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THE TEAM ORIENTEERING PROBLEM WITH STOCHASTIC SERVICE TIMES AND DRIVING-RANGE LIMITATIONS: A SIMHEURISTIC APPROACH

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ABSTRACT

In the context of smart cities, unmanned aerial vehicles (UAVs) offer an alternative way of gathering data and delivering products. On the one hand, in congested urban areas UAVs might represent a faster way of performing some operations than employing road vehicles. On the other hand, they are constrained by driving-range limitations. This paper copes with a version of the well-known Team Orienteering Problem in which a fleet of UAVs has to visit a series of customers. We assume that the rewarding quantity that each UAV receives by visiting a customer is a random variable, and that the service time at each customer depends on the collected reward. The goal is to find the optimal set of customers that must be visited by each UAV without violating the driving-range constraint. A simheuristic algorithm is proposed as a solving approach, which is then validated via a series of computational experiments.

1 INTRODUCTION

In a supply chain, a transport system is typically defined as a robust set of links that allows a continuous flow of resources such as information, money, and products. This set of links connects suppliers, production locations, retailers, and customers (McKinnon et al. 2015). This concept is nowadays evolving due to the market dynamics. Customers continuously place orders, which must be satisfied over the course of a vehicle route. As a consequence, multi-echelon supply chains emerge, thus delaying response times and amplifying uncertainty in the supply chain. The introduction of new technologies allows for considering real-time data that can be useful in order to identify suitable links at each time. As a result, the European Commission (2016) has proposed different initiatives and some governmental projects, such as CITYLOG, to facilitate the emergence of sustainable and smart cities. This initiative leads the promotion of transport logistics on a modular and temporal system in order to improve the distribution process, especially in urban zones. For example, the efficient management of last-mile deliveries has gained a critical role in urban logistics, which has been reinforced by the incorporation of 'greener' vehicles such as bikes, electric vehicles, and unmanned aerial vehicles (UAVs). These transportation means represent potential benefits in terms of delays, traffic congestion, and flexibility in city logistics (Ha et al. 2018). Figure 1 shows a simple example where a heavy vehicle brings the resources close to the urban zone. From there, resources are transferred to lighter vehicles that conduct the pick-up and delivery actions inside the urban area. The last-mile distribution is limited by the payload capacity and the driving range of these vehicles.

The use of UAVs in smart cities is still in an initial stage. However, this potential activity has raised the interest of many businesses due, in part, to the promise of quick responses to dynamic situations (Rao et al. 2016) and even door-to-door deliveries (Goodchild and Toy 2018). Besides, the monitoring of

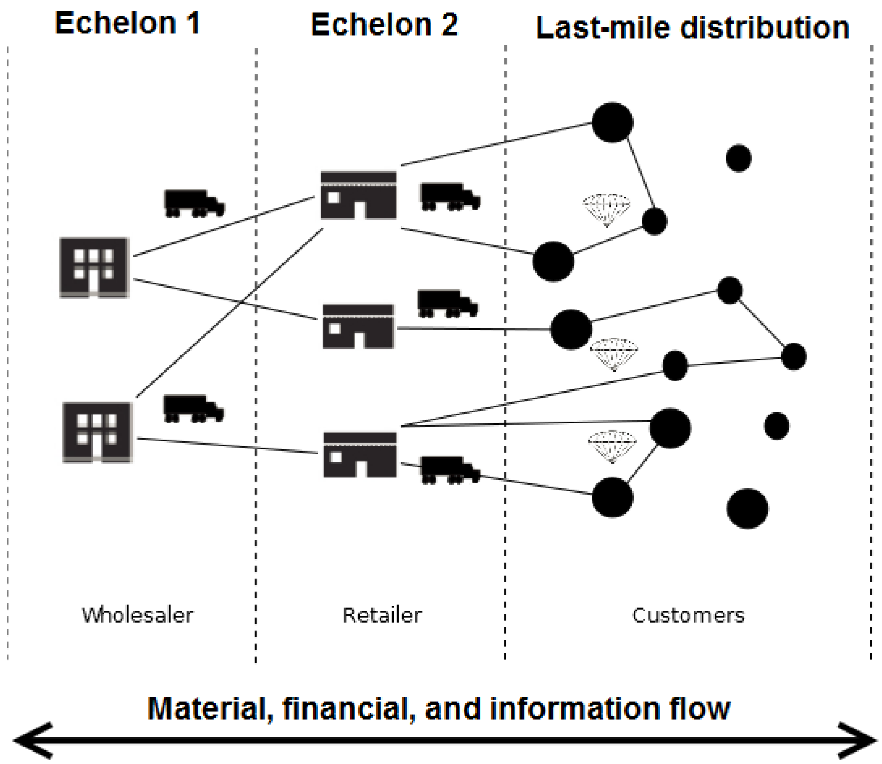

Figure 1: Two-stage delivery in urban areas.

