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WASTE COLLECTION OF MEDICAL ITEMS UNDER UNCERTAINTY USING INTERNET OF THINGS AND CITY OPEN DATA REPOSITORIES: A SIMHEURISTIC APPROACH

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ABSTRACT

In the current pandemic situation, a large quantity of medical items are being consumed by citizens all over the world. If not properly collected and processed, these items can be pollutant or even dangerous for many people. Inspired by a real case study in the city of Barcelona, and assuming that data from container sensors are available in the city open repository, this work addresses a medical waste collection problem both with and without uncertainty. The waste collection process is modeled as a rich version of the open vehicle routing problem, where the capacity constraints are not in the loading dimension but in the maximum time each vehicle can circulate without having to perform a mandatory stop, with the goal of minimizing the total time required to complete the waste collection process. To provide high - quality solutions to this complex problem, a biased - randomized heuristic is initially proposed. This heuristic is then combined with simulation to provide effective collection plans in scenarios where travel times and pick - up times are modeled as random variables.

1 INTRODUCTION

The outbreak of the COVID - 19 pandemic not only has caused a significant global social and economic crisis but also has dramatic effects on the environment. To fight the spread of COVID - 19, governments and health officials around the globe have introduced mandatory policies including lock - downs, quarantines, and border closures. While these measures have positive impacts on the environment due to the reductions in air pollution, they are most likely temporary as pollution levels may rise again when the world recovers from the pandemic. However, consumption of personal protective equipment (PPE), such as masks and gloves, during the pandemic has already generated more than billions of contaminated waste. To date, COVID - 19 continues to be a challenge to global public health. Saberian et al. (2021) estimate that 6.88 billion – approximately 206,470 tons – face masks are generated around the world each day. In many cities, the daily face mask usage (in terms of pieces quantity) can be roughly estimated by simply multiplying the city population size by the acceptance rate of masks (Nzediegwu and Chang 2020).

For instance, the population in Barcelona, Spain, is equal to 1,664,182 people (Statistical Institute of Catalonia 2020). Despite wearing a face mask in public is mandatory in Barcelona, the acceptance rate is estimated to be about 80 %. Hence, we estimate the daily face mask usage in Barcelona to be about 1,331,345 pieces. Many of these masks are made of petroleum - based non - renewable polymers that are non - biodegradable (Dharmaraj et al. 2021), which means that they take hundreds or even thousands

of years to break down in the environment. Most of the used PPE is ultimately relieved to the landfill as well as to the marine environment, contaminating the environment and affecting their fauna and flora population. Therefore, proper treatment of the PPE and, in general, sanitary and medical waste is an urgent need. Neglecting the seriousness of this issue may cause significant environmental and health problems.

One of the feasible approaches to tackle this problem is to assure that both the PPE and medical waste are forwarded for special processing to prevent creating more contaminated waste. In this paper, we apply the concept of Internet of Things (IoT) sanitary waste containers, where specialized medical waste containers are deployed in the most populated areas and sanitary / medical centers of Barcelona, and small sensor devices are installed in every container to measure its saturation level (Figure 1). Data regarding the waste levels of each container are sent to the open data center of the city. These data are retrieved periodically by the competent authorities, and the cargo vehicles are assigned to visit and empty the containers. By employing small sensors in the container, visiting containers that still have enough capacity is avoided, thus reducing the overall transportation cost. In this work, the waste collection problem is modeled as an open vehicle routing problem (OVRP). The OVRP differs from the classical vehicle routing problem (VRP) by considering different origin and end depots (Li et al. 2007). We employ a biased - randomized heuristic algorithm (BRH) to determine the optimal route with the shortest travel time, as described by Beloso et al. (2019). This problem has been traditionally studied under deterministic conditions, where travel and service times are known and fixed. However, related activities are naturally stochastic in real - world problems. Therefore, we integrate a simulation component into the BRH framework to assess the solution robustness under stochasticity, where both travel and service times are stochastic. Hence, the data about the waste levels can be consulted in the cloud, and used to feed a simheuristic algorithm. The simheuristic yields a set of quality solutions that are assessed by decision makers. Key performance indicators, such as cost or reliability levels can be used, as well as descriptive charts. Finally, a single routing plan is selected and employed to perform the waste collection tasks.

