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Agile Optimization for Routing Unmanned Aerial Vehicles under Uncertainty

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***Abstract*—The use of unmanned aerial vehicles (UAVs) is gaining popularity in contexts such as smart cities, city logistics, humanitarian logistics, natural disasters, or military operations. One optimization challenge directly related to the use of UAVs is the so-called team orienteering problem (TOP). In a TOP, each customer can either be visited only once by a single vehicle or not visited at all. Visiting each customer has associated a predefined reward, and the driving ranges of vehicles are typically limited by the duration of electric batteries. Due to the latter constraint, it is usual that not all customers can be visited. The main goal is then to find a set of open tours that maximizes the total collected reward without exceeding the fleet capacity nor the driving range limitation. In this paper, we consider the stochastic version of the problem, in which travel times are modeled as random variables following theoretical probability distributions. To solve this stochastic version of the TOP, a simheuristic algorithm combining a biased-randomized heuristic with simulation techniques is proposed. One of the main goals of our approach is to provide an 'agile' optimization methodology, i.e., one lightweight algorithm that can be easily implemented in real-life scenarios under uncertainty and, at the same time, can provide solutions in real-time (just a few seconds or even less).**

***Index Terms*—Metaheuristics, simulation, team orienteering problem, unmanned aerial vehicles, agile optimization.**

I. Introduction

The term 'smart city' refers to a series of urban systems and domains that are interconnected, via information technologies (ITs), with the purpose of optimizing their operations and management [1]. Smart cities represent a multidisciplinary research field that is under a continuous updating process driven by urban, social, and technology evolution [2]. These advances are generating new services and products for citizens, which also arises new challenges in data gathering, data analytics, and efficient decision making.

Unmanned aerial vehicles (UAVs) are known for autonomous operation and mobility. Though there are first studies available [3] [4], the usage of UAVs in smart cities is not fully explored yet. Until today they were mainly used for and effectively integrated in military activities, surveillance, security, precision agriculture and goods and services deliveries [5] [6], while there are still concerns on their effective and reliable implementation in smart cities. With the use of a reliable and intelligent transportation system (ITS), it would be possible to replace human road support teams by a set of UAVs overflying highways to monitor possible traffic violations and accidents, or for providing specific information to other transport users. Technological support for interacting with other transport users is given by the ITS, dedicating a short-range communication interface to UAV, which transmit information either vehicle-to-vehicle or vehicle-to-infrastructure. Using wireless links when being close to each other, connected UAV impose improved road safety and traffic efficiency. The execution of these specific roles requires coordination of and collaboration within a group of UAVs. In particular, there is a need to design effective routing plans for a group of UAVs that need to visit a series of locations in order to gather some information (e.g., aerial pictures or videos, etc.). Thus, technological progress is required in the fields of advanced algorithms and other IT-based support tools to ensure: *(i)* a safe and effective navigation of UAV within the transportation infrastructure [7]; *(ii)* predictive analytics fed by critical data, which are needed for an efficient use of energy; and *(iii)* the use of computer vision techniques and remote sensing information for processing aerial real-time video footage.

Initially proposed by [8], the team orienteering problem (TOP) is one realistic variation of the well-known vehicle routing problem [9]. The TOP is gaining interest both in the scientific community and the industry due to the increasing use of electric vehicles and unmanned aerial vehicles, where driving range limitations need to be taken into account [10]. Consider the following elements: *(i)* a set of customer nodes, each of them with an associated reward score that can be collected the first time a customer is visited by any UAV; and *(ii)* a team of m UAVs with limited driving-range capabilities. Then, the goal is to determine a set of m open routes (each of them connecting an $origin$ depot with a $destination$ depot), which maximizes the total collected reward by visiting a subset of available customers without violating the driving range constraint.

Notice that each customer can either be visited once or not visited at all. Also, due to the driving range limitation, it is possible that not all customers can be visited. Being an

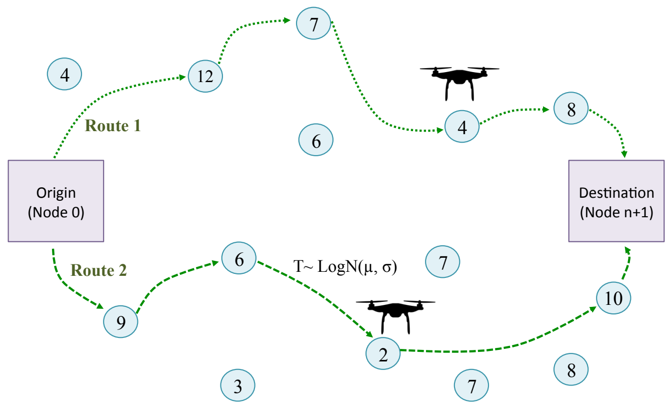


Fig. 1: Routing UAVs and the team orienteering problem

extension of the vehicle routing problem in which a subset of customers have to be selected and a set of routes covering them constructed, the TOP is also a *NP-hard* problem. Accordingly, different metaheuristic approaches have been proposed in recent years to deal with large-scale instances of the deterministic version of the problem. However, the stochastic counterpart, which considers real-life uncertainty in the form of random service and travel times, has received much less attention. This paper analyzes a stochastic TOP variant in which travel times are modeled as random variables (Figure 1). In particular, we consider the problem of recollecting as much reward as possible from visiting customers using a fleet of m UAVs with driving ranges limited by the time-duration of their batteries. An example of practical application could be the use of UAVs to take pictures of different locations after a natural disaster, a terrorist attack, or a humanitarian crisis. Notice that each of these pictures can provide valuable information that can help to improve the conditions of the people affected by the event or even to save their lives by making informed decisions on the more reliable evacuation paths.

