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A GENETIC ALGORITHM SIMHEURISTIC FOR THE OPEN UAV TASK ASSIGNMENT AND ROUTING PROBLEM WITH STOCHASTIC TRAVELING AND SERVICING TIMES

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ABSTRACT

Due to their flexibility, unmanned aerial vehicles (UAVs) are gaining importance in transportation and surveillance activities. The usage of UAV swarms raises the need for coordination and optimization of task assignments. Some of these operations can be modeled as team orienteering problems (TOP). This paper analyzes an open TOP in which a given fleet of homogeneous UAVs, initially located at a single depot, need to be coordinated in order to maximize the collection of rewards from visiting nodes without exceeding a maximum operation time. As in most real-life applications, both traveling times and servicing times at each node are modeled as random variables. To solve this *NP-hard* and stochastic optimization problem, a simheuristic based on the combination of a genetic algorithm with Monte Carlo simulation is proposed.

1 INTRODUCTION

Nowadays, unmanned aerial vehicles (UAVs) offer potentials for many civilian and military applications (Merkert and Bushell 2020). Technological advances in batteries and other components have enabled a growth in the use of drones in commercial applications (Bartsch et al. 2016). Thus, applications in transportation and surveillance activities have been implemented, also promoted by a significant cost reduction and a performance improvement. Limited by size and capability, one single UAV can hardly conduct complex and persistent tasks (Martinez 2010). Hence, it is common to employ UAV swarms, which are comprised of a set of autonomous drones, each of them with their own sensing capabilities, but also capable of reacting to a dynamic environment as well as to the actions of other drones. Therefore, a collective behavior emerges from the sum of the behaviors of individual drones. When equipped with intelligent algorithms, these autonomous systems have great potential for application in many areas (Chung et al. 2018).

To achieve cooperation among different UAVs, a proper assignment of tasks to each UAV is a necessary step in order to achieve the planned goals and maximize the fleet's overall performance. The integrated UAV task assignment and routing problem can be formulated as a team orienteering problem or TOP (Panadero et al. 2020), which can be seen as a special variant of the well-known vehicle routing problem (Faulin et al. 2008; Juan et al. 2009). In the TOP, the goal is to select customer nodes to be visited by a limited fleet of vehicles, which are initially located at a depot. At the same time, the order in which these nodes have to be visited has to be defined. The first time a node is visited, a reward is collected. Thus, the typical goal in a TOP is to maximize the total reward gathered taking into account that each vehicle can

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only operate for a maximum amount of time – i.e., there is a limitation on the maximum time or distance that any route can cover. Our research considers an open TOP, where UAVs can finish their route at any customer (i.e., the maximum time per route does not include the time required to return to the depot from the last node visited). Being an open version, this maximum operation time refers just to the time in which each UAV visits the last customer in its route. To make the problem more realistic, we model traveling times between nodes and servicing times at each node as random variables. A visual representation of this TOP is shown in Figure 1.

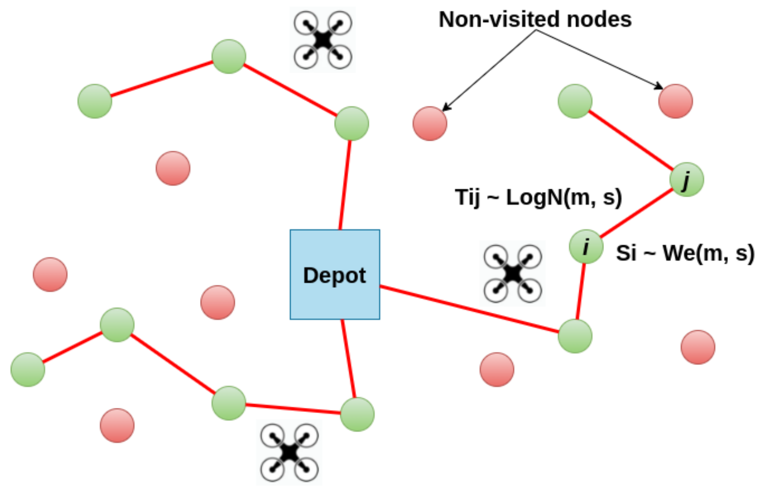


Figure 1: A visual representation of the open TOP with stochastic traveling and servicing times.

Introducing random traveling and servicing times in the problem formulation makes the problem more challenging for classical optimization methods. Therefore, we propose a simheuristic algorithm (Chica et al. 2020) to solve this stochastic and *NP-hard* optimization problem. The proposed simheuristic combines a genetic algorithm (GA) with Monte Carlo simulation (MCS). GAs are computer procedures inspired by the principles of natural selection and genetics to iteratively evolve a population of solutions, which tend to improve at each new generation. A recent review on GA applications can be found in Lee (2018). Thus, the main contribution of this paper is the proposal of a GA-based simheuristic algorithm that can take into account all the aforementioned deterministic and stochastic factors. Simheuristics have been successfully employed to solve stochastic optimization problems in different areas, such as transportation (Reyes-Rubiano et al. 2019), aircraft turnaround operations (Tomasella et al. 2019; Gök et al. 2020), waste collection management (Gruler et al. 2017; Yazdani et al. 2021), facility location (Pagès-Bernaus et al. 2019), disaster management (Yazdani et al. 2020), healthcare operations (Dehghanimohammadabadi and Kabadayi 2020), scheduling (Hatami et al. 2018), or computational finance (Panadero et al. 2018).

The remaining sections of the paper are structured as follows: Section 2 briefly reviews related articles on UAV task assignment and routing problems. Section 3 offers a formal description of the stochastic open TOP considered here. Section 4 provides details on the proposed GA-based simheuristic algorithm and its structure. Section 5 carries out a series of computational experiments to illustrate the performance of our simheuristic algorithm, while the results of these experiments are discussed in Section 6. Finally, the main findings and future research lines are given in Section 7.

