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LAST-MILE DELIVERY OF PHARMACEUTICAL ITEMS TO HETEROGENEOUS HEALTHCARE CENTERS WITH RANDOM TRAVEL TIMES AND UNPUNCTUALITY FEES

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ABSTRACT

This paper analyzes a real-life distribution problem that is related to a pharmaceutical supplier in Spain. Every day, a fleet of vehicles has to deliver the previously requested items to a large set of pharmacies. The distribution has to be conducted with *(i)* the total distance and time incurred by the entire fleet being reasonably low and *(ii)* the time of the delivery meeting the specified time windows or, if that is not possible and some delays occur, the total fee incurred by these unpunctualities being minimized. Unpunctuality fees depend upon how important is the customer for the distributor, and the size of the tardiness gap. To include even more realistic details, travel times are modeled as random variables, which also makes the problem more challenging to solve by employing traditional optimization methods. To solve this stochastic variant of the problem, a simheuristic algorithm is proposed and evaluated.

1 INTRODUCTION

In this work, we investigate an efficient solution to a real-life logistics and transportation problem proposed by a large-size pharmaceutical distributor with headquarters in Spain. The company distributes medicines and other pharmaceutical products to nearly 400 customers, including private pharmacies and clinics, public and private hospitals, and other healthcare centers. The firm's delivery vehicles travel more than one million kilometers per year to supply the customers' requirements of these products. Usually, two delivery plans per day are required: one for the morning shift and another one for the afternoon shift. Every night, after 9 pm, the orders for the next morning delivery are received from pharmacies. Likewise, orders for each afternoon are received during the same day around 2 pm. As a consequence, only a few minutes are available to design the vehicle routing plan for each shift before loading the vehicles with the corresponding products and starting the delivery action.

Apart from the associated order of items, each customer also defines a time window in which it desires to be visited by the delivery vehicle. Hence, visiting a customer outside its time window is still possible,

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but it might cause the customer to be not fully satisfied with the service, and this can be modeled as a penalty fee due to unpunctuality. As it will be explained later in more detail, the amount of this fee might depend upon how important the customer is for the distributor as well as on the gap between the time window and the actual service time. Hence, this logistics and transportation activity can be modeled as a vehicle routing problem (VRP) (Juan et al. 2009), where the goal is to satisfy all customers' demands in each delivery shift while minimizing the total penalty fee and keeping total routing times and distances reasonably low. However, in our case there are some specific details that are different from the classical VRP and that need to be considered as well. On the one hand, the firm employs a fleet of mid-size vans to complete the delivery process. Since most of the medical and pharmaceutical products have a small size, there are no volume-capacity constraints associated with the distribution process. On the other hand, there is a maximum time available for each vehicle to complete its assigned route. Hence, there are soft time-capacity constraints associated with each route. Exceeding this time threshold might generate additional costss generated by drivers' overtime fees. Finally, in order to consider the real-life uncertainty regarding the time it takes for a van to move from one customer to the next one (often depending on traffic conditions), travel times are modeled as random variables. Using historical data, the travel time between each two nodes can be modeled using a best-fit probability distribution, whose parameters might evolve during the day to better represent the existence of peak and valley hours. Figure 1 illustrates the pharmaceutical VRP under study.

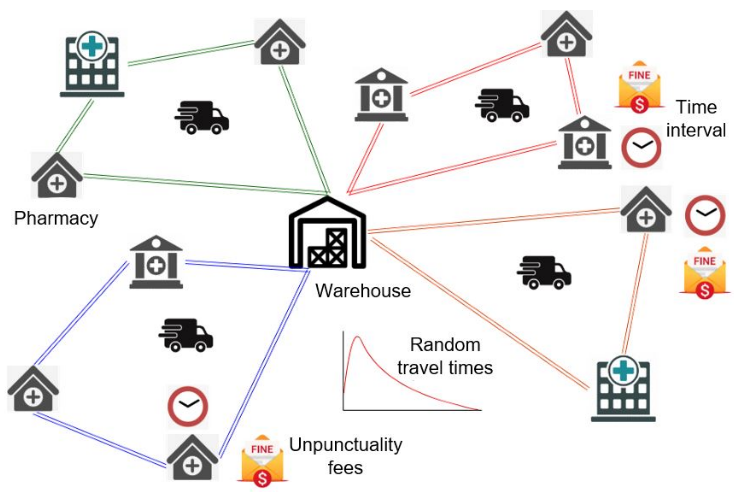

Figure 1: An illustrative schema of the distribution problem being considered.