pollution levels, traffic congestion, and noise levels in urban zones are other traits where UAVs can play a relevant role in the future. Inspired by these challenges, this paper studies a stochastic version of the Team Orienteering Problem (TOP) in which UAVs with limited driving ranges are considered. In some real-life situations, the reward to be collected at a given customer, the travel time between two consecutive customers, or the service time at each customer can be modeled as random variables. Hence, TOP variants with stochastic aspects have started to receive more attention in the scientific literature (Gunawan et al. 2018). The driving-range limitation of UAVs introduces additional difficulties in a TOP with stochastic travel times or stochastic service times, since the UAV might run out of battery life before reaching its destination. Whenever this happens, an undesirable and usually expensive route failure occurs. Hence, reliability issues have to be considered, too.

In a TOP with stochastic rewards, service times are often proportional to the collected reward at a customer, i.e., the more reward needs to be collected, the more time will be required to complete the service (Vansteenwegen et al. 2011). In this paper, we propose a simheuristic algorithm to deal with a TOP with stochastic rewards and service times (Juan et al. 2015a). In addition, route duration is also constrained by the UAVs' driving ranges. Simheuristics can be considered as a specialized case of simulation-based optimization (Law and McComas 2002; April et al. 2003), where only metaheuristics are employed as optimization components and the simulation feedback helps to better guide the metaheuristic searching process in a vast space of feasible solutions. Both simheuristics and simulation-based optimization are examples of simulation-optimization methods, which aim at combining optimization with simulation in different ways. Excellent reviews and tutorials on these matters can be found in Fu (2002), Chau et al. (2014), or Jian and Henderson (2015). In particular, our simheuristic algorithm combines Monte Carlo simulation (MCS) with a multi-start metaheuristic framework. The optimization framework also makes use of biased randomization techniques (Faulin et al. 2008; Juan et al. 2013). All in all, our simheuristic approach aims at finding routing solutions offering both high expected rewards and reliability indexes.

The rest of the paper is structured as follows: Section 2 briefly reviews related work; Section 3 provides a detailed description of the TOP version considered here; Section 4 describes our simheuristic algorithm; Section 5 reports the results of the computational experiments; and, finally, the main findings and future research lines are given in Section 6.

2 LITERATURE REVIEW

The Orienteering Problem (OP) looks for single routes with a maximum length where the visit to a node is motivated by a reward. Each node can be visited at most once and collected rewards define the total reward in a route. Royset (2009) models an OP as a set covering problem, with the goal of maximizing profits related to location visits. Campbell et al. (2011) tackled an OP version considering deterministic benefits and penalties to estimate the impact of stochastic traveling and service times. The problem is solved using a dynamic programming framework that maximizes the expected total reward. Recently, Dolinskaya et al. (2018) extended the previous work by considering an adaptive approach, where the route could be redefined on-the-fly according to unexpected delays or waiting times.

The TOP was introduced by Chao et al. (1996) as a multi-route extension of the OP. Poggi et al. (2010) developed a robust branch-and-cut-and-price algorithm to solve the traditional problem, setting new benchmarks for the problem. Vansteenwegen et al. (2011) developed an iterated local search metaheuristic to solve the TOP with time windows. The approach is aimed at maximizing the rewards, assuming that the service should start within a defined schedule. In this sense, an early arrival leads to waiting times, causing a delay. Dang et al. (2013) proposed a particle swarm optimization to solve the classical version of the TOP. Their main contribution was the fast exploration of a large number of neighborhoods. Souffriau et al. (2013) presented a multi-constraint and time-dependent approach. These authors assume that nodes could consider more than one time window. Their approach is managed as a deterministic problem and solved by means of a hybrid algorithm. Gunawan et al. (2016) presented a survey focusing on the most recent papers and surveys that are related to the TOP and its variants. These authors also studied a number of recent applications and an overview of future trends. They mentioned uncertainties or stochastic aspects that have been studied, especially related to the rewards as well as travel and service times.