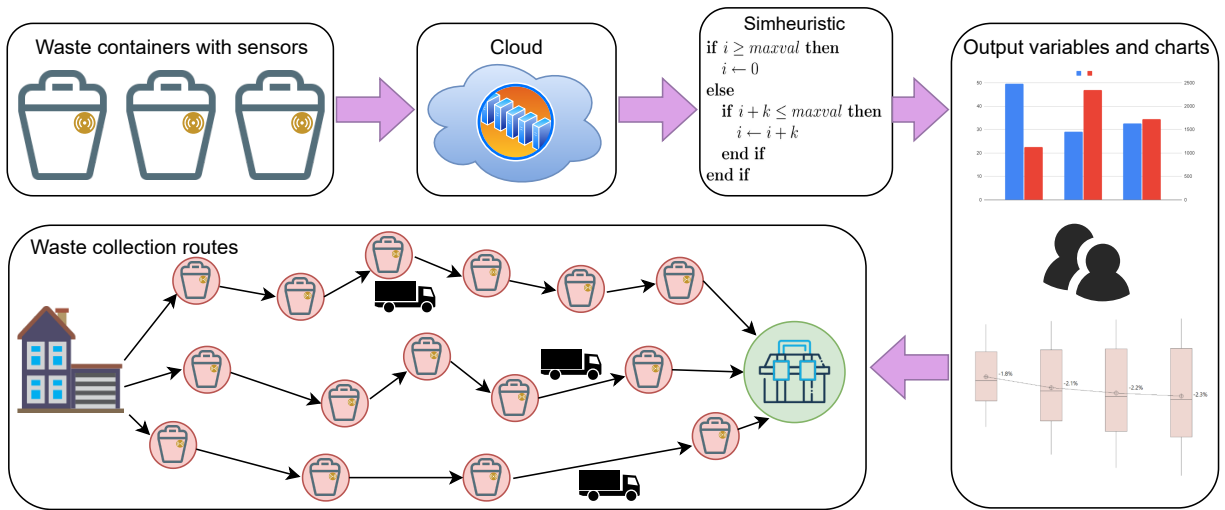


Figure 1: Schema of the information flow in our medical waste collection problem.

Using specialized PPE waste containers brings at least two benefits:

1. Studies have already shown that SARS - CoV - 2 can stay on hard surfaces for long periods of time (Choi et al. 2021). Therefore, inappropriate management of PPE and medical waste may increase the chances of COVID - 19 spread in the environment, and may lead to infection among waste

workers. Using specialized waste containers can reduce the risk of exposure to the SARS - CoV - 2 as PPE and medical waste will be stored and handled differently than other general waste.

2. The collected PPE and medical waste could be recycled for use in other applications, e.g., recycled concrete aggregate for pavement constructions (Saberian et al. 2021). The activity of reusing and recycling PPE and medical waste requires extensive processes of sorting out the materials, whose processing time can be saved by using specialized waste containers.

The rest of the paper is structured as follows: Section 2 reviews related work; Section 3 provides a formal description of our addressed problem; Section 4 presents the biased - randomized heuristic for a deterministic environment, which is then extended to a simheuristic for the stochastic version in Section 5; Section 6 provides experimental results based on a set of benchmark instances; finally, Section 7 presents our main conclusions and future work.

2 RELATED WORK

IoT and cloud computing systems speed up the integration of solutions from different applications and communication technologies, e.g., sensor networks or wireless actuators (Zanella et al. 2014). Opportunities in the field of smart cities and intelligent transportation systems are studied by Jadli and Hain (2020), who propose a new architecture for a smart waste management system. It is based on artificial intelligence techniques with a combination of IoT and surveillance systems. This architecture can help to reduce the costs and automate associated processes. Pardini et al. (2019) review the effect of IoT in waste management by enabling automation through cyber - physical systems. Sarvari et al. (2020) combine IoT and waste management by introducing a dynamic waste collection problem, in which cost is optimized. Real - time data are collected employing fill - level sensors in waste containers.

The open vehicle routing problem is a richer version of the traditional vehicle routing problem (Yousefikhoshbakht et al. 2014), in which origin and end depots do not have the same location, i.e., routes are not 'closed'. In this regard, Li et al. (2007) review and compare many algorithms that solve the OVRP, and propose a record - to - record travel algorithm for standard VRP to manage the open routes. Sariklis and Powell (2000) provide a heuristic method based on a minimum spanning tree with penalties for solving an OVRP. Cao and Lai (2010) consider an OVRP with fuzzy demands and propose a chance - constrained model. Similarly, Gruler et al. (2017) employ a combination of biased - randomization techniques, metaheuristics, and Monte - Carlo simulation to solve the waste collection problem with stochastic elements. Delfani et al. (2020) propose a multi - objective mathematical model for the hazardous waste location - routing problem, where the total cost is minimized. They develop a possibilistic chance - constrained programming approach and use a robust possibilistic programming model to deal with the uncertainty of the model parameters.