In order to solve the above-mentioned stochastic optimization problem, we propose a simheuristic algorithm that combines a heuristic-based component with a simulation component (Chica et al. 2020). The heuristic component is based on a biased-randomized algorithm (Quintero-Araujo et al. 2017), while the simulation component makes use of Monte Carlo sampling. As it will be discussed in the experimental section, our approach is capable of efficiently solving large-size instances of the described problem in just a few seconds, which was the main goal of this study.

This paper is organized as follows: Section 2 reviews related work on similar VRPs and also on the use of simheuristic algorithms to solve routing problems. Section 3 provides more details on the problem being addressed, and its importance for the company. Sections 4 and 5 introduce the solving methodology proposed. The former describes a biased-randomized algorithm for solving the deterministic version of the problem, while the latter extends the previous algorithm into a full simheuristic in order to consider stochastic travel times. Section 6 describes a series of computational experiments, while Section 7 analyzes the obtained results. Finally, Section 8 concludes by highlighting the main contributions of this work.

2 RELATED WORK

The VRP is a well-known challenge in the optimization research community (Caceres-Cruz et al. 2014). Given a set of nodes and one (or many) depots, the goal is to find the most efficient routes through the nodes in order to optimize transportation costs without violating any problem-specific constraint. Mathematically, it is a combinatorial non-polynomial hard problem (Lenstra and Kan 1981), meaning that the space of potential solutions grows very fast as the instance size increases. Therefore, exact methods are not usually the best option when the size of the problem is large, which leads to the use of heuristic-based approaches. Heuristics is the class of algorithms and techniques used to solve complex problems in an efficient and faster fashion than traditional methods, offering near-optimal solutions.

Due to its potential applications both to real-life scenarios and to the development of new algorithms, optimization methods, heuristics, and metaheuristics, the VRP can adopt a more realistic dimension, contemplating realistic optimization functions, dealing with uncertainty, dynamism, problems of inventory, scheduling, etc. As these real-life problems arise, the need of creating rich variants of the VRP is becoming clear. Pellegrini (2005) addresses a specific rich VRP with the consideration of a heterogeneous fleet and multiple time windows. Also, the delivery cannot be offered in some intervals of time, and there is a maximum time for a single tour. A random behavior in the selection of the next customer in the building process of a route is added to the procedure, showing a clear improvement in the results. Likewise, Goel and Gruhn (2008) address the capacity restrictions, time windows, heterogeneous fleet with different travel times, and also multiple pickup and delivery locations, travel costs, different start and end locations for vehicles, as well as other constraints.

Regarding the use of simheuristics, which combine heuristics with simulation, they have been used to extend metaheuristic frameworks, such as the greedy randomized adaptive search procedure (Ferone et al. 2019), the iterated local search (Pagès-Bernaus et al. 2019), or the large neighborhood search (Gruler et al. 2020). These simulation-optimization approaches can deal with stochastic optimization problems.

3 THE INSPIRATION CASE

As mentioned above, the real-life scenario that inspired this work concerns a pharmaceutical wholesaler and distributor based in Spain. The distributor has a fleet of vehicles that should be used as much as possible to amortize the rental costs. These vehicles are currently traveling more than a million kilometers per year in order to efficiently complete a great amount of shipments and make medicines available in several pharmacies and hospitals. The distributor is open from Monday to Friday, from 7 a.m to 9 p.m., and two shipments per day are generally performed (one in the morning and one in the afternoon). Further shipments are carried out on Saturday, Sunday, and during holidays. However, during weekends and holidays the number of open pharmacies is lower, and the distribution problem becomes less challenging. The vehicles used for the morning shipment are the same employed during the afternoon. Since the physical loading of vehicles takes a long time, and it must follow according to the order in which customers are visited, there are only a few minutes left to properly organize the distribution. Hence, in order to be operative in practice, the routing algorithm has to be capable of providing a high-quality solution in a short computational time.

