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SUPPORTING HOSPITAL LOGISTICS DURING THE FIRST MONTHS OF THE COVID-19 CRISIS: A SIMHEURISTIC FOR THE STOCHASTIC TEAM ORIENTEERING PROBLEM

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ABSTRACT

The unexpected crisis posed by the COVID-19 pandemic in 2020 caused that items such as face shields and ear savers were highly demanded. In the Barcelona area, hundreds of volunteers employed their home 3D-printers to produce these elements. After the lockdown, they had to be collected by a reduced group of volunteer drivers, who transported them to several consolidation centers. These activities required a daily agile design of efficient routes, especially considering that routes should not exceed a maximum time threshold to minimize drivers' exposure. These constraints limit the number of houses that could be visited. Moreover, travel and service times are considered as random variables. This logistics challenge is modeled as a stochastic team orienteering problem. Our main performance indicator is the collected reward, which should be maximized. This problem is solved by employing a biased-randomized simheuristic algorithm, which is capable of generating high-quality solutions in short computing times.

1 INTRODUCTION

The COVID-19 pandemic crisis is one of the more recent greatest global challenges. The exponential increase in cases requiring medical care led to a sudden shortage of protective materials, putting medical and support staff at high risk of becoming infected as well. This not only jeopardized necessary attention in hospitals, but also accelerated the spread of COVID-19. Since March 2020, the pandemic has also had a strong impact in countries such as Germany and Spain. As in other regions, a community of volunteers called "Coronavirus Makers" was created in the Barcelona region to provide protective materials to staff in hospitals, nursing homes, and emergency medical care (Tordecilla et al. 2021). The main tool was domestic 3D-printers, which enabled a very quick design and elaboration of elements such as face shields, ear savers, or door openers. The bottleneck in this context was mainly a logistics one, as the lockdown meant that each 3D-printer was in a single home, and collecting the items required optimizing the routing plans to maximize the added value of the items gathered while keeping drivers' safety. This paper describes the experience of bringing together different professional and personal profiles such as academics, volunteers, makers, and entrepreneurs, who typically employ different approaches when dealing with the pandemic. In this case, there was a need to find a quick way to apply knowledge accumulated over years of research to an urgent need, where every day counts. The goal was to support the makers' community in their volunteer initiative to provide health staff with as much protective material as possible, taking into account constraints on the number of volunteer drivers (which might differ from day to day) and on the maximum time any driver can be on the road.

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The makers' community was created to bring creative skills and provide a service to the healthcare system. This was a completely altruistic and non-profit initiative. The goal was to alleviate the need for additional protective materials in hospitals and health centers. This need was caused by resource shortages posed by the unprecedented global outbreak of COVID-19. The initiative was launched in less than 48 hours, and grew at an average rate close to 100 new volunteers per day in the first two weeks. The makers' community from Barcelona and surrounding provinces soon joined the initiative, distributing materials to hospitals as early as mid-March 2020. Due to the forced lockdown, makers cannot (and are not allowed to) transport the printed elements themselves. Hence, a general coordinator must organize an external transportation process to pick up all the elements and deliver them to the healthcare centers. This transportation process was carried out by volunteer drivers, who were required to perform the collection routes as fast as possible in order to minimize their exposure to the virus, even omitting some collection points if necessary. Due to the atypical situation derived from the pandemic crisis in March, at the moment of solving the real case we assumed that both travel and service times were deterministic, since the empty roads facilitated the motion of vehicles. However, considering that routes must be carried out mainly in urban areas, we consider stochastic travel and service times in this work, which is more realistic. Addressing a problem with these characteristics means that a traditional vehicle routing problem (Faulin et al. 2008; Juan et al. 2009) is not appropriate to provide a feasible solution. Instead, a stochastic team orienteering problem or STOP has proved to be a more suitable approach (Keshtkaran et al. 2016). Based on the works by Panadero et al. (2017) and Chao et al. (1996), we define the STOP as a variant of the vehicle routing problem with the following main characteristics: *(i)* the fleet size is limited; *(ii)* each available vehicle must meet a maximum tour length; *(iii)* characteristics *(i)* and *(ii)* imply that only a subset of the customers in the network can be visited; *(iv)* the objective is to maximize the total collected reward obtained after visiting this subset of customers; and *(v)* one or several input parameters are stochastic. Therefore, the development and application of agile algorithms became really helpful to guarantee the agility and efficiency that the route design and implementation processes required, considering as well that this is a typical NP-hard problem (Panadero et al. 2020).