3 PROBLEM DESCRIPTION

The medical waste collection OVRP consists in designing a set of open routes intended to pick up medical waste. This waste has been disposed in multiple collection points across the city that must be visited. These points are connected by edges, which represent streets in cities. Each collection point has a given demand, as well as coordinates, e.g., latitude and longitude. A single vehicle is assigned to each route and visits each collection point once. We are assuming also that the set of vehicles is homogeneous, and that the fleet size is constant. In addition, it is assumed capacity of the vehicles is unlimited because the considered waste (e.g., surgical masks, syringes, hypodermic needles, scalpel blades, etc.) requires virtually negligible space. Since loading capacity is not a constraint, each vehicle has a maximum amount of time to complete its route i.e., a time - dependent capacity arises. Service times refer to the time required to pick up the medical waste at each collection point, while travel times refer to the time invested in traversing each edge. Both travel and service times are considered to be stochastic, since they might depend upon multiple random factors (e.g., traffic conditions, weather conditions, road disruptions caused by car accidents, etc.). We assume that travel times are independent from each other. The vehicle's origin

and destination points are not the same, i.e., the designed routes are open (Figure 1). For instance, each vehicle may depart from the firm's headquarters, visit its assigned collection points, and finish the route in a treatment facility. The Government of Catalonia has established a procedure to perform these activities in its entire territory, including Barcelona (Generalitat de Catalunya 2021; Generalitat de Catalunya 2019). In practice, the headquarters and the treatment facility might have the same location or not, so we consider the more general scenario in which they can be located at different parts of the metropolitan area. The goal is to minimize the total time invested by the fleet of vehicles to complete the collection task. Notice, however, that whenever a route exceeds its maximum time, a mandatory stop for resting has to be performed before resuming the collection plan. Finally, although our addressed problem focuses on medical waste collection, it is worth mentioning that the collection of waste products whose size is much smaller than the vehicle capacity e.g., batteries or cell phones, can be considered as well.

Formally speaking, the problem can be defined on a directed graph $G(N, E)$, in which N is the set of nodes, and E is the set of edges linking these nodes, such that $E \subseteq N \times N = \{(i, j) \mid i \in N, j \in N, i \neq j\}$. The set N is formed by a set I of collection points, a singleton set O representing the origin facility, and a singleton set F representing the end facility, such that $N = I \cup O \cup F$. Each collection point $i \in I$ has a service time S_i , as well as a deterministic and known demand d_i . This demand refers to the quantity of medical items to be collected. Each edge $(i, j) \in E$ is traversed in a time T_{ij} . Both S_i and T_{ij} are random variables and follow known probability distributions. These distributions are assumed to be based on historical data. A set V of uncapacitated vehicles is available to perform the routes. Each collection point must be visited once by only one vehicle. Each vehicle is assigned to only one route. Each route must start in the origin facility and finish in the end facility. The total time of each route must not exceed a given time limit t_{max} . Hence, the problem consists in designing a set of $|V|$ routes that meet the aforementioned constraints, such that the expected total time of performing all routes is minimized. Notice that no loading capacity constraints are considered since, as explained before, it is assumed that the medical items to be collected are of small size.

4 SOLVING THE DETERMINISTIC VERSION

Initially, a biased - randomized heuristic (BRH) is proposed to tackle the deterministic version of the waste collection OVRP. This BRH is later embedded into a multi - start metaheuristic framework (Martí 2003). BRH introduce a certain degree of randomness into a greedy constructive algorithm while preserving the original greedy behavior of the heuristic (Ferone et al. 2019). Consequently, different alternative solutions are generated every time a new execution is performed using a different seed for the pseudo - random number generator. These randomized heuristics are widely employed to solve large - scale NP - hard problems, in order to escape from local optima and improve the overall quality of the solution (Quintero-Araujo et al. 2017; Fikar et al. 2016). Our BRH is a two - stage approach which works as follows:

1. In stage-1, a dummy solution is constructed, which is composed of a set of $|I|$ routes. Each route is designed to serve a collection point $i \in I$, where the vehicle departs from the origin depot, visits the collection point i , and then continues the trip to the end depot.
2. The stage-2 consists in merging these initial routes, in order to reduce both the fleet size and the total travel time. The merging criteria is based on the concept of savings value which is associated to each pair of routes (or edge) and denotes the savings in terms of time in the resultant route traversing this edge. Since the waste collection OVRP considers different locations for the origin and end depots, the savings associated with the edge (i, j) connecting each pair of nodes $i \in I$ and $j \in I$ is computed as follows: $savings_{ij} = t_{sj} + t_{ie} - t_{ij}$. Here, t_{ij} represents the time required to traverse the edge $(i, j) \in E$, t_{sj} represents the time to travel from origin depot s to node j , and t_{ie} represents the time to travel from node i to end depot e . These savings are computed for each pair of nodes $(i, j) \mid i \neq j$ from the network, and the resulting savings list is sorted in descending order according to their corresponding savings, i.e., the edges at the top of the list are the ones

that generate the highest savings when merging the corresponding routes. The edge at the top of the savings list is selected to perform the merging procedure. In our case, the respective routes of a saving edge (i, j) can be merged if: (a) nodes i and j belong to different routes; (b) i and j are exterior in their corresponding routes (i.e., they are directly connected with one of the depots); and (c) the maximum route time allowed is not exceeded. Since the items to be collected are considered negligible in size, the vehicle capacity constraint is not considered. The selected edge is removed from the savings list whether the merging is performed or not. This step is repeated until the savings list is empty, i.e., our procedure continues merging routes feasibly until every edge in the list has been considered.

To introduce a ‘biased randomness’ into this heuristic, a skewed probability distribution is applied to the savings list. Hence, edges at the top are more likely to be selected than those at the bottom of the list, according to the probability distribution being considered. In particular, a geometric distribution is used in this paper, which is controlled by a single parameter β . By selecting $0 < \beta < 1$, the BRH can generate different alternative promising solutions when executed for a predefined number of iterations or amount of time (Juan et al. 2009).

In this way, our BRH is embedded into a multi - start framework. Roughly speaking, the multi-start framework starts generating an initial solution using the BRH setting β to 1 which becomes the best solution so far S^* . This solution is the heuristic set of open routes of collecting points and the total time of all routes (or deterministic time) is the best so far time f^* . Then, the main loop iterates until a stopping criteria is met (maximum time or maximum number of iterations). In each iteration the algorithms calls the BRH getting back a new solution S' and its time f' . The β value is given as an input parameter. If f' is less than f^* then S' replaces S^* , otherwise S' and f' is rejected. Finally, the algorithm stops (when stopping condition reached) and the best - found solution S^* and f^* is returned.

5 A SIMHEURISTIC APPROACH FOR THE STOCHASTIC VERSION

The introduced multi - start BRH is able to find feasible and promising solutions in short computing times. However, this metaheuristic is designed to solve the problem when data inputs are deterministic. In real - life applications, uncertainty is a crucial part of the decision-making process. Therefore, the multi-start BRH is extended into a simheuristic algorithm to deal with a more realistic scenario under uncertainty. Simheuristics have been recently employed in solving complex stochastic optimization problems, such as stochastic inventory routing problems (Gruler et al. 2018; Gruler et al. 2020) or stochastic facility location problems (Pagès-Bernaus et al. 2019). These algorithms combine the use of heuristics / metaheuristics with simulation in order to deal with uncertainty (Juan et al. 2018). Consequently, solutions that offer a good trade - off between the expected total time and solution reliability can be generated. In the context of this paper, reliability refers to the probability that a routing plan can be implemented without failures, i.e., without routes exceeding the maximum time allowed to complete the waste collection process. In our case, we combine the proposed multi - start BRH framework with Monte - Carlo simulation in order to address the case where both the service time of each collection point and the travel time between each pair of nodes are random variables following a given probability distribution which we assume has been obtained by fitting historical data for each collection point and each traveling edge in the network representing the city. Hence, the reliability rate determines the robustness of the deterministic solution under stochastic scenarios, i.e., whether the total travel time of the route is still acceptable / feasible under such scenarios or not, considering the maximum route travel time.