Each customer wants to receive the ordered goods in a specific time window. It is in the distributor's interest to respect this constraint as much as possible to ensure the customer's satisfaction. Hence, the distributor wants to avoid complaints from customers, paying particular attention to the most relevant ones, i.e., those who constitute the largest source of income for the company. Respecting the proposed time windows whenever possible reduces customers' unsatisfaction, which is measured in terms of a penalty fee for unpunctuality. The goal of the problem is to minimize the total penalty costs while satisfying constraints related to the fleet, customers' demands, and maximum traveling time per route. So far, the approach employed by the company was based on rules that were defined long time ago, and the route is usually defined by the logistics manager. When a complaint is received, a slight change to the predefined rules is carried out. Of course, this approach is clearly inefficient, and the company considers the implementation of a new tool as an aspect of paramount importance to increase the satisfaction of its customers by increasing the efficiency of the delivery process.

4 A BIASED-RANDOMIZED ALGORITHM FOR DETERMINISTIC TRAVEL TIMES

Assuming deterministic travel times, a biased-randomized algorithm or BRA (Estrada-Moreno et al. 2019) is introduced in this section. The proposed algorithm relies on a fast constructive heuristic, which follows a time-savings logic while building the routes associated with each available vehicle. Given a central warehouse, a fleet of vehicles initially located at the warehouse, the matrix of travel times between any two nodes of the network, a maximum allowed time per route, and a set of healthcare centers to be serviced – each of them characterized by a preferred time window, and a customer's importance indicator – the constructive heuristic works as follows:

1. Considering the edges connecting any two customers, consider a time-savings list of edges and sort this list from higher to lower savings. The edges at the top of the sorted list represent links between healthcare centers that are close together and, therefore, are good candidates to be visited by the same vehicle – one immediately after the other. On the contrary, edges at the bottom of the sorted list represent links between centers that are not so close. Thus, including them in the same route will give us only moderate savings in time.
2. Considering an unlimited fleet of vehicles, generate a 'dummy' solution by connecting the warehouse with each of the healthcare centers, i.e., a round trip from the warehouse to the customer and back to the warehouse is assigned to a virtual vehicle. Actually, this dummy solution is not feasibl, since it requires as many vehicles as customers, which is not our case. But, it should be feasible in terms of not exceeding the maximum time allowed per route and the time windows provided by our customers – assuming they are reasonable.
3. From the dummy solution and while the number of routes is higher than the number of available vehicles, start an iterative route-merging process. In each iteration, the edge at the top of the time-savings list is selected, and the corresponding routes are merged into a new one as far as: *(i)* both extremes of the edge correspond to external nodes in their respective routes – i.e., they are directly connected to the warehouse; *(ii)* the newly merged route does not exceed the maximum travel time allowed per route; and *(iii)* the aggregated penalty costs associated with possible violations of time windows in the resulting route does not exceed a predefined threshold $\gamma \geq 0$, with γ being a parameter whose value needs to be adjusted during the experimental stage. In instances with extremely tight time windows, it might be necessary to increase the γ value in successive trials until feasible solutions can be achieved. Of course, the larger the γ value, the higher the unpunctuality fees we might have to face.
4. Once the merging process is concluded – i.e., once the number of routes matches the number of available vehicles – a feasible solution is obtained.

With the goal of generating many alternative solutions based on the time-savings logic – from which the best-performance solution will be chosen – the constructive heuristic can be extended into a biased-randomized algorithm by employing a skewed probability distribution, as described in Belloso et al. (2019) and in Dominguez et al. (2016). The geometric distribution is chosen to induce the biased-randomized behavior inside the heuristic. This selection is motivated by the fact that the geometric probability distribution has just one parameter, $\beta \in (0,1)$, which simplifies its fine-tuning process. Whenever β approaches to 1, the algorithm behavior emulates that of the greedy constructive heuristic. If β approaches to 0, then the randomness introduced in the algorithm is similar to the one generated by a uniform probability distribution. Of course, β values in between might generate a more useful behavior, since a certain degree of randomness is introduced into the heuristic without losing the logic behind the time-savings concept. The above-mentioned constructive procedure is, therefore, incorporated into a metaheuristic framework that generates many different solutions making use of the biased-randomization process and uses a hash map data structure to 'remember' the best solution it has found so far – i.e., in previous runs – to visit a given set of healthcare centers.

