A Tandem Drone-ground Vehicle for Accessing Isolated Locations for First Aid Emergency Response in Case of Disaster

Marcos Calle[1], Jose Luis Andrade-Pineda[2], Pedro Luis González-R[1], Jose Miguel Leon-Blanco[1] and David Canca Ortiz[1]

[1]*Department of Industrial Organization and Enterprise Management I, University of Seville, Cº Descubrimientos, Seville, Spain*

[2]*Robotic, Vision and Control Group, University of Seville, Cº Descubrimientos, Seville, Spain*

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Abstract: The collapse of infrastructures is very often a complicating factor for the early emergency actuations after a disaster. A proper plan to better cover the needs of the affected people within the disaster area while maintaining life-saving relief operations is mandatory hence. In this paper, we use a drone for flying over a set of difficult-to-access locations for imaging issues to get information to build a risk assessment as the earliest stage of the emergency operations. While the drone provides the flexibility required to visit subsequently a sort of isolated locations, it needs a commando vehicle in ground for (*i*) monitoring the deployment of operations and (*ii*) being a recharging station where the drone gets fresh batteries. This work proposes a decision-making process to plan the mission, which is composed by the ground vehicle stopping points and the sequence of locations visited for each drone route. We propose a Genetic Algorithm (GA) which has proven to be helpful in finding good solutions in short computing times. We provide experimental analysis on the factors effecting the performance of the output solutions, around an illustrative test instance. Results show the applicability of these techniques for providing proper solutions to the studied problem.

1 INTRODUCTION

The collapse of infrastructures is very often a complicating factor for the emergency actuations after a disaster. In the case of developing countries, this leads to the appearance of isolated areas to be provided with first healthcare aid. For instance, it is sometimes necessary to send blood supplies to the injured in their spots instead of bringing them to the hospitals for blood infusions (Wen et al., 2016). In view of the lack of trained pilots as well as helicopters and land-based local personnel in the disaster areas (Rabta et al., 2018), humanitarian organizations are more and more incorporating Unmanned Aerial Vehicles (UAVs) or drones in their supply of life-saving commodities such as blood (Wen et al., 2016) or pharmaceuticals.

By using UAVs, they can also get a quick and flexible access to certain locations of interest, aiming at collecting crucial information for the ulterior efficient development of the emergency mission itself. Aside from overcoming the accessibility issues, UAVs can be useful for reducing the worker exposure to danger (e.g. in structural integrity assessment after an earthquake or in gauging radiation levels in a nuclear accident (Greenwood, 2015)).

The maximal operation time or endurance for an UAV depends on a variety of factors, such as the type of drone (fixed wing vs. rotorcraft), the flying altitude (e.g., propellers of rotor-crafts must rotate faster at higher altitudes because of lower air density), the weather conditions and obviously, the weight of the UAV.

In this work, we propose using a UAV consisting of a multirotor system that will be operated with battery swaps to overcome the endurance limitation. The UAV will fly over a set of challenging locations for imaging them with the purpose of collecting information to make a risk assessment as the earliest stage of the emergency operations. We will suppose the UAV is equipped to acquire the needed images of the difficult-to-access locations, although this research focuses not in the imagery itself, but in the optimization of the completion time for the quick recognisee of the target locations. This differs from other reported studies in the emergency literature

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where the challenge is in getting the consecutive overlapping of aerial images to build an up-to-date map of a wide area (Qi et al., 2016). We are more interested in analysing the combination of UAVs and alternative means of transport in difficult-to-access areas, which with certain exceptions (Mosterman et al., 2014), (Chowdhury et al., 2017), remains relatively unexplored.

2 PROBLEM DESCRIPTION

The UAV provides us with the flexibility required to visit subsequently a subset of locations (namely, a route), although for practical convenience, an individual would be on charge of monitoring and controlling the flight operations. Thus, we assume that a ground vehicle (GV) will act as a commando vehicle.

The number of target locations to visit on each flight is clearly limited to the capacity (power) of the batteries in the UAV. Our assumption is that the GV will further play the role of recharging station, so that at the end of each of its sorties the UAV will land on it for battery swaps. Aside from being conditioned by the total weight on board (see Figure 1 for an example of an energy consumption pattern), it is noticeable that the number of locations that the UAV is able to visit on each sortie is also limited because of the capacity of the data storage device used for recording the imagery task.

Our problem can shortly be described as how best defining the routing planning for the tandem UAV-GV used to deploy the recognisee task.