Our simheuristic is integrated into the multi - start BRH, which is depicted in Figure 2. This algorithm works as follows. Firstly, an initial solution S^* is generated by using the BRH setting β to 1. Then, from solution S^* , travel times and service times are replaced by their stochastic counterparts, and a short simulation (small number of replications) is performed to estimate the average stochastic time and its

reliability rate, setting the solution S^* as the best deterministic and stochastic solutions so far. During the iterations, the best solution S^* in terms of the deterministic time and stochastic time is kept. Following Rabe et al. (2020), in each iteration, a new solution is generated S' by BRH, but only if this solution S' is promising then the stochastic time of S' is computed by a short simulation. That situation is given when the deterministic time of S' is less than the deterministic time of S^* . But if the stochastic time yielded by S' outperforms the stochastic time of S^* , then S^* is replaced by S' , otherwise S' is rejected. Hence, once these steps are finished, the best solution is tested under a single long simulation (large number of replication) in order to increase both the accuracy of their stochastic time and reliability level.

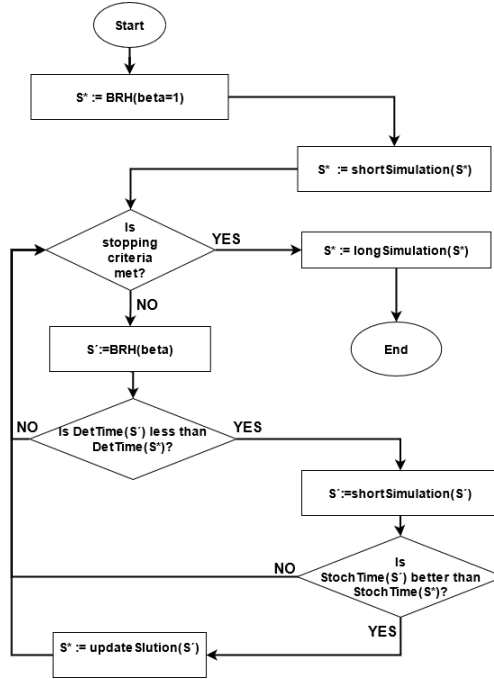


Figure 2: Flowchart of the simheuristic algorithm.

6 COMPUTATIONAL EXPERIMENTS

The data used to test our approach is based on a deterministic real - world case arisen during the first months of the COVID - 19 pandemic in Barcelona. These data are assumed to be provided daily by sensors installed in 96 medical waste containers in the metropolitan area of the city. The origin depot and the destination treatment facility are indicated as red cylinders in Figure 3, and the rest of collecting locations are shown in blue points.

This case study has a four hour time limit (t_{max}) for each route. This time limit was imposed by mobility restrictions during the pandemic lockdown. Additionally, six vehicles are available to perform the routes, and all of them must be used. A few tests considering different fleet sizes were performed. A fleet size of five vehicles or less leads to infeasible solutions, given the time limit t_{max} . To solve the problem, the original deterministic instance is transformed into a stochastic one by considering both a random travel time T_{ij} and a random service time S_i , as detailed next:

- T_{ij} follows a log - normal distribution with a minimum time limit t_{ij}^{min} along the edge (i, j) . This limit represents the deterministic time in optimal travel conditions. That is, if the pure random part of T_{ij} is represented by Θ_{ij} , and $\Theta_{ij} \sim \log N(\lambda, \gamma)$, where $\log N(\lambda, \gamma)$ is a log - normal distribution with location parameter λ and scale parameter γ , i.e.:

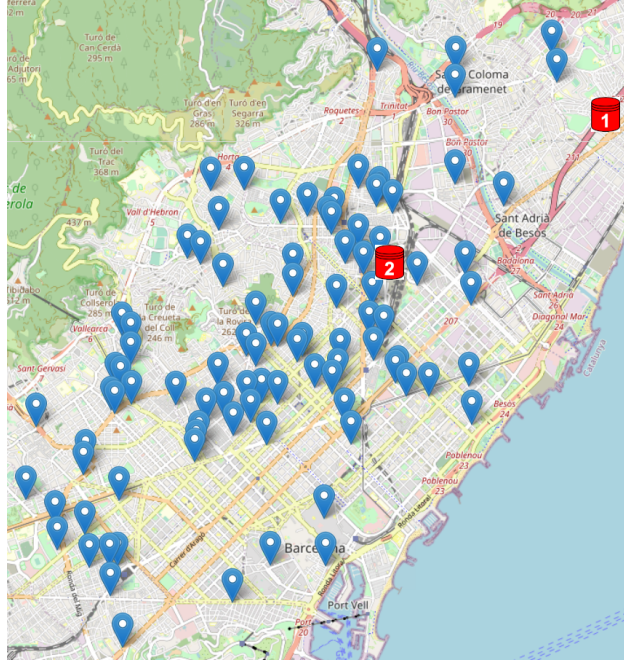


Figure 3: Map of the collection points and depots used for our experimental instance.