Ilhan et al. (2008) are among the first authors to introduce uncertainties in the collected rewards. They discuss the OP with stochastic rewards. Royset (2009) discussed a TOP application using UAVs. Erdoğan and Laporte (2013) tackled the TOP with stochastic rewards using an exact method. Here, service times were based on a finite number of different scenarios. Similarly, Afsar and Nacima (2013) analyze the TOP with stochastic rewards by using column generation. Recently, Panadero et al. (2017) proposed a simheuristic algorithm to solve the TOP with stochastic traveling times, where the expected reward is maximized and the reliability of a solution is also analyzed. Similarly, Gunawan et al. (2018) proposed an iterated local search for solving this problem. Dolinskaya et al. (2018) addressed the problem of searching and rescuing operations in a post-disaster situation. Finally, some TOP applications to UAVs are discussed in Marcosig et al. (2017).

3 PROBLEM DESCRIPTION

Consider an undirected graph $G = (N,A)$, where N is a set of n nodes (including customers as well as an origin and a destination depot) and $A = \{(i, j) : i, j \in N, i < j\}$ is the set of edges connecting all nodes in N. Each route starts at the origin depot and ends at the destination depot (Figure 2).

Each customer $i \in N$ has a stochastic reward (U_i) and a service time (ST_i). Service times follow Equation (1) where k is the factor which sets a relation among the reward and the service time, and $E[U_i]$ is the expected reward. There is a fixed number of homogeneous UAVs. Each edge (i, j) is characterized by a traveling time (t_{ij}), which is assumed to be deterministic. The total traveling time per route is limited by a driving range time ($Tlim$), which represents the battery life of each UAV. Therefore, $Tlim$ constitutes a hard constraint that must be satisfied. This condition cannot be guaranteed in a stochastic scenario with

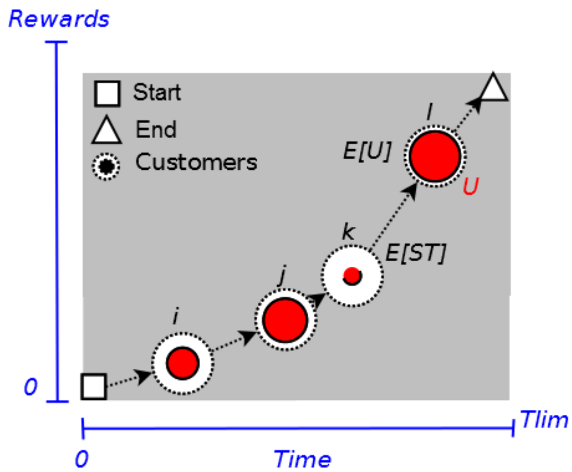

Figure 2: Route with stochastic rewards and maximum duration.

random service times. Hence, route failures might occur in practice, which makes it convenient to consider the reliability level associated with a given solution.

$$ST_i = \begin{cases} 0 & U_i - E[U_i] < 0, \\ k * (U_i - E[U_i]) & U_i - E[U_i] \geq 0. \end{cases} \tag{1}$$

The main objective is to determine the subset of customers to be visited by each route (including the visiting order) which maximizes the expected reward. Hence, whenever a route cannot be completed due to driving range issues (i.e., the UAV running out of battery life), the reward collected so far in that route will be lost (since it never reaches the destination depot). In practice, customers with a high reward will require higher service times, e.g., more pictures will be needed, more data will have to be gathered, etc. Therefore, route duration is a random variable which depends on the customers that integrate each route and the order in which these customers are visited.