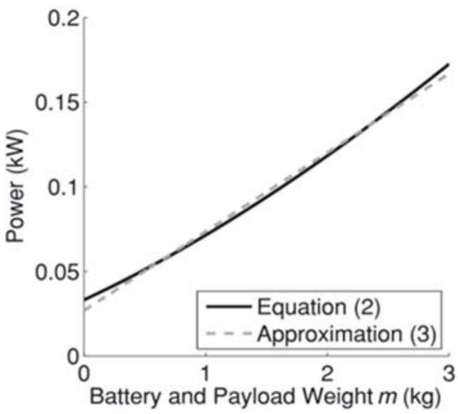

Figure 1: Power pattern in an hexacopter UAV, approximately linear with the total load on board (Source: (Dorling et al.,2017)).

In Figure 2, we sketch one of the flight routes of our UAV in the studied scenario. As a first approximation to the constrained freedom of movements of the GV in the disaster area, our assumption is that the GV just moves along a straight line between two points.

Observe that the route consists of the UAV's take-off from the GV, its visit to a subset of the planned locations (circles) and its flight to intercept the GV trip with the purpose of landing on it and swapping its batteries. In the while, the GV has been moving along the practical road (between rectangles).

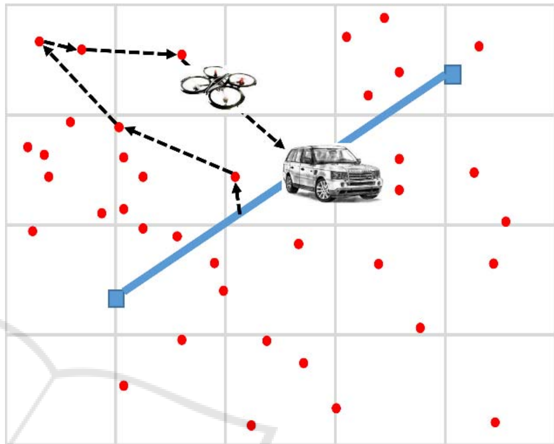

Figure 2: Target Scenario: UAV and GV moves separately. The dashed lines represent fly paths for UAV.

In spite of the sketched example, it is possible that a launch and a rendezvous of the UAV occurs at the same point. Namely, the GV is allowed to stay at a position for a time while the UAV complete a route visiting a variety of sites, if the optimization analysis found it convenient for the general objective of minimizing the time to accomplish the whole task. This differs from many of the tandem UAV-GV approaches in the literature, which mainly turn around the commercial supply chain context with a last-mile delivery based on UAVs. There are very few works considering UAV load capacity greater than one (Luo, et al., 2017), (Rahman, 2017), thereby more than one parcel allowed for serving a certain customer. The fact that the GV can move the UAV between two deployment locations such that it does not spend any energy is a feature that is sometimes considered in such a literature. For instance, (Mathew et al., 2015) assume the UAV travelling through a street network joint to a truck as GV till the tandem gets nearby a customer's doorstep, when the UAV fly to deliver parcels one customer at a time. Differently, (Ha et al., 2018) allows UAV's route comprised of several customers, excluding the possibility to have a launch and rendezvous in the same point though. The latter is allowed in (Mathew et al., 2015) and in the closely related work by (Bin Othman et al., 2017), although none of them considers that the UAV can visit a set of customers in a single flight mission, as is required in our scenario. Nevertheless, the last three referenced works apply a Travelling Salesman Problem with Drone (TSP-D) approach that is relevant to our research. The name TSP with drone is first used in (Agatz et al., 2016) referring to the problem in which a drone helps a traditional transport system like a truck or a van in the delivery of goods.

3 PLANNING DECISIONS

The proposed decision-making process to plan our imagery mission covering all the difficult-to-access locations would provide the following:

- The GV stopping points, with the arriving time and for how long the GV stays at it.
- The sequence of locations visited for each UAV's route, the start point for every route –i.e. the point in take-off- and its landing point.
- The details of the hitch and ride of the UAV over the GV (namely, when the UAV travels carried on the GV while it moves from a position to another).

We approach it using a multiple travelling salesman problem (mTSP) baseline: the target locations (henceforth referred to as "customers") which have to be visited by a number of routes. According to the mTSP terminology (Bektas, 2006), our case study concerns to the 'nonfixed destination case within the multiple depot variation of mTSP', since the UAV can either return to the starting GV position (at which the UAV taken off) or to a different ending position.