Hence, the main contributions of our work are: *(i)* to describe a real-world and deterministic case where biased-randomized algorithms were developed to support hospital logistics during the first months of the COVID-19 crisis; *(ii)* to extend the previous application into a stochastic variant, in which travel and service times are modeled as random variables; *(iii)* to propose a simheuristic approach to properly cope with the stochastic problem; and *(iv)* to provide examples of the application of agile optimization, in which algorithms are used to provide fast solutions to challenging stochastic optimization problems in the area of logistics and transportation. The remainder of this paper is organized as follows: Section 2 presents a brief literature review regarding the team orienteering problem (TOP). Section 3 describes the specific TOP version that we address in this paper. Section 4 outlines the simheuristic employed to solve the problem, which also integrates biased-randomization techniques. Section 5 provides some numerical examples that allow us to test our approach. Finally, Section 6 draws some conclusions and addresses future research perspectives.

2 RELATED WORK ON THE TEAM ORIENTEERING PROBLEM

The TOP can be considered an extension of the traditional vehicle routing problem, where visiting all customers is not possible due to the limitations on the fleet size and on the maximum driving range of each vehicle. Hence, customers have to be prioritized based on their location and also in the reward obtained by visiting them. Therefore, the TOP aims at maximizing the collected reward by visiting a subset of nodes, subject to constraints such as a maximum tour length, a given vehicle capacity, or a limited driving range. The TOP is an extension of the orienteering problem (OP), which has been proven to be NP-hard (Golden et al. 1987). The OP is a problem with the same characteristics as the TOP, except that the former employs a single vehicle to serve the customers, whereas the latter uses a fleet of vehicles. Hence, the TOP is a more challenging problem than the OP. Since the TOP is an NP-hard problem, the use of metaheuristics is required in order to obtain high-quality solutions in short computing times, especially when dealing with large-sized instances (Bayliss et al. 2020). The TOP was first introduced in the literature by Chao et al. (1996). Since then, multiple variants of this problem have been studied, such as the one with time windows (Labadie et al. 2012; Lin and Vincent 2012; Vansteenwegen et al. 2009), multiple periods (Tricoire et al. 2010), soft constraints (Estrada-Moreno et al. 2020), precedence constraints (Hanafi et al. 2020), dynamic rewards (Reyes-Rubiano et al. 2020), rescue operations (Saeedvand et al. 2020), use of electric vehicles (Xu et al. 2020), or use of drones in the context of smart cities (Juan et al. 2020).

The stochastic TOP (STOP) is another variant in which different parameters are modeled randomly. In Panadero et al. (2020), a STOP with stochastic travel times is studied. To cope with this problem, a simheuristic is proposed. It combines a biased-randomized multi-start (BR-MS) metaheuristic approach with Monte Carlo simulation (MCS). According to the authors, their simheuristic approach can generate solutions that combine good expected cost and variability under a stochastic environment. In other words, the best solutions for the deterministic scenario might suffer from a high degree of variance when employed in realistic scenarios with uncertainty.