5 A SIMHEURISTIC FOR STOCHASTIC TRAVEL TIMES

In real-case scenarios, the travel time between two points (i.e., healthcare centers) is not always the same. It might change according to some stochastic and unexpected events, such as traffic conditions, roadworks, or car crashes. To efficiently deal with these aspects, this section extends the previously described biased-randomized algorithm into a full simheuristic, which is capable of generating – in short computational times – efficient solutions to the pharmaceutical VRP with stochastic travel times. Figure 2 outlines an overview of the proposed simheuristic, composed of two stages. During the first step, the algorithm starts by generating a feasible initial solution (*initSol*), using the deterministic version of the constructive heuristic. So far, the costs of the computed solution responds to a deterministic scenario. In order to deal with the stochastic nature of the proposed problem, a Monte Carlo simulation (MCS) is conducted to obtain a rough estimate of the solution's behavior under stochastic conditions. This simulation process consists of a small number of simulation runs accounting for travel time variability between nodes, to estimate *(i)* the expected delay costs and *(ii)* their reliability measured using the coefficient of variation, i.e., the ratio of the standard deviation to the mean. From this point, the *initSol* is assigned as the best solution (*bestSol*) found up to now, and an iterative procedure starts to explore the solution space with the aim of improving the *bestSol*. This iterative procedure is repeated until the stopping conditions (e.g., a maximum computational time or a maximum number of iterations) are met. Hence, using the biased-randomized algorithm it generates a new solution (*newSol*) in each iteration. As mentioned above, the biased-randomized technique induces a random behavior in the heuristic by employing skewed probability distributions, thus transforming the deterministic heuristic into a probabilistic one. In this way, we diversify the exploration of neighborhood of solutions, obtaining a different solution in each iteration of the algorithm. Whenever the costs of a *newSol* outperforms the costs of the *bestSol*, in terms of deterministic costs, the latter is updated with the former, and a new MCS is conducted to account for the variability in traveling times and estimate the expected costs of the solution. Since the number of generated solutions during the search can be large, and the simulation process is time-consuming, in this first step a simulation with just a few runs (fast simulation) is employed to obtain rough estimates of the solution's behavior under stochastic conditions (Rabe et al. 2020). This allows us to generate a pool of 'promising' elite stochastic solutions. In the same way, whenever the stochastic costs of the *newSol* improves the costs of the best stochastic solution found so far, the latter is updated and added to the pool of elite solutions. We have limited the size of this pool to five solutions. Once the iterative exploration of the solution space is concluded, a refinement procedure using a larger number of MCS runs (intensive simulation) is applied to the elite solutions. This allows us to obtain a more accurate estimation of the expected stochastic costs. These new estimates can then be used to re-rank the elite solutions. Both in the exploratory and in the intensive simulation processes, we model the travel time between any two customers by using a log-normal probability distribution, whose mean is given by the deterministic value (i.e., μ), and with a standard deviation defined as $\sigma = k \cdot \mu$, where $k \geq 0$ represents an experimental parameter that can be employed to analyze scenarios with different degrees of variability. For $k = 0$, we have the deterministic scenario as a a particular case. We have employed the log-normal distribution to model the traveling times, since – together with the Weibull probability distribution – these are the most popular probability distributions when modeling random times (Kim and Yum 2008).

6 COMPUTATIONAL EXPERIMENTS

To assess the efficiency and the reliability of the proposed algorithm, a set of 33 benchmark instances widely used by the VRP research community have been modified to fit the characteristics of the problem discussed in this paper. Hence, the number of vehicles and the maximum travel time allowed per route