3.1 Assumptions

We first introduce the notation for the input parameters used within our planning problem:

- m : Customers to visit;
- d_{ij}: Euclidean distance between two positions;
- H: Maximum number of customers that can be 'mapped' before running out of the storage memory;
- v: UAV flight speed;
- V: GV moving speed;
- E: Endurance or maximum flight time;

Then, we list certain assumptions we make to simplify our analysis.

Firstly, that the road travels of GV and the UAV flight between locations occur both at constant speed. The latter comes from our assumption that the energy consumed during the emergency mission is approximately the same as that consumed during hover (Dorling et al., 2017).

Secondly, that the extreme points for each route are taken from stopping positions for the GV (which moves only along the straight road depicted in Figure 2).

Thirdly, that we have to manage the synchronisation of GV and UAV. Specifically, we assume that the GV opening time at a certain position occurs always before than the arrival of the UAV planned for landing on this position. Namely, that the UAV's end of route is planned so that it does not have to wait for the arrival of the GV.

Finally, notice that the minimum number of routes that may arise is $\lceil m/H \rceil$. However, depending on the distance of flight paths, the limited endurance E could force a route to be serving to less than H customers. From it, the worst case is that every route was only serving one customer, and hence the valid set of route indices are:

$$r \in \mathbb{R} = \{\left\lceil \frac{m}{H} \right\rceil, \dots, m\} \tag{1}$$

Although the assumptions considered in this work have been considered individually in the literature, it is noteworthy the novelty of considering them in a joint way in the same problem.

3.2 Variables

Let x_{ijr} be a binary variable indicating that the route r visits node j immediately after node i. Besides, assume that the visiting sequence order of the customers served by a certain route is μ_{ir}. As we explain below, these ordering variables are used for subtour eliminations.

Let to_r be the time at the take-off of the UAV on its route r, and lt_{ir} the land time for the UAV flight from the customer i as the last flight of route r. In order to be ready to check endurance, let us consider the cumulative flight time of the UAV when arrive at the node i, denoted T_i, and the total flight time for the whole route r accounting for the final flight from the last customer i to the GV, denoted TT_{ir}. Let $sInt_r$ be the arrival time for the GV at the interception point at which the route r is terminating. Finally let $LAG(sInt_r)$ be the time the GV stay at this stopping point.

3.3 Constraints

- A route cannot terminate at a customer.
- Each customer i must be visited just once, belong-

ing to only one route.

- There is exactly one input flight and exactly one output flight from every customer visited by a route.
- The endurance E is an upper bound for the cumulative flight time variables T_i and TT_{ir} .
- The early arrival time for the UAV is treated as a hard constraint. Thus, if $lt_{ir} \leq sInt_r$, then node i cannot be part of the route r, since the GV is not ready at time.
- The early leave time for the GV from the take-off point under study is treated as a hard constraint. If $to_r \geq sInt_r + LAG(sInt_r)$, then the GV is not ready to be the take-off point for the UAV on its route r, since the GV has left.
- The subtour elimination constraint, which can be written using H as follows:

$$\mu_{ir} - \mu_{jr} + Hx_{ijr} \leq H - 1, \quad i, j \in C, i < j, r \in \mathbb{R} \tag{2}$$

3.4 Methodological Proposal

Deriving from the previous discussed issues, the planning for covering the set of challenging locations will emerge from solving a MILP formulation with similarities to the non-fixed destination multiple depot m-TSP minimizing the Total Mission Time (*TMT*).

We recall here that the mTSP is a relaxation of the Vehicle Routing Problem (VRP), being well-known that this problem is NP-Hard (Bektas, 2006). In the VRP literature there are many solution approaches initially valid for the mTSP, but they may not be efficient to the mTSP.

Precisely, we have focused our research in getting quick good solutions to the practical decision problem studied. To this aim, we have developed a Genetic Algorithm (GA) tailored for our case study.

4 GA

A Genetic Algorithm (GA), as proposed by Holland (1975), is a population-based metaheuristic inspired by the evolution of species. The algorithm starts with a population of randomly generated solutions (each solution represented by a chromosome), and then continues with a procedure to improve the candidate solutions obtained generation after generation, by using selection, crossing and mutation operators. The improvement of the solutions occurs when a lower value for a fitness function arises. The variable *TMT* is the fitness to evaluate a solution in our problem, evaluated by finding the time when the UAV-GV tandem arrives to the end of the road, after all customers have been visited.

In general, a GA is an unconstrained method, which usually handles constraints by penalizing the objective function. In our case, the constraints not included in the calculation of *TMT* are those relating to:

- The maximum number of customers per route
- The maximum flight time or endurance, E
- The time that the UAV is waiting for the GV arrival at the rendezvous location.
- The total moving time of the UAV-GV tandem.