In a similar way, Bayliss et al. (2020) address a STOP with dynamic rewards. In this case, the stochastic component is related to traveling times, while the reward values for customers are composed of both a static and a dynamic component. The dynamic component accounts for bonuses when customers are visited earlier during a route, and penalties in case these nodes are visited at the end of the corresponding route. To solve this problem, a simheuristic-learnheuristic is proposed, in which these dynamic values are learned from simulation experiments during the search process. Mei and Zhang (2018) have considered the STOP with time windows (STOPTW) in the context of tourist trip design (TTD). Here, a set of points of interest (POI) must be selected to be visited. The visit duration of a POI is modeled as a random variable, which means that some pre-planned trips might become infeasible in practice. To solve the STOPTW, a genetic programming hyper-heuristic is proposed. To account for the stochasticity of this variant, the random duration variables are re-sampled at each generation of the evolutionary algorithm. The results generated by this solution approach outperformed the manually designed policies, achieving, for some cases, an average total score more than twice the total score obtained by the manually designed policies. Likewise, Karunakaran et al. (2019) addressed the STOPTW in TTD, with a stochastic visiting time of POIs. In this case, an evolutionary multi-tasking optimization genetic programming approach is proposed. This methodology is based on island models, in which knowledge is shared through multi-tasking, thus exploiting the implicit parallelism of population-based search algorithms to simultaneously tackle multiple distinct optimization tasks.

3 DESCRIBING THE LOGISTICS CHALLENGE

The hospital logistics case addressed in this work has been modeled as a STOP. The items to be collected are generated by a group of makers located at their respective homes. These homes are connected by edges, which represent streets in cities. In this paper, we consider two types of items: face shields and ear savers. The location of each maker home is known and identified by a coordinated pair *(latitude, longitude)*. Items should be picked up by a set of vehicles, which are driven by a group of volunteers. Each volunteer driver departs from a common origin point, collects the items according to the planned route, and brings them to a given hospital or healthcare center. The coordinates of both the origin and the destination locations are also known. Each house can only be visited by just one vehicle. The number of vehicles is given in advance. These vehicles are considered as virtually unlimited in capacity, since the size of the items to be transported is small. Still, depending on the daily stock of each item at the destination centers, the reward (added value) provided by each unit of each item type might vary from day to day. At the end of each day, makers inform the logistics coordinator about the exact quantity that each of them offers for being picked up on the next morning. This imposes a hard constraint on the computational time that can be employed by the algorithm to solve a new instance of the problem every day, since drivers must have their routing plans available first time in the morning.

A maximum time to complete each single route is provided by the coordinator. The idea is that each driver should not be working for more than a certain number of hours per day, in order to reduce the risk of exposure to the virus and also to avoid legal issues during the lockdown. We assume that both service and traveling times are stochastic, since they might depend on multiple random factors, e.g., traffic and weather conditions, unexpected delays, etc. The service time is the time spent by the driver in performing a pickup activity at each collection point. The traveling time is the time spent by a vehicle in moving from one node to another during its route. The simultaneous consideration of a maximum tour length and stochastic service and traveling times can easily lead to design infeasible routes. Allowing that some collection points are not visited is a manner of avoiding a potential infeasibility. Therefore, the STOP becomes a suitable approach to address our studied problem. Figure 1 displays a simple example of a complete solution for our problem, where some collection points are skipped. Hence, our main objective is to maximize the total reward collected by the set of vehicles, fulfilling the maximum allowed tour length.

