consumption, computed as the sum of the fuel consumptions for each task using equation 10.
- The number of UAVs employed in the mission, known from the chromosome.
- The total flight time, which is computed as the sum of the flight times for each task using equation 1.

The multi-objective fitness function will compare the solution tested with the stored solutions in order to obtain the Pareto-Optimality Frontier (POF) [10].

A general overview of the GA proposal is shown in Figure 3. The selection consists of two steps: a $N$ elitist selection used for retaining the $N$ best individuals in the population, and a roulette wheel selection over those $N$ individuals used for selecting the individuals that will be applied the crossover operator.

The crossover operator will be applied depending on a probability $P_c$ (usually high, $\sim 0.85\%$). When applied, it will combine the chromosomes of parents $K_1$
and \( K_2 \) by randomly selecting a low number \( l \) of genes of each parent and exchanging them to generate children \( C_1 \) and \( C_2 \), as shown in Figure 4.

The mutation operator used is an uniform mutation, which replaces the value of a randomly chosen gene with a random value. The chromosomes resultants from the crossover will be applied this operator depending on a probability \( P_m \) (usually low, \( \sim 0.15\% \)). It will help to avoid stagnation at local minimums.

4 Discussion and future works

In this paper, we propose a hybrid TCSP-GA approach to search feasible solutions for a UAV Mission Planning model. The presented model defines missions as a set of tasks to be performed by several UAVs with some capabilities. The CSP model works with temporal constraints to assure that each UAV only performs one task at a time; and other constraints such as the maximum and minimum altitude reachable, the needed payload or the fuel consumption.

The GA proposal counts with a multi-objective fitness function that penalizes the unfulfilled constraints and minimize three objectives: the fuel consumption, the number of UAVs and the flight time. When implementing this approach, several operators should be tested to find the best performing combination.

Further works should compare this approach with other models, such as the Branch&Bound approach [6] implemented, and Multiobjective Evolutionary Algorithms (MOEAs), e.g. SPEA2 [3] or NSGA-II [11]; in order to observe which one is better in terms of optimality of the solutions and runtime spent.

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