2 RELATED WORK ON UAV TASK ASSIGNMENT AND ROUTING PROBLEMS

Task allocation of UAV fleets has been an active research area during the last decade, and the popular solutions for this problem can be classified according to the type of algorithms employed as exact methods and approximate ones (e.g., heuristic algorithms). Exact methods guarantee to find the globally optimal solution to most small-scale optimization problems, but they are computationally intensive if the problem is *NP-hard*. Among the works using exact methods, Schumacher et al. (2004) analyze the problem of autonomous task allocation and trajectory planning for a fleet of UAVs. They express the entire problem as a mixed-integer linear program. Other exact optimization methods, such as branch-and-bound, branch-and-cut, and dynamic programming, have been used to solve small-sized instances of this problem (Keshtkaran et al. 2016). However, this problem is *NP-hard* and, hence, heuristic algorithms are employed to solve medium-to-large instances of the problem. Rasmussen and Kingston (2008) outline a framework that supports generic task assignment in an efficient tree search. By encoding the assignment into a tree structure, the method is able to find a feasible solution quickly. The remaining computational time can be employed to improve the initial solution via branch-and-bound methods.

Regarding the use of metaheuristics, Shima and Schumacher (2009) proposed a GA to solve a generic UAV task assignment problem where the targets are not necessarily static – i.e., they can be in motion. Also, the fleet of UAVs can be heterogeneous. Again, a GA is proposed for efficiently searching the space of feasible solutions. Fu et al. (2012) proposed another GA to set the trajectory of UAVs in environments with unknown obstacles. The route planning model is based on a 2D digital map, and an adaptive evolutionary planner is adopted to generate routes online and avoid being detected by ground surveillance radar sites. Likewise, Ramirez-Atencia et al. (2017) formulate a multi-objective GA for planning missions involving a fleet of UAVs and a set of ground control stations, with humans controlling the vehicles. The algorithm has been tested with different sets of constraints, such as duration, fuel consumption, and distance. Finally, Ye et al. (2020) propose a modified genetic GA, with a multi-type gene chromosome coding strategy, to solve a cooperative multi-task assignment problem. Their results demonstrate that the modified GA has better optimization performance compared with an ant colony optimization algorithm and a particle search optimization method.

Several papers discuss task assignment under uncertainty scenarios. In Alighanbari and How (2008), the authors presented a new formulation for the UAV task assignment problem for uncertain and dynamic environments. They propose an alternative strategy that combines robust planning with the techniques developed to eliminate churning. The resulting task assignment uses both proactive and reactive techniques to handle the uncertainty in the information. Their method improves worst-case behavior of the plans while, at the same time, it ensures that a limited churning behavior is exhibited by the vehicles. Choi et al. (2009) addressed single and multiple assignment problems by presenting two decentralized algorithms. Bertuccelli et al. (2009) extended one of these algorithms to solve the heterogeneous UAV real-time task assignment problem under uncertainty. When executing multiple missions, UAVs form teams and work cooperatively. In this context, the multi-UAV cooperative control and decision mechanisms, including task assignment, path planning, and tactical decision making, have received a great deal of attention (Chen et al. 2018). Methods like linear programming, dynamic programming, and Markov decision processes have been employed in the multi-UAV task assignment literature (Chen et al. 2014). Since there are cases in which a centralized task assignment is not practical – due to communication limits, robustness issues, and scalability –, the decentralized multi-UAV task assignment problem is studied in Kwak et al. (2013). These authors investigated the optimization of a decentralized task assignment for heterogeneous UAVs. In their work, each UAV selects its targets by employing the consensus-based bundle algorithm. They used a scoring matrix to reflect heterogeneity among the UAVs and targets with different capabilities. In Edison and Shima (2011), a cooperative multiple task assignment problem was built up for heterogeneous UAVs performing classification, attack, and verification tasks. Zhu et al. (2018) focused on the reconnaissance task allocation problem for UAVs, where ground targets with different features and sizes where considered. More recent publications related to stochastic TOPs are those provided by Panadero et al. (2020) and Bayliss et al. (2020). The former introduces random processing times into the analysis of TOPs, while the latter proposes a learnheuristic algorithm that considers the UAVs' physical constraints. However, none of the above analyzed the integrated task assignment and routing problem in an open TOP, which is the main focus of this work.

3 FORMAL PROBLEM DESCRIPTION

This section describes a formal model of the optimization problem being analyzed. Let us consider a complete graph $G = (V, A)$, where $V = \{0, 1, \ldots, n\}$ is the set of nodes, and A is the set of edges connecting them. Node 0 corresponds to the depot, while the remaining nodes are customers offering a positive reward, $r_i > 0$, $\forall i \in V \setminus \{0\}$ ($r_0 = 0$). The reward is collected only the first time a node is visited, so there is no incentive to visit any node more than once. The traveling time between any two nodes, $i, j \in V$ (with $i \neq j$) is modeled as a random variable $T_{ij} > 0$, and the service time at each node $i \in V \setminus \{0\}$ is also a random variable $S_i > 0$. The maximum time for a UAV to complete its open route is a user-defined parameter, $t_{max} > 0$. The set of UAVs is denoted by K. Thus, the maximum number of routes that can be included in any solution is given by $|K|$. Let y_{ik} be a binary variable that takes the value 1 if node $i \in V$ is visited by UAV $k \in K$, and 0 otherwise. Similarly, x_{ijk} is another binary variable that takes the value 1 if the edge (i, j) is traversed by UAV $k \in K$, and 0 otherwise. Under these conditions, the following programming model can be formulated, where $\alpha \in (0, 1)$ is a user-defined value:

$$\text{Maximize } E\left[\sum_{i \in V} \sum_{k \in K} r_i y_{ik}\right] \tag{1}$$