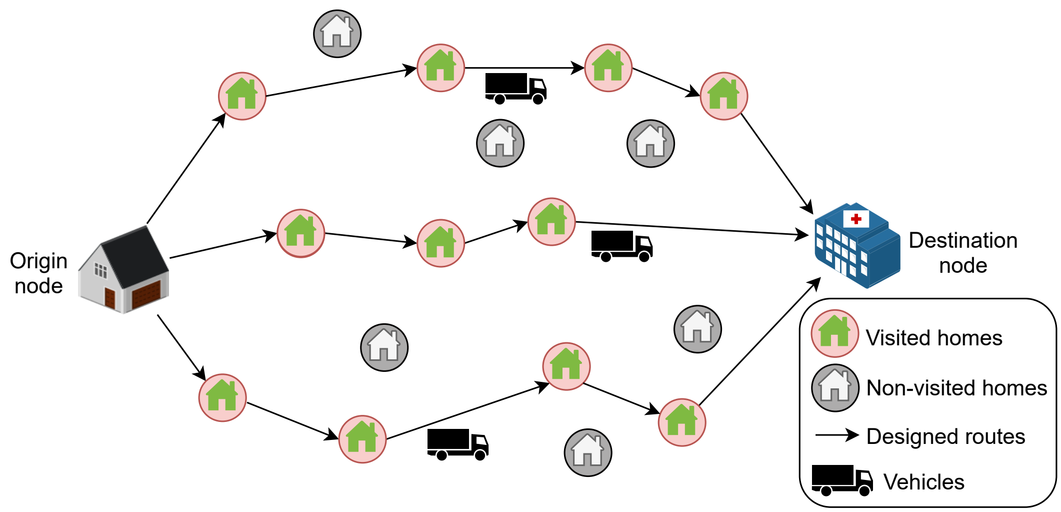


Figure 1: Representation of a complete TOP solution.

Formally speaking, the problem can be defined on a directed graph $G(N,E)$, where N represents the set of nodes, and E represents the set of edges that link these nodes, i.e., $E \subseteq N \times N = \{(i,j) \mid i \in N, j \in N, i \neq j\}$. The set N is formed by three subsets, such that $N = I \cup O \cup F$: a set I of collection points, and the singleton sets O and F, which represent the origin and destination depots, respectively. Each collection point $i \in I$ has a deterministic reward u_i, and a stochastic service time S_i that follows a known probability distribution. The time T_{ij} spent to traverse each edge $(i,j) \in E$ is considered stochastic as well. Routes are performed by a set K of uncapacitated vehicles. Each collection point $i \in I$ must be visited just once, and each vehicle $k \in K$ is assigned to only one route. Each route starts in the origin node in O, and finishes in the destination node in F. The expected total time of each route must not exceed a given time limit t_{max}. Hence, our addressed problem consists in designing a set of $|K|$ routes that meet the aforementioned constraints, such that the total collected reward, $\sum_{i \in I} u_i x_i$, is maximized, where x_i is a binary variable that takes the value 1 if collection point $i \in I$ is visited by a vehicle $k \in K$, and it takes the value 0 otherwise.

4 A SIMULATION-OPTIMIZATION SOLUTION APPROACH

For solving the described STOP in the context of healthcare logistics, we propose a simheuristic approach that combines a biased-randomized multi-start metaheuristic (Belloso, Juan, and Faulin 2019) with Monte Carlo simulation. As already explained, simheuristics are capable of intelligently handling stochastic combinatorial optimization problems by considering both the deterministic and stochastic components during the search for efficient solutions.

4.1 A Biased-Randomized Multi-start Approach

Our multi-start approach relies on multiple executions of a biased-randomized heuristic designed to solve the deterministic version of the TOP under the described application context. This heuristic consists of three stages:

- In the first stage, a dummy solution is created. Each route in this dummy solution is designed to serve one collection point, where a vehicle departs from the origin depot, visits the customer, and then travels to the destination depot. In this stage, the maximum tour length of the routes is considered, and those collection points from their corresponding dummy routes that exceed this maximum drive time are automatically discarded.
- The second stage refers to the creation of a savings list (*SL*). This *SL* comprises all the edges connecting two different locations. For each edge $(i, j) \in SL$, a savings value is computed according to the Equation 1 (Panadero et al. 2020), where t_{ij} is the time required to travel between the collection points i and j, 0 and n are the origin and destination nodes O and F, and u_i and u_j represent the rewards obtained for visiting the collection points i and j, respectively. By integrating the travel time and the reward in this computation, the savings are able to reflect not only the desire to diminish travel times, but also the aim for increasing the number of collected goods. Later, the *SL* is sorted in descending order of savings value.