Finding a solution (set of open routes) that maximizes the total expected reward is usually the main goal of the stochastic team orienteering problem (STOP). However, since solutions to the STOP are applied in a stochastic environment, other statistical properties should be considered too. Thus, for instance, one could be interested in solutions offering a high reliability level, i.e., routing plans with a low probability of violating the driving-range threshold.

This paper proposes a simulation-optimization algorithm to efficiently cope with the STOP. First, a biased-randomized heuristic for solving the deterministic TOP is introduced. This heuristic is then extended into a simheuristic algorithm [11] to solve the stochastic TOP. Due to their effectiveness, simheuristic algorithms are being increasingly used in solving different stochastic variants of the vehicle routing problem, like the stochastic inventory routing problem [12], the stochastic waste collection problem [13], or the stochastic arc routing problem [14].

The remaining sections of this paper are structured as follows: Section II reviews related work on the TOP. Section III describes our biased-randomized heuristic for solving the deterministic TOP. Section IV describes our extension to a simheuristic to solve the STOP. A round of computational experiments for the STOP are described in Section V. Finally, Section VI summarizes the highlights of this paper and proposes some future research lines.

II. Related Work

The team orienteering problem was first introduced in [8]. To solve the TOP, they propose a heuristic approach where the stops that are farthest from the start and the finish nodes are selected as seeds for the team members, and all possible remaining points are inserted into the routes using the cheapest insertion rule. If unassigned points remain, new team routes are constructed. Additional approaches used to solve the deterministic TOP have been proposed in the literature. Although we can find some exact methods, such as branch-and-cut [15] or branch-and-cut-and-price algorithms [16] to solve the TOP, only small-scale instances can be solved with these methods.

[15] propose a particle swarm optimization (PSO) method to solve the TOP. Similarly, [17] present a multi-start simulated annealing (SA) algorithm to address the TOP. It integrates an SA stage inside a multi-start procedure to reduce the possibility of getting trapped in a local optima. Genetic algorithms (GA) have been also proposed in this area. For instance, [18] introduce a GA which imitates the natural process of evolution to solve the TOP. Other approach to solve the TOP is proposed by [19]. These authors present a Pareto mimic algorithm, which uses a mimic operator to generate a new solution by imitating an incumbent solution.

The stochastic version of the orienteering problem has only received attention in recent years. To the best of our knowledge, previous work has only considered the single-route problem rather than the STOP that we analyze here. There is also some variation in which aspects of the problem are stochastic. For example, the original stochastic single-vehicle orienteering problem (OP) [20] defines the OP with stochastic profits, which assumes that only the scores associated with each node are stochastic – in particular, it is assumed they follow a Normal probability distribution. There are also other works that study the OP with stochastic travel times [21]–[24]. This version can be classified as the orienteering problem with stochastic weights. Notice that our work extends these previous ones by considering multiple vehicles or routes.

In developing solutions to the STOP, one critical question is how to deal with open routes which exceed the designated time limit imposed by the driving-range constraint. In [25], exceeding the time limit incurs in a penalty cost that is proportional to the amount exceeding it. A similar approach is used in [26]. An alternative concept is presented in [27], where the probability of exceeding the time limit must be lower than a threshold value. The problem presented by [21] is partially different, since they do not force the vehicle to return to a set of depots but, instead, it can stop at any location once the time limit is reached. Also, penalties are incurred if a vehicle does not manage to visit a scheduled node within the time limit. In contrast, [24] keep the hard constraint on the tour length that is used in the deterministic version of the problem and abort the route if the expected arrival time to the destination depot is equal to the remaining time. In the previous works, solving methodologies such as VNS metaheuristics and two-stage stochastic optimization were employed.

III. A Biased-Randomized Heuristic for Routing UAVs

A novel constructive heuristic for the TOP has been designed as a first step in our solving approach. One of the main goals of our proposed heuristic is to provide an 'agile' optimization methodology. The term 'agile' referring to sotfware development methodologies ('agile' programming) was introduced by Beck et. al. [28], and it refers to any rapid and easy software development of high-quality. Inspired in this definition, we propose an 'agile' optimization methodology to develop optimization lightweight algorithms, which can be easily implemented in a short period of time, and they can be used in a efficient way in real-life scenarios under uncertainty, providing solutions in real-time (just a few seconds).

The proposed heuristic, which has been designed following this 'agile' optimization methodology, it is inspired on the well-known savings heuristic for the vehicle routing problem [29]. It has to be adapted to consider the particular characteristics of the TOP, i.e.: *(i)* the origin depot could be different from the destination one; *(ii)* not all the customers have to be visited; and *(iii)* the reward collected by visiting nodes must be considered during the construction of the routing plan. The goal was to design a new savings-based heuristic able to outperform the traditional one employed for solving the TOP [30].