Subject to:

$$\sum_{j \in V} x_{jik} = y_{ik}, \qquad \forall i \in V,\ \forall k \in K \tag{2}$$

$$\sum_{k \in K} y_{0k} \leq |K| \tag{3}$$

$$\sum_{k \in K} y_{ik} \leq 1, \qquad \forall i \in V \setminus \{0\} \tag{4}$$

$$\sum_{(i,j) \in \delta^+(S)} x_{ijk} \geq y_{bk}, \qquad \forall S \subseteq V \setminus \{0\}, \forall b \in S, \forall k \in K \tag{5}$$

$$P\left(\sum_{(i,j) \in E} T_{ij} x_{ijk} + S_i y_{ik} \leq t_{max}\right) \geq \alpha, \qquad \forall k \in K \tag{6}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in V, \forall k \in K \tag{7}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall (i, j) \in E, \forall k \in K \tag{8}$$

In the previous formulation, Equation (1) refers to the maximization of the expected reward collected by the fleet of UAVs. Constraints (2) state that, if we visit node i, we need to go from any vertex j to vertex i, while Constraints (4) guarantees that we visit this node just once and with only one vehicle. Constraint (3) imposes that the number of used UAVs does not exceed the number of available vehicles. Constraints (5) guarantee that our routes will be connected by getting each possible subset of our vertices set ($S \subseteq V$) and connecting both with an edge connecting $i \notin S$ with $j \in S$, thus generating the set $\delta^+(S) = \{(i, j) \in E \mid i \notin S, j \in S\}$. Constraints (6) ensure that the route of the vehicle k is completed before the deadline (t_{max}) with some probability α. Finally, Constraints (7) and (8) define y_{ik} and x_{ijk} as binary variables.

4 A GENETIC ALGORITHM SIMHEURISTIC

As mentioned before, in order to solve the stochastic and open version of the TOP described in this paper, we propose a novel approach combining a GA with MCS. In the stochastic version of the problem, random times could make a planned route to exceed its maximum allowed time (driving range). This situation is known as a route failure, i.e., the planned route cannot be satisfactorily completed in the given time. This situation requires to compute not only the expected reward, but also the reliability of a proposed solution – i.e., the probability that a planned solution can be implemented in practice without route failures. Simheuristic algorithms constitute an effective simulation-optimization approach to cope with these problems, since they do not only allow for estimating the expected reward, but also to analyze the reliability levels associated with a proposed routing plan. In this paper, the optimization component of our simheuristic is a GA. GAs are an evolution-inspired metaphor, which work on an evolving population of individuals. Each individual represents a solution (phenotype), and it is coded by a chromosome (genotype) composed of a set of genes. Also, each individual has a fitness value that measures its quality. The high-quality individuals (parents) are selected to be in a mating pool. During the mating process, recombination (crossover) operators are applied to each pair of individuals. Also, small changes (mutations) are also applied to the new children (offspring) solutions. Thus, by combining two parents it is possible to generate one or two children, which are expected to inherit some of the good characteristics that made the parents to be good solutions. Each new offspring will replace the low-quality individuals from propagating sub-optimal genes. By iterating selection and mating, there is a high probability of keeping the individuals' good properties while improving them at each generation. The generation of new populations and children is iterated until a stopping criterion is met.

Roughly speaking, our simheuristic keeps the best solution in terms of expected reward, which is estimated by the simulation component. Given a promising solution for the deterministic version of the problem, a MCS is executed in order to compute the average reward obtained by the proposed solution when it is employed in a scenario under uncertainty. In addition, its associated reliability is also estimated using the same MCS process. One key and novel aspect of our GA implementation is the chromosome representation and decoding process. As Figure 2 shows, each solution is represented by one chromosome that contains a permutation of all the customers. Since the chromosome contains just one type of genes (customers), it is a simple but effective representation to carry out crossover and mutation operations. During the decoding process, the algorithm extracts all the routes contained in the chromosome. This is accomplished by taking into account the maximum time allowed per route. In this process, the algorithm associates both a reward and a travel time to each route. Afterwards, the extracted routes are sorted from higher to lower reward, and then by their associated time. Finally, the algorithm selects as many routes from the sorted list as possible, taking into account the restricted number of vehicles in the fleet. Using this decoding process, the algorithm explores all the possible routes and selects the elite routes in terms of reward.

5 COMPUTATIONAL EXPERIMENTS

The proposed simheuristic was implemented using Python 3.7 and executed in a standard PC with 8 GB of RAM and an Intel Core *i*7 processor at 2.3 GHz. In order to test our approach, we have extended the classical benchmarks for the deterministic version of the TOP (Chao et al. 1996). This extension consists in assuming that both the traveling and servicing times are random variables that follow some probability distributions. In real-life applications, historical data should be fitted by the appropriate probability distribution. However, for testing purposes, we have assumed that traveling times follow log-normal probability distributions, while servicing times have been modeled using Weibull probability distributions. In the case of traveling times, we have assumed that $E[T_{ij}] = t_{ij}$, where t_{ij} refers to the deterministic traveling time required to move from node i to node j. Also, following Panadero et al. (2020), we have considered that $Var[T_{ij}] = c \cdot t_{ij}$, where c is an experimental parameter employed to define the level of variability. Notice that when $c = 0$, we are