Next, we detail our GA implementation, where the objective function is to minimize the TMT, defined as the summation of the cumulative flight time of the UAV and cumulative moving time of the UAV-GV tandem.

4.1 Coding Scheme

The chromosomes in our study are comprised of $3m$ genes.

The first m components are devoted to code the position of the take-off point for each route (which would be contained in the straight road in Figure 2), measured from the origin, xto_i. Next m components are the distance specification of the selected landing points, xr_i. The last m components define the route assigned to serve each customer, u_i. Thus, we code each solution according to the following structure:

$$sol. = \{xto_1, \ldots\ xto_m, xr_1, \ldots\ xr_m, u_1, \ldots\ u_m\} \tag{3}$$

Thus, each chromosome is explicitly representing the take-off and rendezvous points for routes and the assignment of routes to each customer. Nevertheless, other performance details such as the number of routes, the time at which the GV arrive at a point and the lapse time spent there, implicitly are also contained into it.

4.2 Pseudo-code

The pseudo-code for the GA can be resumed in pseudocode (algorithm 1):

```
generate population of candidate solutions
compute fitness of candidate solutions
while termination criterion is false
  generate children solutions by crossover
  mutate children solutions
  compute fitness of new candidate solutions
  replace parent solutions
return best solution
```

Algorithm 1: Pseudo-code of the Genetic Algorithm.

At line 1, the candidate solutions are randomly initialized over the entire search space. Prior to the first iteration of the GA, the algorithm evaluates the candidate solutions of the generated population, at line 2. After a fixed number of iterations (that were experimentally determined to get good solutions within reasonable computing time), a termination criterion is applied at line 3.

The crossover operation is the first step at every iteration of the GA, involving two parent solutions and generating two child solutions (at line 4). In fact, three variants of this two-point crossover have been implemented in our algorithm: a crossover variant for the take-off points of the flights, a crossover variant for the rendezvous locations of the flights, and a crossover variant for the assignments of the customers to the UAV flights. Then, the algorithm proceeds with the application of a mutation operator on the children solutions (at line 5), by inverting a subsection of the mutating solution. Again, three different mutation operations have been implemented depending on whether we were mutating the take-off points of the flights, the rendezvous locations of the flights, or the assignments of the customers to the UAV flight missions. Once done the evaluation of the new candidate solutions generated at the concerned iterations (at line 6), the algorithm proceeds to replace the parent solutions by the children solutions (at line 7). We apply elitism, where the n best solutions of the parents' generation replace the worst solutions of the children's generation.

4.3 Implementation

We have implemented this algorithm with Python 3 programming language with the help of the evolutionary algorithm toolkit DEAP (Fortin et al., 2012), an abbreviation for 'Distributed Evolutionary Algorithms in Python'. DEAP is an evolutionary computation framework that allows rapid prototyping of diverse genetic algorithms, including genetic algorithms, genetic programming, evolution strategies, covariance matrix adaptation evolution strategy, particle swarm optimisation, and many more.

In our GA, the data set obtained after assessing a particular solution consists of (a) the best visiting sequence of the customers assigned to each flight, (b) the flight time of the UAV for each flight, (c) the waiting time of the GV for each flight, and (d) the total moving time of the UAV-GV tandem.

In order to test our solution approach, we have used clouds of spread locations taken from the clients' position within Capacitated VRP benchmark instances. For example, the CVRPLIB - Capacitated Vehicle Routing Problem Library.

In what follows, we present the performance obtained when tackling with the A-n32-k5 instance proposed by Uchoa et al., (2014).

We have studied the possible influence of three factors. To study the influence of the customers layout, two different roads have been included in the first factor, (see Figure 3). As the second factor, two different UAV speeds have been studied, (a) v=20 km/h and (b) v=30 km/h. In both cases, the GV and UAV-GV tandem moves at same speed, which is V=60 km/h. As the third factor, we have studied three different values for the maximum number of visits in each route: $H=3,4,5$. The endurance of the UAV is in all the cases limited to $E=1.2$ hours.