$$s_{ij} = \alpha(t_{in} + t_{0j} - t_{ij}) + (1 - \alpha)(u_i + u_j) \tag{1}$$

- The last stage aims at selecting the best saving edges to perform the merge of their corresponding routes. In this way, the edge at the top of the list, i.e., the one with the highest savings value, is selected. The merge is performed whenever the resulting route is feasible, regarding the maximum tour length. The selected edge is removed from the list whether it has resulted in a successful merging process or not. This process is repeated until the *SL* is empty.

The described heuristic is deterministic and extremely fast. For being deterministic, the same solutions are generated whenever the same inputs and parameters feed the system. To change this behavior, we have extended the heuristic into a biased-randomized (BR) approach (Quintero-Araujo et al. 2017). Biased-randomized techniques use skewed probability distributions and MCS to induce an 'oriented' (non-uniform) random behavior in deterministic procedures, transforming them into probabilistic algorithms while preserving the logic behind the original greedy heuristic. In other words, the BR smooths the original greedy behavior of the heuristic. In our case, we have employed the geometric probability distribution, with a single parameter $\beta \in (0, 1)$, which controls the relative degree of greediness in the randomized behavior of the algorithm. This strategy replaces the greedy selection of the next element from the *SL*, thus facilitating the generation of multiple alternative solutions. Therefore, our BR heuristic is embedded into a multi-start framework (Marti 2003), which computes several solutions until a maximum number of iterations or execution time is achieved. The best solution is returned at the end of the process.

4.2 A Simheuristic Approach

Despite offering the capability of exploring different regions of the solution space, BR algorithms are not able to consider uncertainty scenarios, such as those that can be found in real-life applications, e.g., random traveling times, random processing and service times, etc. Therefore, we have extended our BR heuristic into a simheuristic algorithm to better deal with the stochastic variant of the TOP considered in this paper. Our approach starts by generating a feasible solution for the deterministic problem variant. While the deterministic solutions are generated by the BR heuristic, the solutions for the stochastic problem are achieved by replacing the deterministic travel times of the deterministic solution with the stochastic ones. These stochastic values are computed by employing a probability distribution. Hence, for each edge of the solution, multiple random observations are generated using MCS, i.e., the final stochastic value for each edge is given by the average of the multiple simulations runs. The use of multiple simulation runs for generating stochastic travel times allows us to measure a solution reliability, which refers to the solution feasibility under uncertainty conditions.

Once the initial solutions are generated for both problem variants, a multi-start framework is started. In this case, a solution is generated for the deterministic problem. This current solution is submitted to a simulation process only if its reward is greater or equal to the best-found solution. At this stage, a reduced number of simulation runs (the short simulation process) are processed, since this simulation stage can be time-consuming. The current solution replaces the best-found deterministic solution only if: *(i)* its reward is greater than the best-found deterministic solution reward; or *(ii)* its reward is equal to the best-found deterministic solution reward, but its travel time is smaller. For the stochastic case, the best-found stochastic solution is replaced by the current solution if: *(i)* its reward is greater than the best-found stochastic solution reward; or *(ii)* its reward is equal to the best-found stochastic solution reward, but its expected traveling time is smaller. This process is repeated until a stop criterion is met. Later, a larger number of simulation runs (the long simulation process) are processed in both the best-found deterministic and stochastic solutions, in order to collect more reliable statistic information regarding the solutions' performance. Finally, these best-found solutions are returned.