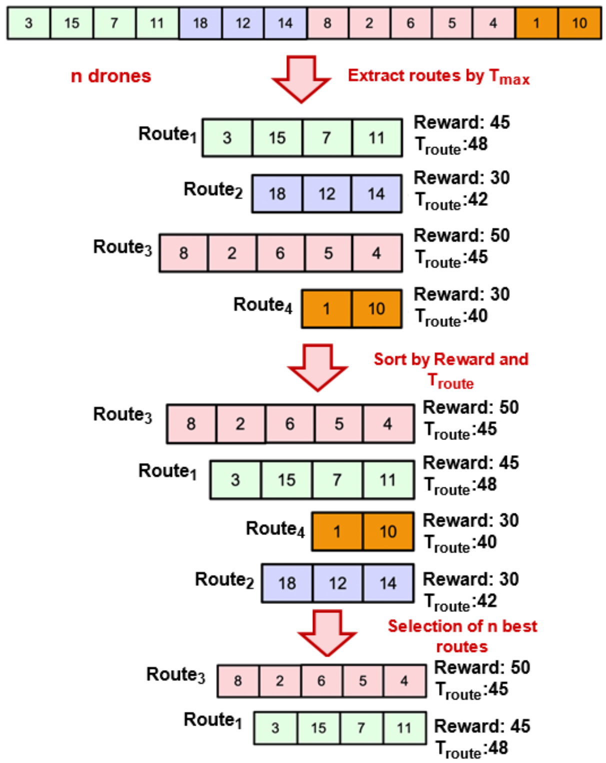


Figure 2: Chromosome representation and decoding.

defining an ‘ideal’ deterministic scenario without variability. In order to consider different scenarios, we have used three levels of variability: low (L, with $c = 0.15$), medium (M, with $c = 0.25$), and large (L, with $c = 0.50$). Regarding servicing times, S_i, we have considered that $E[S_i] = 0.5$, while $Var[S_i] = 0.04$ – i.e., the shape and scale parameters of this Weibull are 2.69 and 0.56, respectively. The selection of the log-normal and Weibull probability distributions is not casual, since these are highly flexible distributions that are frequently employed to model non-negative continuous variables such as times.

The algorithm was executed five times with different seeds, selecting the best solution of all executions. For each run, we considered a total population of 400 individuals, with a maximum of $2,000$ generations (iterations) or until a maximum time of 100 seconds was reached. Figure 3 depicts an example of convergence analysis for instance *p1.2.r*, where the algorithm reaches the best found solution after nearly 900 iterations. As a selection method, the algorithm uses a ternary tournament selection with replacement. Both the probability rate of the crossover and the mutation were set to 0.5.

Table 1 displays the results for some selected instances with different characteristics, but just considering traveling times as random variables (i.e., no servicing times are considered in this first experiment). The first column of the table identifies the instance, while the next column reports our best deterministic (*OBD*) solution found. Each instance is characterized by the nomenclature *px.y.z*, where: x denotes the set – each set depicts a concrete scenario with a specific number of nodes and their locations, y is the number of UAVs (which varies between 2 and 4 depending on the instance), and z represents the maximum driving range. We have divided the remaining columns into two different parts. In the first part, we evaluate *OBD* (both in terms of rewards and reliability) under a stochastic scenario and using different levels of variability. Columns *OBD-x* and Rel_{OBD-x}, with $x \in \{L,M,H\}$, show the expected rewards collected and the associated reliability – i.e., the percentage of runs that the OBD solution can be completed without experiencing any route failure.

To compute these columns, we have executed the GA disabling the simulation part. After that, we have employed the full simheuristic (including the simulation module) to obtain our best stochastic solutions *OBS*. During the simulation process, it has been considered that whenever a route exceeds the maximum time threshold, the reward gathered in that route accounts to zero. Similarly, in the second part of Table 1, columns $OBS-x$ and Rel_{OBS-x} show the expected reward obtained by *OBS*. Figure 4a summarizes the average gap of the different stochastic solutions with respect to the *OBD* for the different variance levels. Figure 4b outlines the average reliability of the stochastic solutions. Similarly, Table 2 shows the results for the same set of instances, when both traveling and servicing times are considered as random variables. Figures 4c and 4d show, respectively, the average gaps of the stochastic solutions with respect to the *OBD* and the reliability level.

Table 1: Computational results considering stochastic travel times.

		Deterministic in Stochastic Scenario						Stochastic Scenario					
		Low Variance c = 0.15		Medium Variance c = 0.25		High Variance c = 0.50		Low Variance c = 0.15		Medium Variance c = 0.25		High Variance c = 0.50	
Instance	OBD	OBD-L	Rel_{OBD-L}	OBD-M	Rel_{OBD-M}	OBD-H	Rel_{OBD-H}	OBS-L	Rel_{OBS-L}	OBS-M	Rel_{OBS-L}	OBS-H	Rel_{OBS-H}
p1.2.p	270	194.85	0.51	189.46	0.49	180.35	0.44	242.13	0.81	220.73	0.68	209.16	0.61
p1.2.q	280	223.72	0.56	216.48	0.53	205.44	0.49	263.27	0.95	253.04	0.88	251.03	0.93
p1.2.r	285	274.15	0.93	261.44	0.84	239.24	0.71	273.31	0.92	275.6	0.97	264.27	0.89
p1.3.p	255	229.28	0.72	221.55	0.65	208.75	0.54	244.61	0.87	233.31	0.75	215.84	0.6
p1.3.q	265	183.11	0.3	176.79	0.28	166.56	0.23	226.37	0.83	217.77	0.73	206.95	0.62
p1.4.p	240	220.7	0.72	209.46	0.58	193.12	0.42	229.36	0.9	222.85	0.8	209.48	0.62
p2.2.h	365	242.01	0.41	233.99	0.39	224.62	0.36	300.47	0.87	301.34	0.98	289.65	0.9
p2.2.i	410	291.03	0.48	276.74	0.44	263.71	0.4	333.32	0.72	310.72	0.63	272.61	0.42
p2.2.j	430	316.53	0.55	301.24	0.49	283.13	0.43	337.47	0.62	317.24	0.54	293.43	0.47
p2.3.k	425	259.52	0.24	254.47	0.22	249.88	0.21	359.1	0.74	339.87	0.62	305.77	0.42
p2.4.h	230	184.78	0.44	174.87	0.35	163.91	0.27	223.69	0.92	218.97	0.84	208.94	0.69
p2.4.i	260	205.83	0.35	198.91	0.32	188.56	0.26	237.67	0.62	228.97	0.52	213.61	0.39
p3.2.r	800	776.11	0.93	749.87	0.86	697.63	0.74	776.84	0.93	749.4	0.86	697.21	0.74
p3.2.s	800	604.51	0.54	572.49	0.49	532.46	0.43	795.23	0.99	780.61	0.95	751.23	0.86
p3.3.r	800	561.23	0.43	548.61	0.39	532.99	0.36	738	0.99	737.17	0.99	723.93	0.93
p3.3.s	800	673.58	0.55	665.69	0.53	643.91	0.49	747.68	0.82	729.8	0.75	694.47	0.64
p3.3.t	800	786.84	0.96	768.23	0.89	731.14	0.76	798.81	1	794.07	0.98	777.83	0.9
p3.4.r	770	613.77	0.35	607.57	0.33	600.38	0.32	711.03	0.65	705.23	0.62	697.13	0.59
p3.4.s	770	738.52	0.82	721.29	0.74	687.15	0.6	765.5	0.98	760.35	0.96	737.5	0.86
p3.4.t	800	758.27	0.84	734.48	0.74	695.93	0.6	788.95	0.96	773.54	0.91	756.46	0.84
Averages:	**502.75**	**416.917**	**0.5815**	**404.1815**	**0.5275**	**384.443**	**0.453**	**469.6405**	**0.8545**	**458.529**	**0.798**	**438.825**	**0.696**