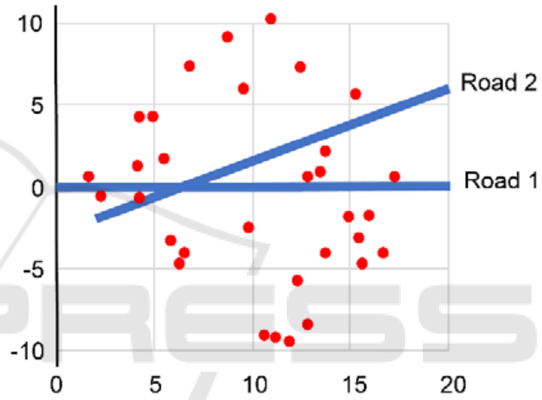

Figure 3: Problem layout.

The GA implemented in this study starts with an initial population of 100 solutions randomly generated, and it stops after 100 generations. We have repeated this for 30 runs, and written down the average times of best solution over the 30 runs. Each of the formerly described mutation operator is applied to each of the three components with a probability of a 2%. Similarly, each of the mentioned crossover operators is applied with a 50% probability.

5 COMPUTATIONAL RESULTS

This section presents the results obtained by the proposed GA.

Table 1 contains the averages of 30 runs of the algorithm for each combination of problem parameters, namely, road configuration, UAV flying speed and maximum number of visits in each route. This makes 360 runs. The 'Mission time' caption refers to the *TMT*, expressed as the hours passed between the depart from the origin of the road and the

Table 1: Summary of experimental average results.

Road	UAV speed (km/h)	H	Mission time (hours)	Tandem time		UAV flight time		GV waiting time	
				(hours)	%	(hours)	%	(hours)	%
1	20	3	11.60	0.64	5.54	10.96	94.46	10.78	92.89
		4	11.41	0.66	5.81	10.74	94.19	10.56	92.60
		5	11.34	0.67	5.89	10.68	94.11	10.47	92.30
	30	3	7.43	0.54	7.33	6.88	92.67	6.69	90.00
		4	7.14	0.48	6.77	6.65	93.23	6.46	90.49
		5	7.02	0.50	7.11	6.52	92.89	6.32	90.06
2	20	3	12.49	0.63	5.01	11.86	94.99	11.68	93.57
		4	12.00	0.55	4.58	11.45	95.42	11.27	93.91
		5	11.82	0.58	4.90	11.24	95.10	11.07	93.65
	30	3	7.95	0.48	6.04	7.47	93.96	7.29	91.77
		4	7.57	0.40	5.30	7.17	94.70	7.01	92.63
		5	7.49	0.40	5.35	7.09	94.65	6.94	92.66

arrival of the GV carrying the UAV to the end of the road. The ‘Tandem time’ caption refers to the total average traveling time of the GV carrying the UAV and the percentage it weights in total mission time. The ‘UAV flight time’ caption presents the average total flying time of the UAV. The ‘GV waiting time’ caption shows the average total time that the GV spends waiting for the UAV. Observe we have included the percentage referred to the *TMT* value, thereby allowing for quickly reading the weights of Tandem time, UAV flight time and GV waiting time.

We further include illustrations for the four time columns in Table 1.

Figure 4 shows total mission time for each scenario. Figure 5 shows the average UAV flight time vs H. Figure 6 shows variability in the time spent by the GV-UAV tandem, in their short travels between flights.

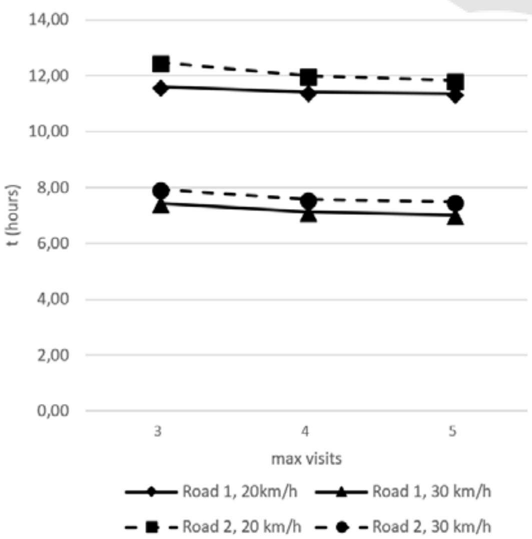

Figure 4: Average total mission time vs H.