Algorithm 1 provides a high-level description of the constructive heuristic. It starts by generating an initial dummy solution (line 1), in which one route per customer is considered –i.e., for each customer $i \in A$, a vehicle departs from the origin depot (node 0), visits i, and then resumes its trip towards the destination depot (node $n+1$) (Figure 2a). If any route in this dummy solution does not satisfy the driving-range constraint, the associated customer is discarded from the problem, since it cannot be reached with the current fleet of vehicles. Next, we compute the 'savings' associated with each edge connecting two different customers (line 2), i.e.: the benefits obtained by visiting both customers in the same route instead of using distinct routes.

In order to compute the savings associated with an edge, one has to consider both the travel time required to traverse that edge as well as the aggregated reward generated by visiting both customers. Thus, we define the concept of savings, s'_{ij} as described in Equation 1. Notice that it takes into account the trade-off between the classical time-based savings, s_{ij}, and the aggregated reward, $u_i + u_j$, i.e.:

$$s'_{ij} = \alpha \cdot s_{ij} + (1-\alpha) \cdot (u_i + u_j) \tag{1}$$

Algorithm 1 Savings-based heuristic for the TOP

1: sol ← generateDummySolution(Inputs)
2: savingsList ← computeSortedSanvingsList(Inputs, α)
3: **while** (savingsList is not empty) **do**
4: arc ← selectNextArcAtRandom(savingsList, β)
5: iRoute ← getStartingRoute(arc)
6: jRoute ← getClosingRoute(arc)
7: newRoute ← mergeRoutes(iRoute, jRoute)
8: travelTimeNewRoute ← calcRouteTravelTime(newRoute)
9: isMergeValid ← validateMergeDrivingConstraints(travelTimeNewRoute, drivingRange)
10: **if** (isMergeValid) **then**
11: sol ← updateSolution(newRoute, iRoute, jRoute, sol)
12: **end if**
13: deleteEdgeFromSavingList(arc)
14: **end while**
15: sortRoutesByProfit(sol)
16: deleteRoutesByProfit(sol, maxVehicles)
17: **return** sol

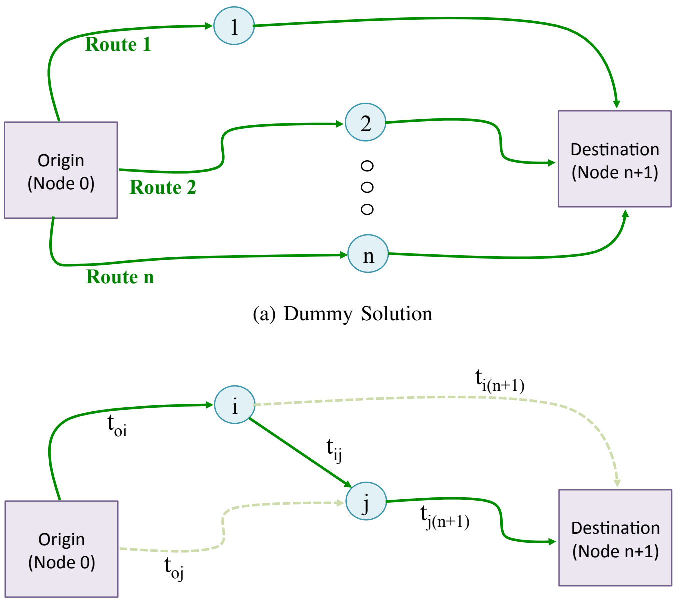
where $s_{ij} = t_{i(n+1)} + t_{0j} - t_{ij}$ (Figure 2b), and $\alpha \in (0,1)$. The specific value of α needs to be empirically tuned, since it will depend on the heterogeneity of the customers in terms of rewards. Thus, in a scenario with high heterogeneity, α will be close to zero. On the contrary, α will be close to one for homogeneous scenarios. Notice that for each edge there are two associated savings, depending on the actual direction in which the edge is traversed. Thus, each edge generates two different arcs.

After computing all the savings, the list of arcs can be sorted from higher to lower savings. Then, a route-merging process, based on the savings list, is started. In each iteration, the savings list of arcs is randomized using a biased probability distribution, and an arc is selected (line 4). As discussed in detail in Juan et al [31], the biased randomization of the savings list allows arcs to be selected in a different order in each iteration, where arcs with higher savings are more likely to be selected than those with lower savings, while at the same time, the logic behind the savings heuristic is maintained. In our case, a skewed Geometric Distribution is employed to induce this biased randomization behaviour. The Geometric Distribution uses one single parameter, β, which is relatively easy to set since $0 < \beta < 1$. After completing some preliminary tests with different values for and analysing the corresponding outcomes, we decided to set $\beta = 0.3$ in our computational experiments. The selected arc connects two routes, which are merged into a new route as far as this new route does not violate the driving-range constraint (line 9). Finally, the list of routes are sorted according to the total reward provided (line 15) to select as many routes from this list as possible taking into account the restricted number of vehicles in the fleet.

This heuristic is encapsulated within a multi-start process. This allows to run the biased-randomised heuristic several times, thus increasing our chances of finding a better solution.

IV. A Simheuristic for Routing UAVs under Uncertainty

Algorithm 2 provides an overview of our multi-stage simheuristic approach, which extends the biased-randomized



(a) Dummy Solution

(b) Time-based savings

Fig. 2: Dummy solution (top) and time-based savings (down).

heuristic in order to deal with the STOP. In the first stage, a feasible initial solution *(initSolution)* is constructed using the savings-based heuristic described in Section III (line 1). During the second stage, an adaptive heuristic enhances the initial feasible solution by iteratively exploring the search space and conducting a 'reduced' number of simulation runs that allow to: *(i)* obtain observations on the total time employed by the current solution (from which the expected time and other statistics can be estimated); and *(ii)* provide feedback that can be used by the heuristic to better guide the search (e.g., by updating the base solution according to the estimated statistics). From this stage, a reduced set of 'elite' solutions is obtained.