5 COMPUTATIONAL EXPERIMENTS

Based on the real-world instances presented by Tordecilla et al. (2021), we illustrate the performance of our approach using three of these instances. They correspond to real cases from March 25th, March 26th, and April 4th, 2020, respectively. They have been selected given the differences in their inputs, as shown in Table 1. Initially, the number of collection points represents how many volunteers are offering 3D elements that day. Next, the maximum allowed tour length (MATL) indicates how much time is available to perform a single route. A service time is also considered. The parameter shown in Table 1 corresponds to the mean of a log-normal probability distribution. Hence, if S_i is a random variable representing the service time, $S_i \sim logN(\mu_i, \sigma_i^2)$, where μ_i and $\sigma_i^2 = 0.05\mu$ are the expected value and variance or the servicing time at collection point i, respectively. In the real-world case, μ_i decreased from 7 minutes in the instance *mar-25* to 4 minutes in the instance *apr-04*, which was due to the experience acquired by the drivers between both days. Finally, the number of vehicles represents the number of volunteer drivers available to collect the elements that day.

Table 1: Inputs and results for three real instances.

	Instance								
Input	**mar-25**			**mar-26**			**apr-04**		
Number of collection points	95			77			22		
MATL (min)	300			300			250		
Mean service time (min)	7			7			4		
Number of vehicles	6			4			1		
Output	**Greedy**	**BDS**	**BSS**	**Greedy**	**BDS**	**BSS**	**Greedy**	**BDS**	**BSS**
Deterministic total time (min)	1417.16	1394.92	-	1137.06	1123.56	-	246.39	248.35	-
Stochastic total time (min)	1454.81	1431.32	1428.69	1167.11	1152.71	1169.04	255.94	257.69	247.96
Deterministic MTL (min)	299.89	294.27	-	298.96	298.24	-	246.39	248.35	-
Stochastic MTL (min)	306.51	302.33	299.28	306.96	306.07	297.20	255.94	257.69	247.96
Visited collection points	95	95	95	77	77	77	14	15	14
Total collected demand	847	847	847	805	805	805	218	236	218
Reward	8104	8104	8104	7666	7666	7666	51800	51980	51800
Reliability	0%	0%	96%	0%	0%	100%	0%	0%	100%

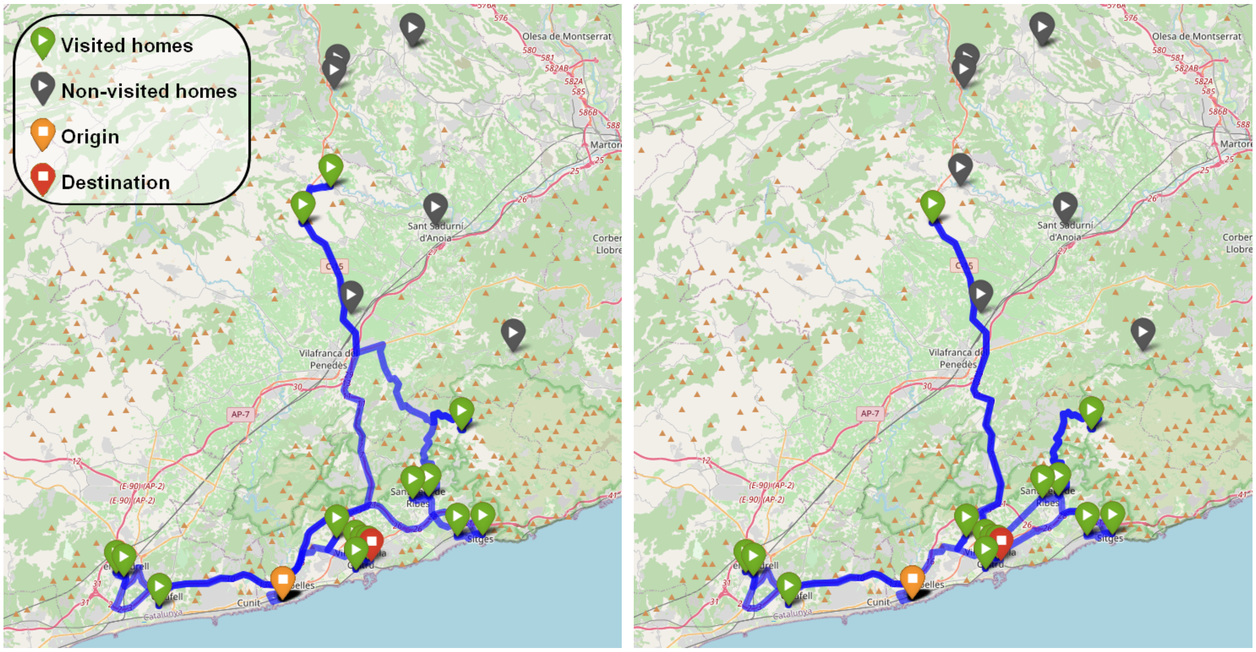
We also consider a random travel time T_{ij} between two nodes i and j, where $T_{ij} = t_{ij}^{min} + W_{ij}$, with t_{ij}^{min} being the minimum time requested to travel from i to j assuming 'perfect' travel conditions, and W_{ij} is a random variable such that $W_{ij} \sim logN(\mu_{ij}, \sigma_{ij}^2)$. Sampled observations from T_{ij} and W_{ij} are denoted by