4 SOLVING METHODOLOGY

Our solving approach relies on a simheuristic algorithm, which integrates simulation techniques into a metaheuristic framework (Grasas et al. 2016). As any other simheuristic algorithm, it is composed of two different components: an optimization one, which searches for promising solutions, and a simulation one, which assesses the promising solutions in a stochastic environment and guides the search process. Regarding the optimization component, we use a multi-start meta framework in which the constructive phase uses biased-randomization techniques. These techniques have been successfully applied in the past to improve the performance of classical heuristics, both in scheduling applications (Juan et al. 2014) as well as in vehicle routing ones (Juan et al. 2015b; Dominguez et al. 2016). Figure 3 describes our simheuristic algorithm, which encompasses several stages:

- First, an initial 'dummy' solution is built by constructing a route connecting each customer with the origin and destination nodes. In order to merge some of these routes so that a single vehicle can visit more than one customer, the concept of 'savings' is introduced as follows: the time-based savings of merging any two routes is given by the savings in time associated with completing the merged route instead of the two original ones. This concept is extended to the concept of 'preference', which is a linear combination of savings and accumulated reward (thus, if we face two potential merges with similar time-based savings, the one generating a greater accumulated reward will be prioritized). The concept of preference is used to generate a sorted list of potential merges,

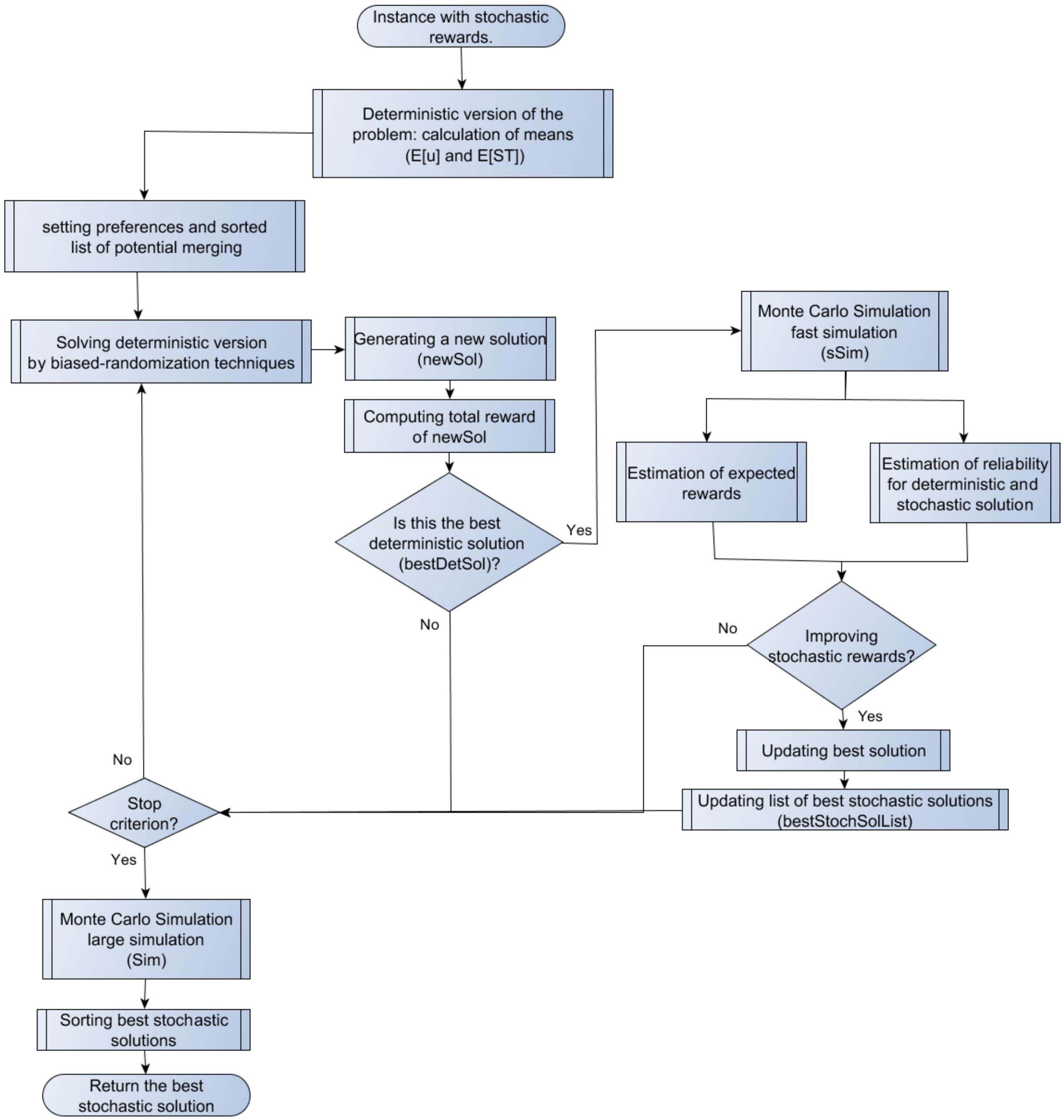

Figure 3: Scheme of our algorithm.

and these are completed following the corresponding order, from higher to lower preference. Of course, a merge can be completed only if the total expected time after the operation does not exceed the driving-range threshold. Notice that the previously described process constitutes a simple but effective heuristic that provides, by construction, a 'good' solution for the deterministic version of the problem.