Notice that during the second stage, whenever a *newSol* is 'promising', it is sent through a fast Monte Carlo simulation process (line 8) to estimate the following values: *(i)* the expected return; and *(ii)* its reliability, measured in terms of the percentage of routes that are effectively completed without violating the driving range constraint. Also, whenever the stochastic value of the *newSol* outperforms that of the *baseSol* and / or that of some elite solution *(eliteSols)*, these solutions are updated to *newSol*.

Algorithm 2 Simheuristic approach

```
1: initSolution ← ComputeInitSolution(Inputs)
2: fastSimulation(solution)                          ▷ Monte Carlo Simulation
3: baseSol ← initSolution
4: while (ending condition is not met) do
5:     newSol ← savingBasedHeuristic(Inputs, α, β)   ▷ biased-randomized heuristic
6:     if (detProfit(newSol) improves detProfit(baseSol) then
7:         fastSimulation(newSol)                    ▷ Monte Carlo Simulation
8:         if (stochProfit(newSol) improves stochProfit(baseSol) then
9:             baseSol ← newSol
10:            if (stochProfit(baseSol) improves worstStochProfit(eliteSols) then
11:                eliteSols ← update(eliteSols, baseSol)
12:            end if
13:        end if
14:    end if
15: end while
16: return eliteSols
```

V. Computational Experiments: Stochastic Case

There are not STOP instances to compare with in the literature. For that reason, we have extended the deterministic instances proposed in [8] into stochastic ones.

In our computational experiments, we have modeled the travel times T_{ij} using Log-Normal probability distributions. As discussed in [32], the Log-Normal distribution is a more natural choice than the Normal distribution when modeling non-negative random variables, such as the elapsed time until an event occurs (e.g., the time it takes the vehicle to traverse a given edge). In a real-world application, historical data could be used to model each T_{ij} by a different probability distribution. The Log-Normal has two parameters, namely: the location parameter, μ, and the scale parameter, σ. According to the properties of the Log-Normal distribution, these parameters will be given by the following expressions considering stochastic travel times between nodes i and j:

$$\mu_{ij} = \ln(E[T_{ij}]) - \frac{1}{2}\ln\left(1 + \frac{Var[T_{ij}]}{E[T_{ij}]^2}\right) \tag{2}$$

$$\sigma_{ij} = \left|\sqrt{\ln\left(1 + \frac{Var[T_{ij}]}{E[T_{ij}]^2}\right)}\right| \tag{3}$$

In our experiments, which extend classical deterministic instances into stochastic ones, it is assumed that $E[T_{ij}] = t_{ij}$ ($\forall i, j \in N$), being t_{ij} the travel time provided in the deterministic instance. Similarly, it is considered that $Var[T_{ij}] = c \cdot t_{ij}$, being $c \geq 0$ a design parameter. Notice that the deterministic instances are a particular case of the stochastic ones, which are obtained for $c = 0$. In our experiments, we have used the value $c = 0.05$.

The classic deterministic benchmarks consist of 7 different classes, Table I refers to class 1, and it shows: *(i)* the best-known solution for the deterministic variant of the problem (BKS), obtained from the existing TOP literature; *(ii)* our best solution for the deterministic variant of the problem (OBS-D); *(iii)* the computational time in seconds to obtain the OBS-D; *(iv)* the gap between the BKS and the OBS-D; *(v)* the reward of OBS-D when it is applied as a solution of the stochastic variant of the problem (OBS-D-S); *(vi)* our best solution for the stochastic variant of the problem (OBS-S); and *(vii)* the computational time in seconds to obtain the OBS-S.

Figure 3 shows, for the analyzed class, the percentage gaps between: *(i)* the best-found deterministic solution when applied into stochastic conditions (OBS-D-S) and itself when applied in a deterministic environment (OBS-D); and *(ii)* the best-found stochastic solution when applied into stochastic conditions (OBS-S) and the best-found solution for the deterministic version (OBS-D). Notice that the OBS-S boxplot is

TABLE I: Results for class 1 benchmark instances.

