A Simheuristic Algorithm for the Team Orienteering Problem

Javier Faulin*,Angel A. Juan†‡, Lorena Reyes*, Javier Panadero†, Carlos Ospina*, Jose M. Mozos†
**ISC - Institute of Smart Cities.*
Public University of Navarre
Pamplona, 31006, Spain
{javier.faulin, lorena.reyes}@unavarra.es
cospinatrujillo@gmail.com
†*IN3 - Computer Science Dept.*
Universitat Oberta de Catalunya
Barcelona, 08018, Spain
{ajuanp, jpanaderom, jmozosr}@uoc.edu
‡*Euncet Business School*
Terrassa, 08225, Spain

***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

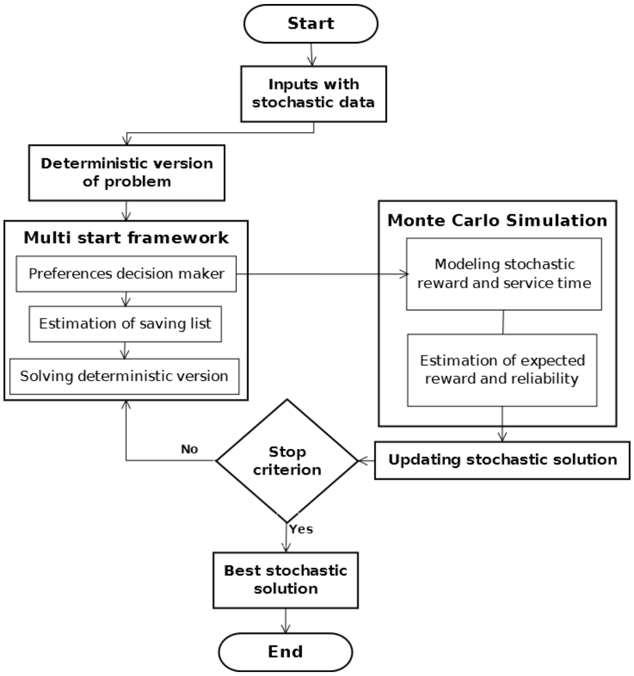

Fig. 1: Scheme of our algorithm.

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

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**

expected that as c converges to zero, the results from the stochastic version converge to those obtained in the deterministic scenario.

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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