- Secondly, we employ biased-randomization techniques (Grasas et al. 2017) to transform the previously described heuristic into a probabilistic algorithm. This allows for running the solving algorithm multiple times, thus generating a set of alternative solutions of good quality for the deterministic version of the TOP (*newSols*). In particular, the selection of the next element from the savings list is driven according to a geometric distribution. Hence, merging operations with a larger preference are more likely to be selected, but the selection process is not greedy anymore.

- Thirdly, MCS is incorporated in the aforementioned optimization framework to assess the quality of each newly generated solution, use the feedback from the simulation to better guide the search process, and estimate its reliability level, i.e., the probability that it can be completed without failures. A detailed description about how these steps are done can be found in de Armas et al. (2017). Thus, during the construction phase a feasible solution (*newSol*) is iteratively constructed, one element at a time. According to the total reward or the total expected reward, respectively, a promising solution is defined for the deterministic and stochastic versions of the problem. Therefore, the best deterministic solution (*bestDetSol*) refers to the one with the highest total reward. Moreover, an acceptance criterion is included. The acceptance criterion is employed to decide whether *newSol* is classified as promising or not. If *newSol* is not promising, then it is discarded and another iteration starts. Otherwise, a MCS is applied to assess its main statistics (expected mean, reliability, etc.). If the *bestDetSol* presents a lower total reward, it is replaced by *newSol*. In this stage, the simulation component only considers a short number of runs (*sSim*) to avoid jeopardizing the time of the optimization component. At the end of this stage, a reduced set of 'elite' solutions (*bestStochSolList*) that show high expected rewards and reliability levels is obtained.
- Finally, a more intensive simulation (one with a larger number of runs, *lSim*) is carried out over each of the elite solutions in order to obtain more accurate estimates on their expected reward and reliability levels.

5 COMPUTATIONAL RESULTS

Our simheuristic algorithm was implemented in Java code and run on a personal computer with 8 GB of RAM and an Intel Core i7 at 1.8 GHz. The parameters of the simheuristic algorithm, *sSim* and *lSim* were defined as 600 and 6,000 runs, respectively.

Since there are no benchmark instances for the TOP with stochastic rewards and constrained driving ranges, we modified and extended a deterministic data set from the literature. Then, the deterministic values were considered as mean values to generate the stochastic rewards. We assumed that stochastic rewards, U_i, follow a truncated normal distribution with parameters $\mu(U_i)$ and $\sigma(U_i)$). This distribution represents a 'natural' choice for modeling non-negative random variables. Then, Equation (2) defines the reward for each node i, which is assumed to be a positive value. The value of $\sigma(U_i)$ is estimated as: $c \cdot \mu(U_i)$, where c is a parameter that allows for exploring different levels of uncertainty. It is expected that as c converges to zero, the results from the stochastic version converge to those obtained in the deterministic scenario.

$$U_i = \begin{cases} 0 & N(\mu(U_i), \sigma(U_i)) \leq 0, \\ N(\mu(U_i), \sigma(U_i)) & N(\mu(U_i), \sigma(U_i)) > 0. \end{cases} \tag{2}$$

In order to validate the quality of our approach in the deterministic environment, where results are available in the literature, we compare our results with the best-known solution (*BKS*) for each instance. The gap is reported in Table 1. We solve the 7 instances from the *set d* proposed by Chao et al. (1996), which are available at https://www.mech.kuleuven.be/en/cib/op/instances. One instance per group is randomly selected in each set: $p1.4.l$, $p2.4.k$, $p3.4.t$, $p4.4.d$, $p5.4.v$, $p6.2.d$, and $p7.4.e$. Each instance involves a number of UAVs (fleet size), number of nodes, and maximum route duration $Tlim$. The traveling time is estimated under the assumption that $UAVs$ travel at a unitary speed. The performance of our approach is reported in the multicolumn *OA*, both for the deterministic and the stochastic solution. Notice that our simheuristic algorithm reaches the (deterministic) *BKS* for all tested instances, even when the run time was limited to 60 seconds.