	Deterministic execution				Stochastic execution		
Instance	BKS Reward [1]	OBS-D Reward [2]	Time (s) [3]	Gap (%) [4](1-2)	OBS-D-S E[Reward] [5]	OBS-S E[Reward] [6]	Time (s) [7]
p1.2.b	15	15	0	0.0	14.3	14.3	4
p1.2.c	20	20	0	0.0	18.2	18.2	4
p1.2.d	30	30	0	0.0	26.0	26.3	4
p1.2.e	45	45	0	0.0	41.7	42.2	4
p1.2.f	80	80	0	0.0	64.6	70.5	5
p1.2.g	90	90	0	0.0	75.8	83.7	4
p1.2.h	110	110	0	0.0	97.5	103.6	17
p1.2.i	135	135	0	0.0	94.5	122.9	4
p1.2.j	155	155	0	0.0	123.1	141.0	5
p1.2.k	175	175	0	0.0	124.2	163.3	7
p1.2.l	195	195	5	0.0	125.8	179.5	9
p1.2.m	215	215	9	0.0	170.2	201.4	16
p1.2.n	235	235	0	0.0	152.9	218.8	5
p1.2.o	240	240	4	0.0	204.4	230.7	7
p1.2.p	250	250	0	0.0	167.3	230.9	5
p1.2.q	265	265	1	0.0	205.4	247.8	7
p1.2.r	280	280	21	0.0	168.9	259.9	4
p1.3.c	15	15	0	0.0	14.3	14.3	6
p1.3.d	15	15	0	0.0	15.0	15.0	6
p1.3.e	30	30	0	0.0	24.9	27.0	6
p1.3.f	40	40	0	0.0	31.8	32.6	23
p1.3.g	50	50	0	0.0	44.2	48.4	6
p1.3.h	70	70	1	0.0	66.3	66.3	11
p1.3.i	105	105	0	0.0	87.2	94.1	6
p1.3.j	115	115	0	0.0	90.7	102.2	6
p1.3.k	135	135	0	0.0	109.2	121.4	17
p1.3.l	155	155	0	0.0	124.0	138.8	13
p1.3.m	175	175	16	0.0	127.7	159.5	9
p1.3.n	190	190	1	0.0	152.2	175.1	15
p1.3.o	205	205	0	0.0	163.5	183.0	11
p1.3.p	220	220	1	0.0	177.5	199.0	32
p1.3.q	230	230	1	0.0	190.0	218.0	6
p1.3.r	250	250	17	0.0	207.2	233.5	27
p1.4.d	15	15	0	0.0	14.3	14.3	8
p1.4.e	15	15	0	0.0	15.0	15.0	8
p1.4.f	25	25	0	0.0	23.2	23.2	8
p1.4.g	35	35	0	0.0	30.1	34.3	8
p1.4.h	45	45	0	0.0	37.9	40.8	9
p1.4.i	60	60	0	0.0	48.5	55.0	8
p1.4.j	75	75	8	0.0	63.1	67.2	8
p1.4.k	100	100	27	0.0	86.3	86.3	8
p1.4.l	120	120	0	0.0	107.1	116.0	9
p1.4.m	130	130	0	0.0	112.0	124.9	10
p1.4.n	155	155	0	0.0	121.4	135.7	8
p1.4.o	165	165	0	0.0	129.6	149.0	28
p1.4.p	175	175	6	0.0	152.2	159.1	16
p1.4.q	190	190	6	0.0	167.1	171.9	8
p1.4.r	210	210	0	0.0	170.8	191.1	9
		Average:	3	0.0			10

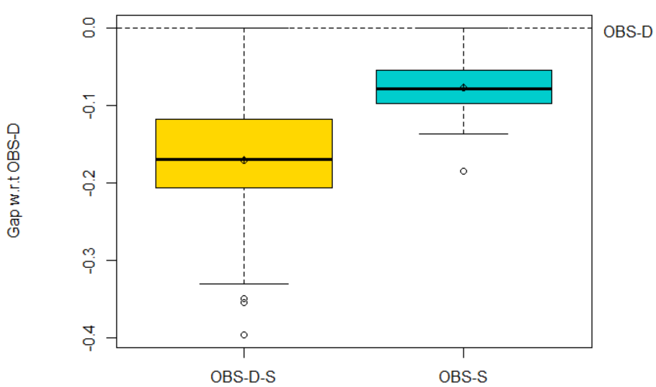


Fig. 3: Boxplot comparison of gaps OBS-D-S and OBS-S w.r.t. OBS-D.

always closer to the OBS-D value than the OBS-D-S boxplot. In other words, employing the best-found deterministic plan into a stochastic environment usually leads to suboptimal solutions. Notice also that the OBS-D value can be seen as an upper bound for the expected reward under stochastic conditions.

VI. Conclusion

The incorporation of unmanned aerial vehicles in urban areas describe promising research fields whose full potential are still to be explored in future. Still, these innovations raise a number of concerns and challenges that complicate decision-making processes for citizens and city managers. New hybrid optimization-simulation and optimization-machine-learning algorithms have to be developed to efficiently face these challenges. Scenarios for dynamic and uncertain real-life features have to be included.

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A Simheuristic Algorithm for the Team Orienteering Problem

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***Abstract*—Unmanned aerial vehicles (UAVs) or drones are being utilized by logistics systems in the context of smart cities. Here, we present a current application of the uses of drones through the Team Orienteering Problem (TOP). The TOP is a combinatorial optimization problem aimed at a practical approach for the urban transportation problems, such as traffic monitoring, freight transport, information transfer, safety, emergency situations management and other uses. This abstract copes with a TOP version in which a fleet of drones has to visit a series of customers. We assume that each visit to customers relies on a stochastic reward which implies a variable service time. Thus, a simheuristic algorithm is proposed as a solving approach integrating simulation inside a multi-start heuristic framework. A series of computational experiments contribute to illustrate the potential benefits of our work.**

***Index Terms*—Team Orienteering Problem, stochastic Rewards, variable service times, simheuristic algorithm..**

I. 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. The introduction of new technologies allows to consider real-time data that can be useful in order to identify suitable links at each time. Moreover, the European Commission has proposed different initiatives and some governmental projects to facilitate the emergence of sustainable and smart cities. Likewise, this transport system ensures quick responses to dynamic conditions of markets.