Table 2: Computational results considering stochastic times for both travel and service.

		Deterministic in Stochastic Scenario						Stochastic Scenario					
		Low Variance c = 0.15		Medium Variance c = 0.25		High Variance c = 0.50		Low Variance c = 0.15		Medium Variance c = 0.25		High Variance c = 0.50	
Instance	OBD	OBD-L	Rel_{OBD-L}	OBD-M	Rel_{OBD-M}	OBD-H	Rel_{OBD-H}	OBS-L	Rel_{OBS-L}	OBS-M	Rel_{OBS-M}	OBS-H	Rel_{OBS-H}
p1.2.p	245	156.06	0.41	151.83	0.39	146.84	0.37	203.25	0.73	185.31	0.61	181.51	0.61
p1.2.q	250	199.28	0.64	189.62	0.58	177.75	0.51	231.31	0.89	218.4	0.79	204.42	0.69
p1.2.r	260	160.42	0.38	156.33	0.36	151.16	0.34	234.36	0.95	229.22	0.91	214.95	0.8
p1.3.p	230	191.24	0.58	181.23	0.49	169.18	0.4	202.3	0.7	196.91	0.64	187.17	0.55
p1.3.q	225	177.38	0.49	168.09	0.41	157.52	0.34	193.67	0.64	195.56	0.69	184.86	0.58
p1.4.p	215	142.75	0.18	139.19	0.17	133.94	0.14	160.93	0.34	156.45	0.3	149.06	0.25
p2.2.h	290	198.34	0.46	190.72	0.42	183.41	0.4	252.42	0.95	245.41	0.9	188.55	0.42
p2.2.i	330	206.16	0.36	200.54	0.35	195	0.33	265.18	0.68	253.57	0.62	238.95	0.55
p2.2.j	335	216.45	0.41	210.25	0.39	204.11	0.37	249.21	0.61	225.26	0.47	207.04	0.39
p2.3.k	355	221.35	0.24	216.84	0.23	212.02	0.21	249.3	0.48	217.09	0.23	213.01	0.22
p2.4.h	230	163.3	0.23	158.38	0.21	151.96	0.18	175.2	0.3	170	0.27	163	0.23
p2.4.i	230	175.83	0.33	168.56	0.28	160.19	0.23	209.45	0.68	193.42	0.53	184.93	0.44
p3.2.r	760	680.39	0.81	645.46	0.73	595.17	0.62	714.83	0.92	688.95	0.86	634.76	0.76
p3.2.s	780	632.94	0.54	628	0.54	609.82	0.51	736.78	0.91	707.4	0.83	682.41	0.78
p3.3.r	700	529.46	0.38	510.73	0.35	485.4	0.3	630.23	0.79	610.28	0.71	578.78	0.6
p3.3.s	750	573.01	0.35	557.96	0.33	533.49	0.3	706.03	0.91	682.14	0.82	642.45	0.68
p3.3.t	790	526.44	0.29	508.76	0.27	486.36	0.23	665.34	0.65	629.64	0.55	584.22	0.44
p3.4.r	710	592.39	0.42	575.42	0.36	553.39	0.3	676.35	0.78	657.17	0.68	626.47	0.54
p3.4.s	730	586.09	0.51	563.34	0.43	531.61	0.34	686.4	0.91	673.6	0.83	647.32	0.7
p3.4.t	790	583.92	0.33	570.39	0.3	549.15	0.25	707.95	0.87	688.94	0.78	650.89	0.61
Averages:	**460.25**	**345.66**	**0.417**	**334.582**	**0.3795**	**319.3735**	**0.3335**	**407.5245**	**0.7345**	**391.236**	**0.651**	**368.2375**	**0.542**