Table 1 presents the expected reward associated with the deterministic solution (d), which is compared with our best stochastic solution (c). According to these results, the best stochastic solution provides an expected reward which is, on the average, up to 4.17% better than the expected reward provided by the best deterministic solution when employed in a stochastic environment. Additionally, two other experiments have been carried out: first, three different levels of stochasticity in the rewards are tested ($c = 0.25$, $c = 0.5$, and $c = 1$). Secondly, we solve the instances considering different values of the fleet size. In general, adding more vehicles to the fleet has two alternative effects: *(i)* the same level of expected reward can be obtained with a higher degree of reliability (since more vehicles can visit the same customers but using 'less demanding' routes); and *(ii)* a higher expected reward can be obtained (although the resulting solution does not have to keep the same reliability level as the one obtained with less vehicles and less expected reward).

Table 1: Comparison of the simheuristic algorithm results and the best known solutions (*BKS*).

Instance	Nodes	UAVs	$Tlim$	*BKS*	*OA*			
				(a)	BDS (b)	BSS (c)	BDS* (d)	gap(%) (d-c)
p1.4.l	32	4	15	120	120	95.89	95.58	0.33
p2.4.k	21	4	11.2	180	180	128.21	127.82	0.30
p3.4.t	33	4	27.5	670	670	487.29	485.50	0.37
p4.4.d	100	4	20	38	38	27.46	27.16	1.08
p5.4.v	66	4	27.5	1320	1320	938.63	901.8	4.17
p6.2.d	64	2	15	192	192	124.71	123.47	1.01
p7.4.e	102	4	25	123	123	33.93	33.77	0.46
							Average	1.10

BDS:best deterministic solution. **BSS**:best stochastic solution. * Expected reward for BDS.

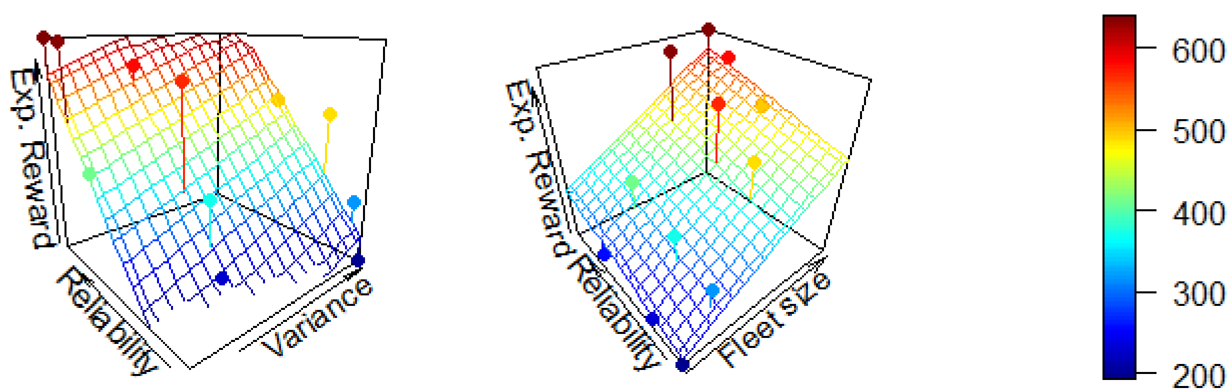

Figure 4: Expected rewards for deterministic and stochastic solutions (Instance p3.4.t).

Table 2: Different sizes of UAVs fleet.