t_{ij} and w_{ij}, respectively. Notice that W_{ij} represents a random delay caused by uncertainty conditions, such as traffic or weather. A web mapping service is employed to estimate t_{ij}^{min}. In our numerical experiments, we will assume that $\mu_{ij} = \sigma_{ij}^2 = 0.05t_{ij}^{min}$, $\forall(i,j) \in E$. It is worth clarifying that, despite the deterministic part of the problem is totally based on real data (Tordecilla et al. 2021), the probability distributions and their parameters for both S_i and W_{ij} are experimental values selected to test our simheuristic approach. The parameter α employed to compute the savings is set to 0.6. This value was selected after performing a series of fine-tuning experiments. Also, based on previous studies (Ferone et al. 2019), we set the β parameter of the geometric probability distribution as a random value in the interval $(0.05, 0.25)$. In each iteration of our approach, β is randomly chosen inside this interval. The number of runs for the short simulation process and the long simulation process is set to 100 and 1000, respectively. A more thorough study for setting a suitable number of simulation runs is proposed by Rabe et al. (2020). The maximum computational time employed by our approach is set to 60 seconds. The algorithm is implemented in Python 3 and executed in a personal computer with 16 GB RAM and an Intel Core *i*7-8750H processor at 2.2 GHz.

The rows titled as *Output* in Table 1 show our main obtained results. Each tested instance yields three types of solutions. First, our best deterministic solution (BDS), which is the best-found solution assuming that all parameters' values are perfectly known. Second, our best stochastic solution (BSS), which is the best solution found by our simheuristic, considering random service and traveling times. Moreover, the results obtained by the greedy deterministic heuristic (Section 4.1) are introduced. This greedy heuristic does not consider the biased selection of candidates, but a procedure corresponding to a 'manual planning', since the best current candidate is always selected when constructing the solution. It is worth saying that the BDS solutions are equivalent to those generated under the deterministic environment addressed in March 2020. Both the deterministic and the stochastic total times are the sum of the times of each designed route. The former represents the time yielded considering unrealistic perfectly known conditions. Hence, this parameter does not make sense for the BSS. Conversely, the stochastic total time is the time obtained after the BDS and the BSS have been simulated. Table 1 also shows the deterministic and the stochastic maximum tour length (MTL). The MTL represents the time spent by the longest route in the solution. Notice that, in all instances, the BDS stochastic MTL exceeds the corresponding MATL. Alternatively, the BSS fulfills this time.