$$t_{ij} = t_{ij}^{\min} + k\theta_{ij},$$

where k is a variability level, and t_{ij} and θ_{ij} are realizations of T_{ij} and Θ_{ij} , respectively. In our experiments, we consider $\lambda = 0$, $\gamma = 1$, and $k \in \{5, 6, 7, 8, 9, 10\}$. These values were selected so that diverse variability levels are tested. Hence, the experiment results lead to a more comprehensive analysis. Additionally, t_{ij}^{\min} is estimated for each edge using a web mapping service.

- $S_i \sim \log N(\lambda, \gamma)$. Inspired by the real - life data, in our experiments we compute λ and γ such that $E[S_i] = 420$ seconds, and $Var[S_i] = 5$, where $E[S_i]$ and $Var[S_i]$ are the expected value and the variance, respectively.

The variability level k leads to six different scenarios: very - low, low, medium - low, medium - high, high, and very - high. Regarding the algorithm parameters, we have set the β parameter used for the BRH as a random value in the interval $(0.05, 0.25)$ (i.e., in each new iteration, the β value is randomly selected inside this interval, which according to our initial experiments seems to provide reasonably good solutions). The number of short simulation runs is set to 100, while the number of runs for the long simulation is set to 1,000. A more thorough study about the number of appropriate simulation runs can be found in Rabe et al. (2020). Finally, in case that the route stochastic time exceeds t_{max} , it is penalized with an extra time of 1,500 seconds. This time is justified by the need of adding a mandatory stop every time a driver reaches the maximum driving time allowed.

The algorithm is implemented in Python 3 and executed in a personal computer with 16 GB of RAM and an Intel Core *i7-8750H* at 2.2 GHz. For each variability level, the maximum computational time employed is set to 60 seconds. For each uncertainty scenario, Table 1 shows the comparison between our best deterministic solution (OBD, which is the best solution we have been able to find for the deterministic version of the problem) and our best stochastic solution (OBS, which refers to the best solution we have found under uncertainty conditions). Each time value in this table is shown in the format *hours:minutes:seconds*, and includes both the time spent traveling throughout the route and the service time. When comparing the total time of all routes, the longest - route time (LRT) represents the maximum found time for a single route.

The results show that, in the deterministic scenario, the maximum time of four hours is never exceeded, and all the six available vehicles are used. The deterministic total time is the time obtained after adding the total time of all routes in the solution when considering scenarios under absolute certainty. Obviously, this time is the same regardless of the variability level.

Table 1: Results for a case study considering different levels of uncertainty.

Variability level	Our best deterministic solution (OBD)				Our best stochastic solution (OBS)		
	Longest-route time	Deterministic total time	Stochastic total time	Reliability	Longest-route time	Stochastic total time	Reliability
Very-low	3:58:37	22:26:05	23:03:32	15.63%	3:55:26	22:44:20	97.50%
Low	3:58:37	22:26:05	23:13:00	4.75%	3:55:26	22:48:41	91.33%
Medium-low	3:58:37	22:26:05	23:22:45	1.40%	3:55:26	22:54:05	81.04%
Medium-high	3:58:37	22:26:05	23:31:43	0.31%	3:55:26	23:01:15	64.54%
High	3:58:37	22:26:05	23:40:00	0.07%	3:55:26	23:08:31	48.70%
Very-high	3:58:37	22:26:05	23:48:40	0.02%	3:55:26	23:16:33	32.53%
Average	3:58:37	22:26:05	23:26:37	3.70%	3:55:26	22:58:54	69.27%