		0.5 fleet		1 fleet		1.5 fleets	
c	Instance	BSS	Reliability	BSS	Reliability	BSS	Reliability
0.25	p1.4.l	78.27	0.86	118.26	0.93	142.91	0.94
	p2.4.k	131.29	0.69	172.15	0.83	172.40	0.85
	p3.4.t	413.58	0.63	636.68	0.71	639.59	0.78
	p4.4.d	35.80	0.94	35.74	0.94	35.77	0.94
	p5.4.v	623.26	0.49	1232.98	0.51	1577.04	0.56
	p6.2.d	90.27	0.64	180.59	0.64	260.72	0.68
	p7.4.e	31.51	0.99	45.51	0.99	45.44	0.99
0.5	p1.4.l	68.30	0.74	111.59	0.83	136.13	0.87
	p2.4.k	117.51	0.57	152.46	0.68	154.58	0.78
	p3.4.t	372.52	0.49	569.67	0.56	584.62	0.71
	p4.4.d	32.20	0.87	32.03	0.87	32.19	0.87
	p5.4.v	558.91	0.39	1103.70	0.40	1413.73	0.43
	p6.2.d	81.67	0.54	162.58	0.53	234.73	0.56
	p7.4.e	28.18	0.91	40.99	0.93	40.91	0.92
1	p1.4.l	58.22	0.61	95.89	0.70	117.90	0.74
	p2.4.k	99.11	0.48	128.21	0.60	128.94	0.68
	p3.4.t	315.95	0.39	487.29	0.46	499.20	0.59
	p4.4.d	27.14	0.79	27.46	0.79	27.20	0.80
	p5.4.v	471.49	0.32	938.63	0.31	1202.95	0.34
	p6.2.d	69.82	0.45	124.71	0.47	199.22	0.45
	p7.4.e	23.32	0.84	33.93	0.85	33.87	0.85
Average			0.65		0.69		0.75

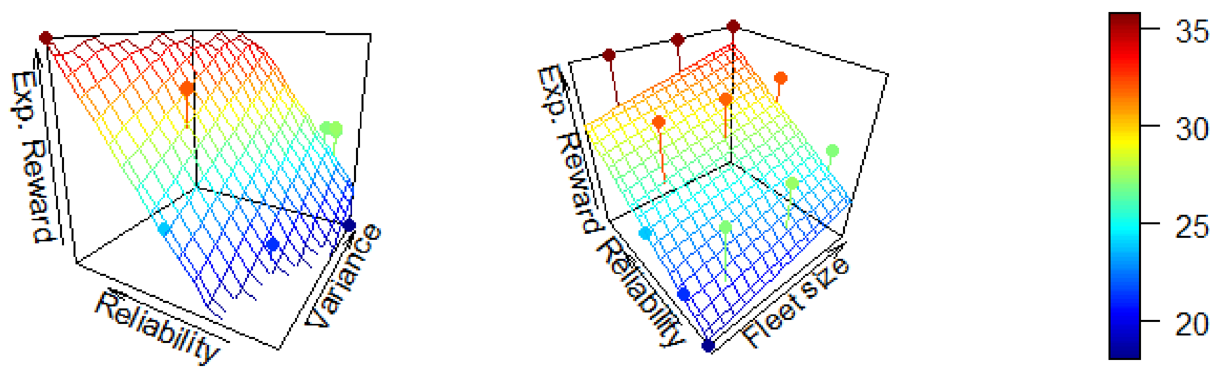

Figure 5: Expected rewards for deterministic and stochastic solutions (Instance p4.4.d).

Figures 4 and 5 present the solution performance, according to different variance levels, in terms of reliability and expected reward. The instances $p3.4.t$ and $p4.4.d$ were randomly selected. In Figures 4 and 5, the surface (colorful netting) represents the expected reward for the deterministic solution, while dots are used to represent values reached by the stochastic solution. The numbers in the color-bar from each figure indicate the value range reached by stochastic solutions.

Finally, Table 2 summarizes the results obtained for different fleet sizes. As expected, the average reward increases along with the fleet size. Notice, however, that this is not always a noticeable improvement, since it depends on the specific instance configuration.

6 CONCLUSIONS

This paper presents a simheuristic algorithm to solve a stochastic version of the team orienteering problem, where driving-range limitations of unmanned aerial vehicles are also considered. In this version of the problem, both rewards at each customer as well as service times are random variables. The latter might generate feasibility issues, since a route can request more time to be completed than the one provided by the battery capacity. As a result, the reliability of each solution is also considered in our methodology.

Our algorithm combines a multi-start biased-randomized metaheuristic with Monte Carlo simulation. The simulation component is not only used to assess the quality of promising solutions generated by the optimization component, but it is also employed to estimate the reliability level of each solution. As shown in the experimental section, solutions for the deterministic version of the problem should not be used in solving the stochastic version, since they become suboptimal under uncertainty scenarios.

As future work, we plan to test our approach in more instances and to include stochastic travel times, too. Also, the proposed algorithm could be extended to include sustainability indicators that provide a richer evaluation of the routing plans.

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