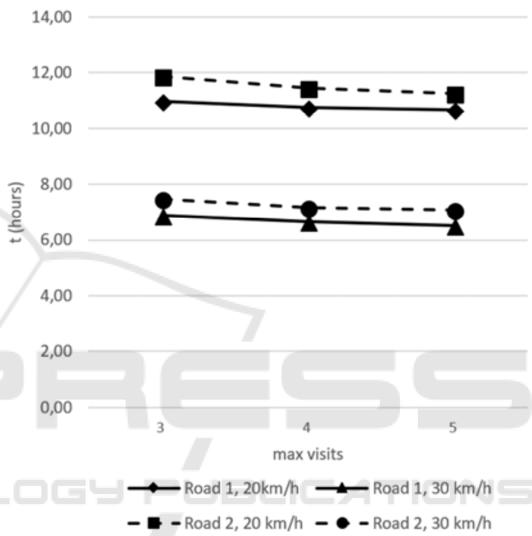

Figure 5: UAV average total flying time vs H.

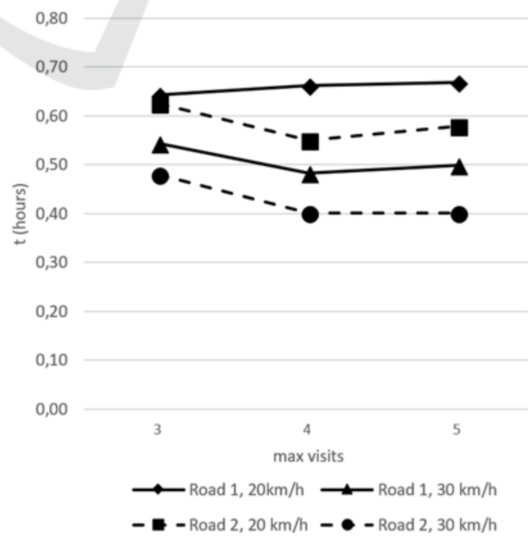

Figure 6: GV-UAV tandem average total traveling time.

Finally, Figure 7 shows the total time that the GV spends waiting for the UAV return (once deployed the recognisee route). Noticeably, the GV is most of time in the status 'stopped'.

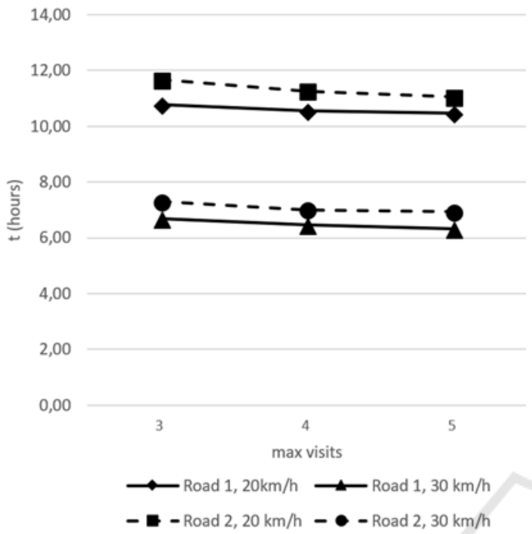

Figure 7: GV average total waiting time.

As shown in the results, the factors (a) the UAV speed and (b) the maximum number of visits in each route influence the planning, and therefore the resulting *TMT*. Thus, as the UAV speed increases and/or the number of visits is less restricted, the value *TMT* is reduced.

In these scenarios, the moving time of the UAV-GV tandem is significantly low, between 5% and 7% of the total mission time, so the moving speed of the GV is not the most influential issue on the total mission time. This implies that the UAV flight speed is the most relevant factor on the total mission time, which ranges from 93% to 95% of the mission time. The relevance of the UAV speed justifies the need to continue the research line of planning optimization of these missions.

As a final remark, we notice that the studied scenarios exhibit long waiting times for the GV at rendezvous locations, which ranges from 90% to 94% of the total mission time.

6 CONCLUSIONS

In this work, we propose using an UAV to visit a set of challenging locations in a humanitarian mission, in tandem with a GV for monitoring and controlling the flight operations, which is used as well as a recharging station for restoring the endurance of the UAV. To solve the problem of planning the tandem's operations, we have implemented a GA algorithm able to find good quality solutions in reasonable computing times. The algorithm has been programmed using Python 3 and DEAP library.

This work has considered a set of practical considerations: (1) the limitations of the GV to access the locations to visit, and (2) the different limitations imposed by the drone in this type of missions. This set of limitations does not allow us for comparing the results obtained in this work with other nearby approaches proposed in the literature.

Although the results are promising, we need to improve different aspects to incorporate more constraints that bring the problem closer to reality, such as considering the aerodynamics. The obtained results highlight the high relevance of the UAV flight speed in this mission type, which justifies the need to continue the research line of planning optimization of these missions. Next step in this research consists in employing other methods, such as PSO, which results could be compare with the current results.

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