Once the deterministic solution is obtained, it is simulated in a stochastic environment to get the expected total time of this plan when implemented in a scenario under uncertainty conditions. The associated reliability value is also estimated, which is the estimated probability that the collection plan can be completed without any route exceeding its maximum allowed time. The OBS columns show the same key performance indicators as the OBD columns. However, these indicators are obtained when running our simheuristic algorithm. The results show a clear superiority of the simheuristic algorithm, since the stochastic total time is lower than the OBD's for all instances under all variability levels. Moreover, the reliability of the OBS is higher than the OBD's, i.e., our simheuristic is able to guarantee a higher probability of not exceeding the time limit of each route. Furthermore, since the time limit of four hours is never exceeded, our solution never incurs a penalty time. Notice also that the LRT of the OBS is smaller than the OBD's. Since the OBD does not consider stochastic conditions, routes' times can be really close to the four - hour limit. Nonetheless, the closer the LRT to the time limit, the greater the probability to violate this constraint in a stochastic environment. Hence, the LRT of the OBS is smaller. Finally, our results show a sharp decrease in the quality of the deterministic collection plan when increasing the variability level. Figure 4 displays the distribution of the stochastic total time results when running long simulations. Shown plots correspond to the very - low (VL) and the very - high (VH) variability levels, as well as to the OBD (pink charts) and the OBS (green charts). The cross circle indicates the mean value of each sample. Under stochastic scenarios, our results show an evident total time decrease when modeling our problem through a simheuristic approach, instead of considering a deterministic solution. The higher the considered variability is, the sharper the total time decrease. Furthermore, our simheuristic reduces the results variability, which can be noticed by comparing the range between the extreme points in each box plot.

7 CONCLUSIONS AND FUTURE WORK

In a context shaped by the increasing use of medical items at every household across the world, the effective collection of all these pollutant (and sometimes dangerous) items becomes a social priority. Hence, it is not surprising that initiatives, such as the one described here, emerge in many smart cities, where the combined use of sensor devices, Internet of Things, and open data repositories can support intelligent decision making when designing efficient pick - up routing plans.

In our case, we study a medical waste collection problem by modeling it as a rich and stochastic version of the open vehicle routing problem. Typical loading constraints are not considered here due to the small size of most medical items. However, maximum driving time per route have to be taken into account. Also, the introduction of random travel and pick - up times makes the optimization problem more challenging.

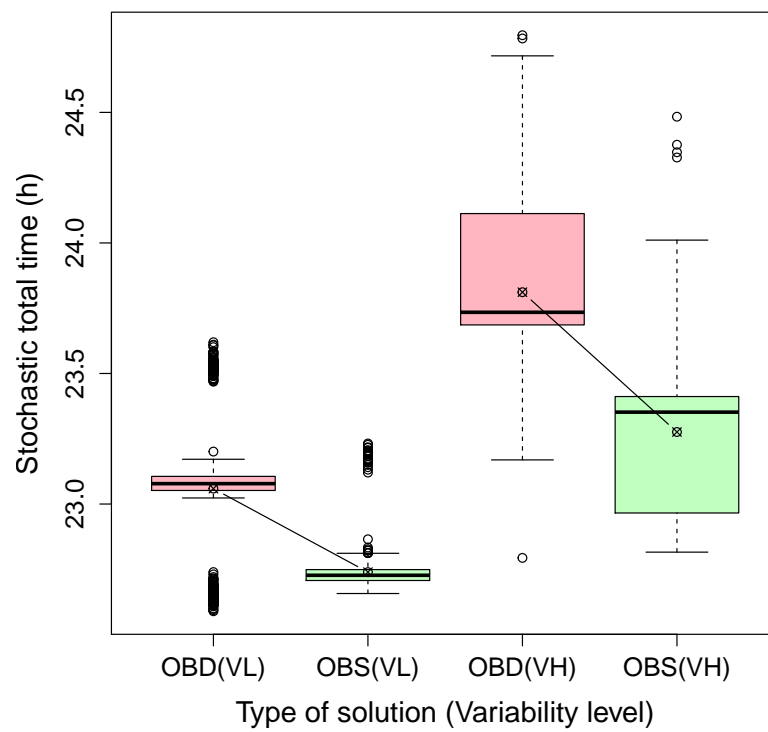


Figure 4: Total time results of the long simulations under different variability levels.

In order to deal with this complexity, we first propose a biased - randomized heuristic, which is later on extended to a full simheuristic combining an optimization module with a simulation one. This allows us to obtain better solutions with higher reliability levels. Our experiments also illustrate how a good collection plan under deterministic conditions can become a sub - optimal plan as uncertainty is introduced in the scenario.

Regarding future work, we plan to consider a situation in which data on each container are available at a higher frequency, thus allowing for ‘agile’ collection plans that need to be dynamically adjusted as new information is provided by sensors to the open data repositories. Additionally, loading capacity constraints can be considered, which becomes relevant whenever larger items must be transported.

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