Practical applications of the TOP rely on stochastic rewards and service times associated to the customers visits. Hence, we propose a simheuristic algorithm to deal with a TOP with stochastic rewards and service times. This combinatorial optimization problem can be described as 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 $A = \{(i,j)/i,j \in N\}$ is the set of edges connecting all nodes in N. Each customer $i \in N$ has a stochastic reward (U_i) and a service time (ST_i). Similarly, each edge (i, j) is characterized by a traveling time (t_{ij}). The total traveling time per route is limited by a driving range time ($Tlim$), which represents the battery life of each UAV. The objective is to determine the subset of customers to be visited by each route (including the visiting order) which maximizes the expected reward considering the $Tlim$ as a hard constraint.

The solution approach can be considered as a specialized case of simulation-based optimization, 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. In particular, our simheuristic algorithm combines Monte Carlo simulation (MCS) with a multi-start metaheuristic framework. All in all, our simheuristic approach aims at finding routing solutions offering both high expected rewards and reliability indexes. Finally, an expanded version or this work can be read in [1], which presents a stochastic version of the TOP using UAVs.

II. Solution approach

Our solving approach relies on a 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 searching process. Regarding the optimization component, we use a multi-start meta framework in which the constructive phase uses biased-randomization techniques [2], [3]. Figure 1 describes our simheuristic algorithm.

In the multi-start procedure, a feasible solution is built for deterministic version of the problem. There, the concept of 'savings' is introduced as a criterion for merging routes, and it is based on 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

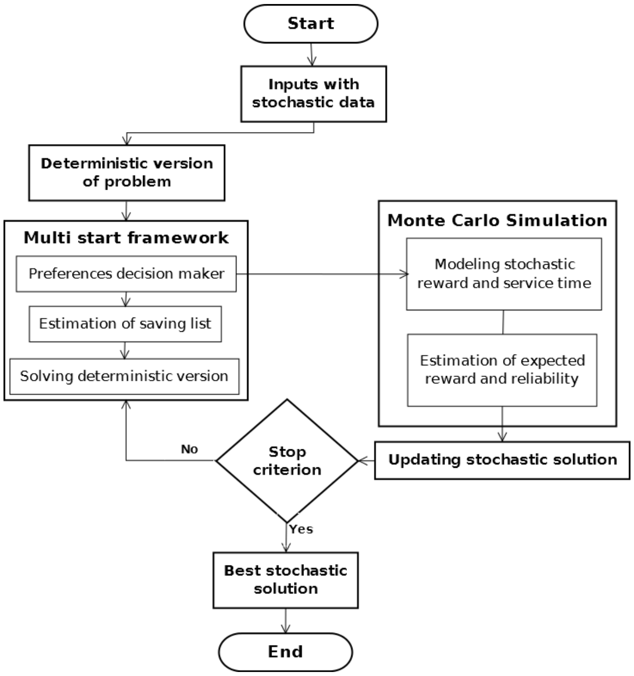

Fig. 1: Scheme of our algorithm.

combination of savings and accumulated rewards. Then, a merging that generates a greater accumulated reward will be prioritized over another one with similar time-based savings. Only a merging can be completed if the total expected time after the operation does not exceed the driving-range threshold. The concept of preference is used to generate a sorted list of potential mergings, and these are completed following the corresponding order, from higher to lower preference. Furthermore, we employ biased-randomization techniques, selecting the promising mergings using a probabilistic algorithm following a Geometric Distribution. Hence, merging operations with a larger preference are more likely to be selected.

Once a feasible solution with a high reward is determined, it is defined as the best deterministic solution. Then, MCS is incorporated to assess the quality of this solution, in terms of the expected reward and reliability (the probability that each route does not exceeds the driving-range). Thus, a feasible solution is iteratively constructed, building one element at a time in the multi-start procedure. As a result, the simulation procedure provides a feedback to simheuristic algorithm to better guide the searching process. At the end of this stage, the solution with the highest expected reward and reliability level is defined as the best stochastic solution.

III. Computational results

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. We assumed that the stochastic rewards, U_i, follow a Truncated Normal Distribution with parameters $\mu(U_i)$ and $\sigma(U_i)$). The value of $\sigma(U_i)$ is estimated as: $c{\cdot}\mu(U_i)$, where c is a parameter that allows 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.

TABLE I: Comparison of the simheuristic algorithm results and the best known solutions (BKS).

Instance	Tlim	BKS	BDS	BSS (a)	BDS* (b)	$\frac{b-a}{b}$ (%)
p3.4.t	27.5	670	670	487.29	485.50	0.37
p4.4.d	20	38	38	27.46	27.16	1.08
p5.4.v	27.5	1320	1320	938.63	901.8	4.17
Average						**1.88**

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). We solve the 3 instances from the $set\ d$ proposed by [4]. 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 columns BDS, BSS, BDS*, both for the deterministic and the stochastic environments 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 I presents the expected reward associated with the deterministic solution BDS, which is compared with our best stochastic solution BDS*. According to these results, the best stochastic solution provides an expected reward which is, on the average, up to 1.88% better than the expected reward provided by the best deterministic solution when employed in a stochastic environment. As a result, solutions for the deterministic version of the problem should not be used in solving the stochastic version, since they become suboptimal under uncertainty scenarios.