Since the considered problem is solved as a TOP, some collection points can be skipped. This is the case of the instance *apr-04*. Originally, 22 volunteers should be visited that day, however, since the MATL must be fulfilled, having only one vehicle is not enough to visit them all. Hence, the BDS achieves a maximum reward when visiting 15 collection points, while the greedy solution and the BSS achieve it by visiting 14. This fact implies that the BSS reaches a total collected demand and a reward smaller than the BDS. Nevertheless, since the BDS stochastic MTL exceeds the MATL, this solution has been proved to be infeasible. Therefore, although the BSS is a lower-quality solution, it is the best-found feasible solution when considering a realistic stochastic environment. Considering the greedy solution, it shows a similar behavior: Despite collecting a less reward than the BDS, and the same amount as the BSS, its reliability is null. Figure 2 displays the best-found routes by the BDS (2a) and the BSS (2b). Orange and red markers represent the origin and destination points, respectively. Green markers are the visited collection points, and gray markers represent the non-visited ones. Figure 2b shows that an additional collection point is skipped by the route designed in the BSS, in order to meet the MATL constraint. Notice also that the routes designed by each solution type are not the same. For instance, those edges that are not traversed in the BSS are those that may show more variability due to the uncertainty derived from the real world, such as traffic congestion or weather conditions.

Finally, Table 1 shows a reliability indicator as an additional measure of the solution quality. We define the reliability of a solution as the probability that it does not fail. All routes within a solution are assumed to be independent. We consider that a route fails when the total time spent to traverse it is greater than the MATL. Hence, if K is the set of routes in a solution, a_k is the total number of simulation runs in



(a) Best deterministic solution. (b) Best stochastic solution.

Figure 2: Designed routes by the BDS and the BSS for the instance *apr-04*.

which the route $k \in K$ fails, and n is the total number of performed simulation runs, the reliability R is computed according to Equation 2. Therefore, the reliability results for all instances show that both the greedy solution and BDS fail completely in guaranteeing the maximum tour length, while the BSS is able to achieve a high reliability regardless of the stochastic environment.

$$R = \prod_{k \in K} \left(1 - \frac{a_k}{n}\right) \cdot 100\% \tag{2}$$

6 CONCLUSIONS

This work has shown the application of a simheuristic algorithm to a real-world routing case posed by the 2020 COVID -19 crisis in Barcelona. Collection activities of 3D-printed elements must be performed; however, since the drivers are volunteers, both the number of available vehicles and the time to traverse a route are limited. Therefore, this case was treated as a stochastic team orienteering problem (STOP), where both travel and service time are to be considered stochastic. The obtained results show the suitability of using a STOP for this type of problems, since it allows for skipping some collection points with low reward in order to fulfill the time limit. Furthermore, our approach considers not only these rewards to construct the routes, but also the travel times between each pair of collection points. This double criterion enables to design good-quality solutions. Multiple indicators were used to evaluate this quality, namely: the total travel time, the maximum tour length, the visited collection points, the reward, and the reliability. Two types of solutions are generated: the best deterministic solution (BDS) and the best stochastic solution (BSS). The BDS is the best-found solution when perfectly known conditions are considered, although these are unrealistic. Moreover, the simulation of the BDS shows the infeasibility of this solution under stochastic conditions. As an alternative, our simheuristic provides the BSS, which achieves outstanding values for the considered indicators, preserves the feasibility of the solution, and far outperforms the BDS in terms of reliability. Future research includes the design of more refined solution search procedures, such as local search heuristics or other metaheuristics. In addition, a highly agile algorithm can be implemented, which does not require time-consuming fine-tuning processes. An algorithm with these characteristics is useful not only to struggle against a situation like the current pandemic, but also to quickly design routes in the case of the occurrence of other catastrophic events. Additionally, the current solution approach is designed to cope with a single-period problem, which implies that some distant and/or low-reward nodes are more likely to be skipped during the design of the route plans. Therefore, a multi-period problem can be considered, such that those makers that are not visited in a day have a visit priority on the next days. Such visits would also depend on the reward that these makers are currently offering.

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