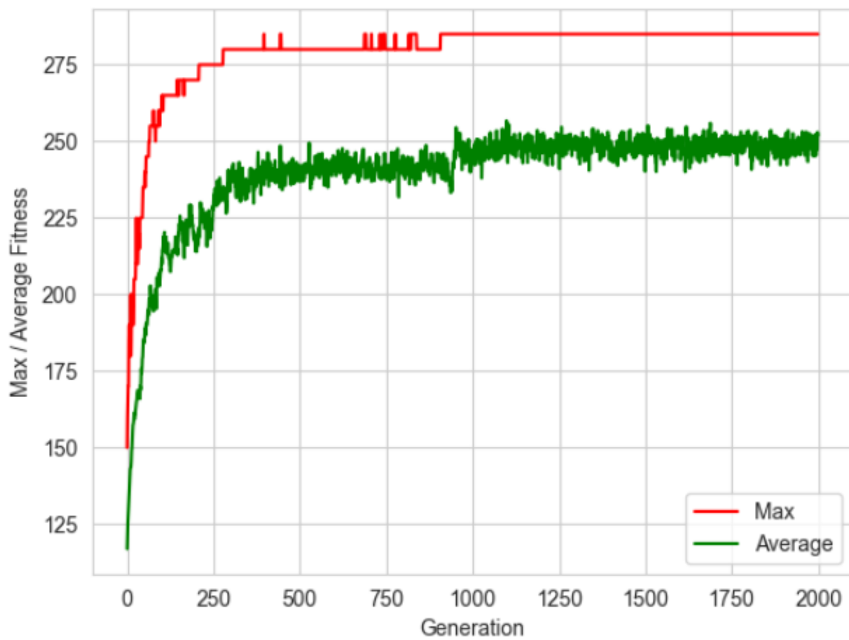


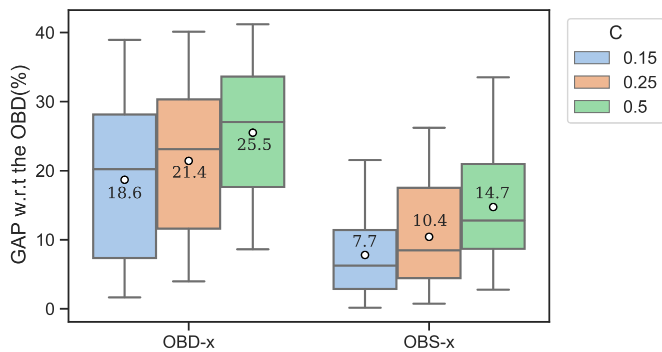
Figure 3: Analysis of convergence of the maximum and average fitness over generations for the instance *p1.2.r*.

6 ANALYSIS OF THE RESULTS

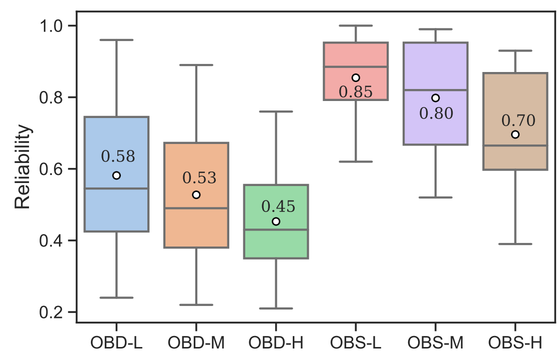
As shown in Table 1, the solutions provided by our simheuristic, *OBS-x*, clearly outperform the deterministic solutions, *OBD-x*, when these are considered in a scenario under uncertainty. Thus, for instance, in the high-variance scenario we are able to increase the reward up to 218.77 units for one of the instances, with an average improvement of 54.38 units. Apart from increasing the expected reward, the solutions generated by the simheuristic approach also offer a lower variability than the ones provided by the deterministic approach (Figure 4a). The interquartile range for *OBD-x* is located, in general, above 20 % of GAP and our *OBS-x* is under 10 % in low- and medium-variance and between 10 % and 20 % in high-variance. The size of the interquartile range is bigger in *OBD-x*, getting sizes over 20 points in low- and medium-variance and around 10 points in high-variance, while *OBS-x* has sizes less than 10 points in all scenarios. *OBS-x* offers a better reliability than *OBD-x* in all tested instances and variance scenarios (Figure 4b). Table 2 gives the results when considering both stochastic traveling times and stochastic servicing times. As it can be seen in Figure 4c, the gap between *OBD-x* and *OBS-x* increases with respect to the previous results, in which only stochastic traveling times were considered. Notice also that the reliability of the solutions decreases as we increment the variability level (Figure 4d). The results provided by *OBD-x*, when considered in a deterministic (ideal) scenario, can be considered as upper bounds for our simheuristic. Likewise, the results provided by *OBD-x* in a stochastic scenario constitute lower bounds for our approach. All in all, these results reveal the importance of integrating simulation methods when dealing with stochastic optimization problems.

7 CONCLUSIONS AND FUTURE WORK

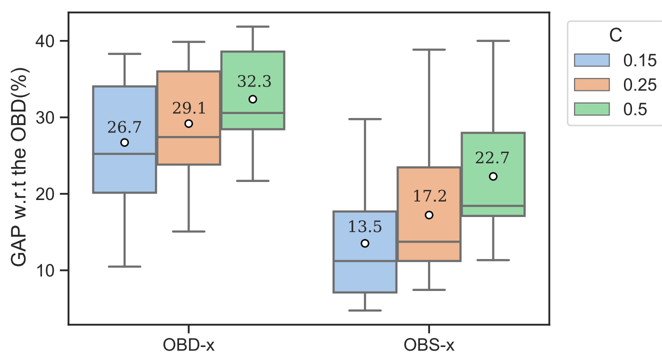
In this article, we model an unmanned aerial vehicle task assignment and routing problem as an open team orienteering problem with stochastic traveling and servicing times. In this version, we assume that whenever a route exceeds its maximum operation time, all rewards collected are lost. The aforementioned operation time does not take into account the return trip to the depot, since it is assumed this can always be completed using a stand-by battery. In order to solve the problem, a novel simheuristic is proposed. This



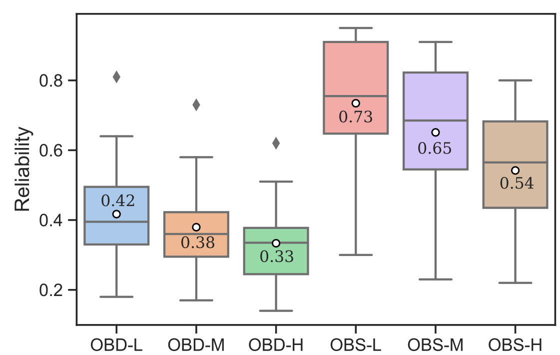
(a) Gaps (in %) comparing the stochastic solutions with different level of variance w.r.t the OBD, in a scenario with random travel times.