IV. Conclusion

This work presents a simheuristic algorithm to solve a stochastic version of the TOP, where driving-range limitations of unmanned aerial vehicles are also considered. Under uncertain conditions is hardly to ensure feasible solutions, i.e., a route can request more time to be completed than the one provided by the battery duration. Our simheuristic algorithm allows to assess the quality of promising solutions and the estimation of the solution reliability.

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Current Trends in Simheuristics: from smart transportation to agent-based simheuristics

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***Abstract*—Simheuristics extend metaheuristics by adding a simulation layer that allows the optimization component to deal efficiently with scenarios under uncertainty. This presentation reviews both initial as well as recent applications of simheuristics, mainly in the area of logistics and transportation. We also discuss a novel agent-based simheuristic (ABSH) approach that combines simheuristic and multi-agent systems to efficiently solve stochastic combinatorial optimization problems. The presentation is based on papers [1], [2], and [3], which have been already accepted in the prestigious Winter Simulation Conference.**

***Index Terms*—simheuristics, stochastic optimization, logistics & transportation, agent-based simheuristics.**

I. Introduction

Real-life optimization problems are often *NP-hard* and large-scale in nature, which makes traditional exact methods inefficient to solve them.Thus, the use of heuristic and metaheuristic algorithms to obtain high-quality solutions in low computing times is required. With the increasing advances in computing hardware and software, simulation has become a 'first-resource' method for analyzing complex systems under uncertainty [4]. Thus, simulation is frequently employed in areas such as logistics and transportation, manufacturing, supply chain management, or smart cities. These systems are modeled and then simulated to get insights on their performance under different base scenarios. Simulation, however, is not an optimization tool. Thus, whenever a decision maker aims to find an optimal configuration for a system, she requires the use of optimization methods. Often, the associated optimization problems are addressed by assuming deterministic inputs and constraints, which allows us to simplify them but at the cost of not considering the real-life uncertainty that characterizes these systems.

Simheuristic algorithms integrate simulation methods inside a metaheuristic optimization framework to deal with large-scale and *NP-hard* stochastic optimization problems. Hybridization of simulation techniques with metaheuristics allows us to consider stochastic variables in the objective function of the optimization problem, as well as probabilistic constraints in its mathematical formulation. As discussed in [5], the simulation component deals with the uncertainty in the model and provides feedback to the metaheuristic component in order to guide the search in a more efficient way. Notice also that, when dealing with stochastic optimization problems, performance statistics other than expected values must be taken into account: while in deterministic optimization one can focus on finding a solution that minimizes cost or maximizes profits, a stochastic version of the problem might require that we analyze other statistics such as its variance, different percentile values, or its reliability level.

The main goals of this presentation are: *(i)* to provide a commented review of recent applications of simheuristics in the area of transportation; and *(ii)* to analyze trends as well as open research lines.

II. Recent Applications in Transportation

[6] discuss the need for optimizing urban waste collection in modern smart cities and formulate the problem as an extension of the vehicle-routing problem. The authors first develop a competitive metaheuristic, based on a variable neighborhood-search framework, to solve the deterministic variant. Then, they extend their approach into a simheuristic to cope with unexpected waste levels inside the containers. Their algorithm is tested using a large-scaled benchmark set for the waste-collection problem with several realistic constraints. Their results include a risk analysis considering the variance of the waste level and vehicle safety capacities.

The uncapacitated facility-location problem with stochastic service costs is analyzed in [7]. First, the authors propose an extremely fast savings-based heuristic, which generates real-time solutions for the deterministic version of the problem. This can be extremely useful in telecommunication applications, where 'good' solutions are needed in just a few milliseconds for large-scale networks.

[8] propose a simheuristic algorithm for solving the arc-routing problem with stochastic demands. Here, the authors use Monte Carlo simulation to extend the RandSHARP heuristic, which was originally designed to solve the deterministic version of the problem. During the design of the routing plan, they make use of safety stocks, which allow vehicles to deal with unexpectedly high demands during the actual distribution process.

[9] consider a stochastic version of the capacitated facility-location problem, proposing two facility-location models representing alternative distribution policies in e-commerce (outsourcing vs. in-house distribution). The multi-period inventory-routing problem with stochastic customer demands is analyzed in [10]. A variable neighborhood search is extended into a simheuristic algorithm to consider variations in the forecasted demands. With the aim of finding optimal refill policies for each customerperiod combination, the authors take into account that the quantity serviced at the beginning of one period will affect the inventory levels at the end of that period.

III. Current Trends

Some of the following trends in the use of simheuristics can be identified and are expected to play a relevant role in future publications on this topic, therefore constituting open research lines to be yet fully explored:

- *A higher level of simulation-optimization integration*: a deeper integration between the metaheuristic component and the simulation component, including increasing use of the feedback provided by the simulation better to guide the search for better solutions.
- *Additional objectives*: a rising interest in considering optimization goals different from the expected value of a solution for the stochastic optimization problem; this includes measuring other statistics reliability/robustness levels, and even considering multi-objective optimization problems.
- *Systems of increasing complexity*: moving from isolated logistics or transportation problems to integrated problems that reflect the complexity of supply networks, where interactions between different echelon stages also need to be considered in order to increase global efficiency.
- *Use of more sophisticated simulation approaches*: as the complexity of the systems increases, more advanced simulation approaches are required to take into account the dynamic and possibly nonstationary time-evolution of the system and the interactions among its many components.
- *Enhanced identification of promising solutions*: to speed up the computations, during a typical simheuristic process only a reduced set of solutions are classified as 'promising' and sent to the simulation component; enhanced strategies to classify a new solution as a promising one can be employed.
- *Statistically significant number of runs*: in some of the examples reviewed in this paper, a 2-stage approach is used; in the first stage the promising solutions are simulated using a reduced number of runs, while in the second stage longer simulations are executed on the 'elite' solutions provided in the first stage to increase the statistics' accuracy and precision. However, statistical concepts could be employed to set the precise number of runs required in each stage in order to obtain estimates with a given level of precision.
- *Extending the application fields*: so far, most simheuristics have been applied in the area of transportation, logistics,and production.However, similar stochastic optimization problems can be found in other application fields such as telecommunications, finance, health-care systems, and smart cities.
- *Heuristic-supported simulation*: while the examples reviewed here refer to optimization problems in which simulation is used to support the search carried out by the metaheuristic, it is also possible to use heuristics or metaheuristics to optimize certain system parameters during a large simulation experiment.
- *Integration with machine learning*: being a flexible and relatively simple approach, simheuristics can be integrated with machine-learning approaches and, in particular, with learnheuristics in order to consider optimization problems with dynamic inputs.
- *Multi-population simheuristics*: all the examples reviewed here are based on single-population metaheuristics; however, integration of simulation within multi-population metaheuristics (e.g., genetic algorithms, etc.) might be worth exploring too since different individuals in a population might be based on different statistics obtained from the simulation component.
- *Agent-based simheuristics*: similar to the way agent-based modeling and simulation extends the more traditional concept of discrete-event simulation and benefits from distributed and parallel computing systems, one could consider agent-based simheuristics as a multi-agent extension of the simheuristic concept, where each agent is an autonomous and differentiated simheuristic algorithm that interacts with the rest of the agents while searching for a near-optimal solution to a complex and stochastic combinatorial optimization problem.

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Designing e-commerce supply chains

A stochastic facility–location approach

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***Abstract*— e-Commerce activity has been increasing during recent years, and this trend is expected to continue in the near future. e-Commerce practices are subject to uncertainty conditions and high variability in customers' demands. Considering these characteristics, we propose two facility–location models that represent alternative distribution policies in e-commerce. These models take into account stochastic demands as well as more than one regular supplier per customer. Two methodologies are then introduced to solve these stochastic versions of the well-known capacitated facility–location problem. The first is a two-stage stochastic-programming approach that uses an exact solver. However, we show that this approach is not appropriate for tackle large-scale instances due to the computational effort required. Accordingly, we propose a simheuristic approach that solves large-scale instances in short computing times. An extensive set of benchmark instances contribute to illustrate the efficiency of our approach, as well as its potential utility in modern e-commerce practices.**

Keywords—component; formatting; style; styling; insert (key words)

I. The e-commerce supply chain design problem

The e-commerce in developed countries is steadily increasing, reaching a noticeable share of all commerce during the last years. One of the main strategic decisions that e-commerce enterprises must face is the location of their facilities or distribution centers (DCs). Note that this decision has an impact on the daily logistics activity and, consequently, on the customers' quality of service.

This summary presents the work of Pagés-Bernaus (2017) [1] published recently. The work presents mathematical models that represent the decisions how the online distributors select the DC locations and how to perform the subsequent assignment of customers to these facilities.

The goal of this work is to study this supply-chain design problem and to analyze the impact of different delivery policies in the presence of uncertainty. Since the capacity at each DC is limited, the problem is modeled as a Capacitated Facility Location Problem (CFLP) with stochastic demands. There are two CFLP variants differing in whether customers can be served from one DC (single source) or more (multiple source). In this paper, it is assumed that customers can be served from a number R of different facilities. So, each customer will have at most R facilities as regular providers. This variant is denoted as the CFLP with regular providers (CFLPrp).

II. Solution approach and computational results

To solve the proposed models, we propose two approaches: one based on Deterministic Equivalent Model (DEM) and another based on simheuristics methods, which in this case the method proposed hybridizes an ILS metaheuristic with simulation. The SimILS is an Iterated Local Search based method, where the local search stage focuses on providing configurations of open/closed facilities, as well as on the selection of the regular DCs. In the simulation stage, customers' assignment decisions are made. Since the simulation stage is time-consuming, only "promising" solutions are tested in a stochastic environment.

The computational experiments are performed on the Beasley. For the small–medium instances, both approaches provide solutions of similar quality (with an average gap of −0.18% for model A and −0.41% for model B in favor of the stochastic-programming approach). However, the time employed by the SimILS approach is one order of magnitude smaller. Moreover, for the larger instances G4 the SimILS increases the required computing time but is able to provide feasible solutions.

III. Conclusions

This summary presents two facility–location models, which consider stochastic demands as well as a restricted number of regular suppliers per customer. These models were inspired in a real e-commerce supply design problem. We propose two different approaches to solve the models representing this problem. On the one hand, we use a two-stage stochastic-programming methodology. On the other hand, we propose a simheuristic algorithm, combining an ILS metaheuristic with simulation. According to the computational results obtained, the stochastic-programming approach is efficient but limited to small- and medium-sized instances. On the contrary, the proposed simheuristic approach is able to solve large-sized instances in reasonable computing times, while providing also competitive results for smaller instances

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