(b) Reliability of the stochastic solutions with different level of variance, in a scenario with random travel times.



(c) Gaps (in %) comparing the stochastic solutions with different level of variance w.r.t the OBD, in a scenario with random travel and service times.



(d) Reliability of the stochastic solutions with different level of variance, in a scenario with random travel and service times.

Figure 4: Computational results.

is based on a genetic algorithm which integrates a specifically designed chromosome representation and decoding. The proposed representation schema allows us to accelerate the convergence of the algorithm towards near-optimal solutions.

A series of intensive computational experiments contributes to validate our approach and shows how routing plans that are near-optimal in a deterministic scenario can quickly become sub-optimal plans as we introduce more uncertainty conditions in the system. In these experiments, we have modeled traveling times as random variables following log-normal probability distributions, while servicing times have been modeled using Weibull probability distributions.

As future research, we plan, on the one hand, to explore the effect on the reliability level when considering different probability distributions in the nodes for the servicing times and, on the other hand, to consider that some of the traveling or servicing times cannot be fitted by a probability distribution and, hence, fuzzy techniques need to be combined with simulation and metaheuristics to deal with this general case.

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REFERENCES

Alighanbari, M., and J. P. How. 2008. "A Robust Approach to the UAV Task Assignment Problem". *International Journal of Robust and Nonlinear Control: IFAC-Affiliated Journal* 18(2):118–134.

Bartsch, R., J. Coyne, and K. Gray. 2016. *Drones in Society: Exploring the Strange New World of Unmanned Aircraft*. Abingdon, UK: Taylor & Francis.

Bayliss, C., A. A. Juan, C. S. Currie, and J. Panadero. 2020. "A Learnheuristic Approach for the Team Orienteering Problem with Aerial Drone Motion Constraints". *Applied Soft Computing* 92:106280.

Bertuccelli, L., H.-L. Choi, P. Cho, and J. How. 2009. "Real-Time Multi-UAV Task Assignment in Dynamic and Uncertain Environments". In *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, 5776. August 10-13, Chicago, Illinois: American Institute of Aeronautics and Astronautics.

Chao, I.-M., B. L. Golden, and E. A. Wasil. 1996. "The Team Orienteering Problem". *European Journal of Operational Research* 88(3):464–474.

Chen, Y., D. Yang, and J. Yu. 2018. "Multi-UAV Task Assignment with Parameter and Time-Sensitive Uncertainties using Modified Two-Part Wolf Pack Search Algorithm". *IEEE Transactions on Aerospace and Electronic Systems* 54(6):2853–2872.

Chen, Y. F., N. K. Ure, G. Chowdhary, J. P. How, and J. Vian. 2014. "Planning for Large-Scale Multiagent Problems via Hierarchical Decomposition with Applications to UAV Health Management". In *Proceedings of the 2014 American Control Conference*, 1279–1285. Portland, Oregon: June 4^{th}–6^{th}, Institute of Electrical and Electronics Engineers, Inc.

Chica, M., A. A. Juan, C. Bayliss, O. Cordón, and W. D. Kelton. 2020. "Why Simheuristics? Benefits, Limitations, and Best Practices when Combining Metaheuristics with Simulation". *SORT-Statistics and Operations Research Transactions* 44:311–334.

Choi, H.-L., L. Brunet, and J. P. How. 2009. "Consensus-based Decentralized Auctions for Robust Task Allocation". *IEEE Transactions on Robotics* 25(4):912–926.

Chung, S.-J., A. A. Paranjape, P. Dames, S. Shen, and V. Kumar. 2018. "A Survey on Aerial Swarm Robotics". *IEEE Transactions on Robotics* 34(4):837–855.

Dehghanimohammadabadi, M., and N. Kabadayi. 2020. "A Combined Multi-Objective Simulation-Optimization and AHP Approach: A Healthcare Case Study". *International Journal of the Analytic Hierarchy Process* 12(1):1–20.

Edison, E., and T. Shima. 2011. "Integrated Task Assignment and Path Optimization for Cooperating Uninhabited Aerial Vehicles using Genetic Algorithms". *Computers & Operations Research* 38(1):340–356.

Faulin, J., M. Gilibert, A. A. Juan, X. Vilajosana, and R. Ruiz. 2008. "SR-1: A Simulation-based Algorithm for the Capacitated Vehicle Routing Problem". In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Moench, O. Rose, T. Jefferson, and J. W. Fowler, 2708–2716. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Fu, S.-Y., L.-W. Han, Y. Tian, and G.-S. Yang. 2012. "Path Planning for Unmanned Aerial Vehicle based on Genetic Algorithm". In *Proceeings of the 2012 IEEE International Conference on Cognitive Informatics and Cognitive Computing*, 140–144. August 22–24, Kyoto: Institute of Electrical and Electronics Engineers, Inc.

Gök, Y. S., M. Tomasella, D. Guimarans, and C. Ozturk. 2020. "A Simheuristic Approach for Robust Scheduling of Airport Turnaround Teams". In *Proceedings of the 2020 Winter Simulation Conference*, edited by K.-H. Bae, S. Fen, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, 1336–1347. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Gruler, A., C. Fikar, A. A. Juan, P. Hirsch, and C. Contreras-Bolton. 2017. "Supporting Multi-Depot and Stochastic Waste Collection Management in Clustered Urban Areas via Simulation-Optimization". *Journal of Simulation* 11(1):11–19.

Hatami, S., L. Calvet, V. Fernández-Viagas, J. M. Framiñán, and A. A. Juan. 2018. "A Simheuristic Algorithm to Set Up Starting Times in the Stochastic Parallel Flowshop Problem". *Simulation Modelling Practice and Theory* 86:55–71.

Juan, A. A., J. Faulin, R. Ruiz, B. Barrios, M. Gilibert, and X. Vilajosana. 2009. "Using Oriented Random Search to Provide a Set of Alternative Solutions to the Capacitated Vehicle Routing Problem". In *Operations Research and Cyber-Infrastructure*, edited by J. W. Chinneck, B. Kristjansson, and M. J. Saltzman, 331–345. New York: Springer.

Keshtkaran, M., K. Ziarati, A. Bettinelli, and D. Vigo. 2016. "Enhanced Exact Solution Methods for the Team Orienteering Problem". *International Journal of Production Research* 54(2):591–601.

Kwak, D. J., S. Moon, S. Kim, and H. J. Kim. 2013. "Optimization of Decentralized Task Assignment for Heterogeneous UAVs". *IFAC Proceedings Volumes* 46(11):251–256.

Lee, C. K. H. 2018. "A Review of Applications of Genetic Algorithms in Operations Management". *Engineering Applications of Artificial Intelligence* 76:1–12.

Martinez, S. 2010. "UAV Cooperative Decision and Control: Challenges and Practical Approaches". *IEEE Control Systems Magazine* 30(2):104–107.

Merkert, R., and J. Bushell. 2020. "Managing the Drone Revolution: A Systematic Literature Review into the Current Use of Airborne Drones and Future Strategic Directions for their Effective Control". *Journal of Air Transport Management* 89:101929.

Pagès-Bernaus, A., H. Ramalhinho, A. A. Juan, and L. Calvet. 2019. "Designing e-Commerce Supply Chains: A Stochastic Facility–Location Approach". *International Transactions in Operational Research* 26(2):507–528.

Panadero, J., J. Doering, R. Kizys, A. A. Juan, and A. Fito. 2018. "A Variable Neighborhood Search Simheuristic for Project Portfolio Selection under Uncertainty". *Journal of Heuristics* 26(3):353–375.

Panadero, J., A. A. Juan, C. Bayliss, and C. Currie. 2020. "Maximising Reward from a Team of Surveillance Drones: A Simheuristic Approach to the Stochastic Team Orienteering Problem". *European Journal of Industrial Engineering* 14(4):485–516.

Ramirez-Atencia, C., G. Bello-Orgaz, M. D. R-Moreno, and D. Camacho. 2017. "Solving Complex Multi-UAV Mission Planning Problems Using Multi-Objective Genetic Algorithms". *Soft Computing* 21(17):4883–4900.

Rasmussen, S., and D. Kingston. 2008. "Assignment of Heterogeneous Tasks to a Set of Heterogeneous Unmanned Aerial Vehicles". In *Proceedings of the 2008 AIAA Guidance, Navigation and Control Conference and Exhibit*, 6316. August 18-21, Honolulu, Hawaii: American Institute of Aeronautics and Astronautics.

Reyes-Rubiano, L., D. Ferone, A. A. Juan, and J. Faulin. 2019. "A Simheuristic for Routing Electric Vehicles with Limited Driving Ranges and Stochastic Travel Times". *SORT-Statistics and Operations Research Transactions* 1:3–24.

Schumacher, C., P. Chandler, M. Pachter, and L. Pachter. 2004. "UAV Task Assignment with Timing Constraints via Mixed-Integer Linear Programming". In *Proceedings of the 2004 AIAA Unmanned Unlimited Technical Conference, Workshop and Exhibit*, 6410. September 26, Chicago, Illinois: American Institute of Aeronautics and Astronautics.

Shima, T., and C. Schumacher. 2009. "Assigning Cooperating UAVs to Simultaneous Tasks on consecutive Targets using Genetic Algorithms". *Journal of the Operational Research Society* 60(7):973–982.

Tomasella, M., A. Clare, Y. S. Gök, D. Guimarans, and C. Ozturk. 2019. "STTAR: A Simheuristics-Enabled Scheme for Multi-Stakeholder Coordination of Aircraft Turnaround Operations". In *Proceedings of the 2019 Winter Simulation Conference*, edited by N. Mustafee, K. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y. Son, 488–499. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Yazdani, M., K. Kabirifar, B. E. Frimpong, M. Shariati, M. Mirmozaffari, and A. Boskabadi. 2021. "Improving Construction and Demolition Waste Collection Service in an Urban Area using a Simheuristic Approach: A Case Study in Sydney, Australia". *Journal of Cleaner Production* 280:124138.

Yazdani, M., M. Mojtahedi, and M. Loosemore. 2020. "Enhancing Evacuation Response to Extreme Weather Disasters Using Public Transportation Systems: A Novel Simheuristic Approach". *Journal of Computational Design and Engineering* 7(2):195–210.

Ye, F., J. Chen, Y. Tian, and T. Jiang. 2020. "Cooperative Multiple Task Assignment of Heterogeneous UAVs Using a Modified Genetic Algorithm with Multi-Type-Gene Chromosome Encoding Strategy". *Journal of Intelligent & Robotic Systems* 100:615–627.

Zhu, W., L. Li, L. Teng, and W. Yonglu. 2018. "Multi-UAV Reconnaissance Task Allocation for Heterogeneous Targets Using an Opposition-based Genetic Algorithm with Double-Chromosome Encoding". *Chinese Journal of Aeronautics* 31(2):339–350.

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