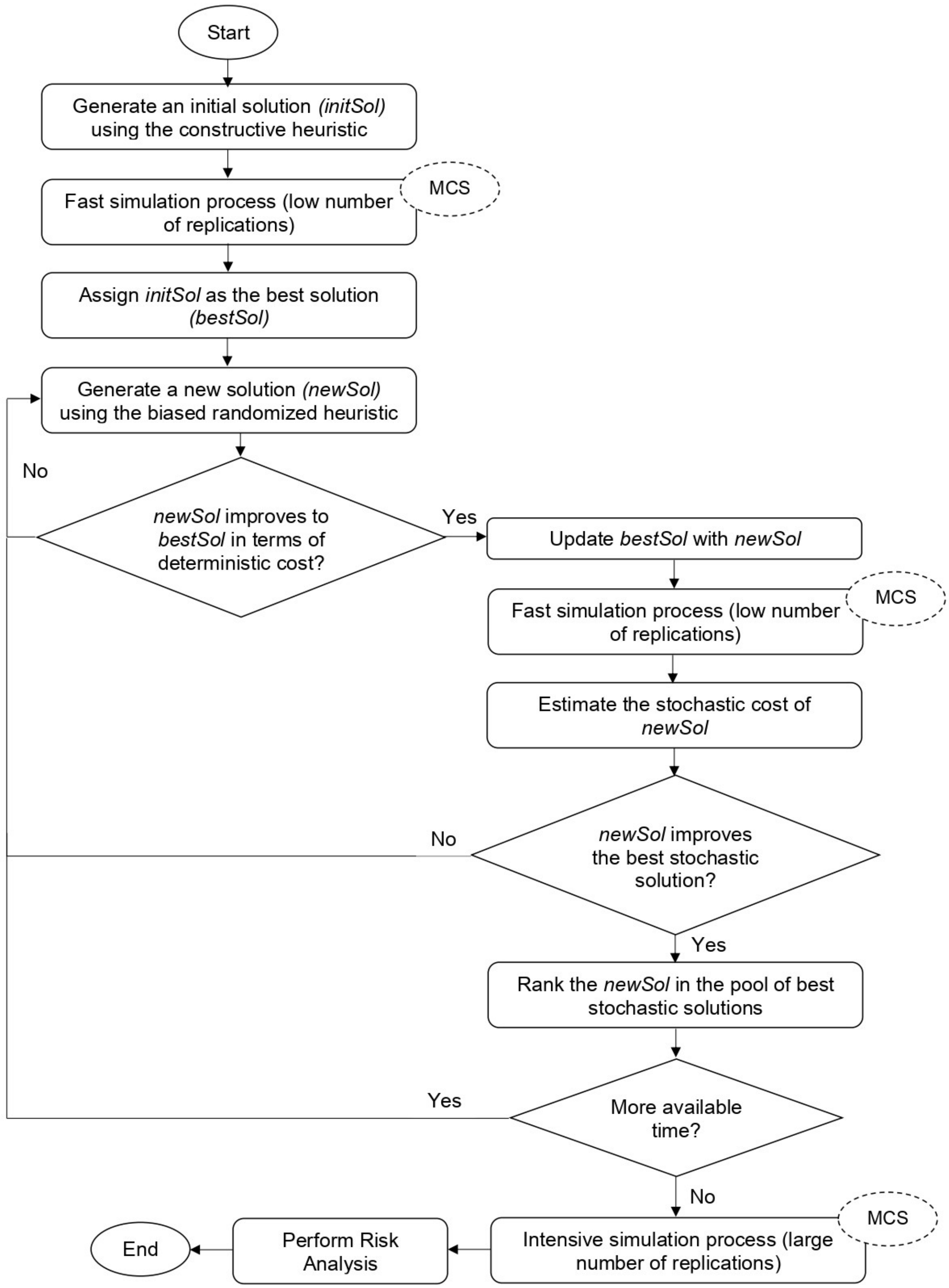

Figure 2: Diagram of the proposed multi-start simheuristic.

were not modified. Concerning the time windows, a simple procedure to define them has been designed. Thus, given a specific benchmark composed of a set of customers and a fleet of n homogeneous vehicles, we have randomly clustered the customers into n groups of equal (or similar) size. Using a round-trip route, enhanced with a *2-opt* local search, the nodes of each cluster have been connected to the depot. The time in which each customer i is visited by the associated route, τ_i is registered. Finally, the time window for customer i is defined as $(\tau_i - d, \tau_i + d)$, where $d > 0$ is a design parameter that allows us to control the tightness or amplitude of the time windows. Of course, the tighter the time windows, the more challenging the problem becomes. In occasion of these computational experiments, since we are not considering the opening time, which can be considered 0 for each node, to make the problems sufficiently challenging, d has been set equal to 1.

One of the advantages of the proposed algorithm is the existence of a very small number of parameters to be configured. Indeed, the only parameter to define is the geometric distribution (i.e., β), which, according to Grasas et al. (2017) is uniformly selected in between 0.1 and 0.3 at each iteration. Regarding the calculation of the delay costs, the importance of each customer has been defined according to its demand, which is an input value already reported in the original benchmarks. Hence, in spite of predicting the costs corresponding to a certain delay and a certain importance of the customer, a linear regression has been trained on the historical data of the company. Hence, given a certain delay in servicing a specific customer, the estimated costs might be predicted using a linear model with intercept 5.42 and coefficients of 0.98 for the delay and 452.25 for the customer's importance.

The solutions provided by the simheuristic are compared to those obtained by *(a)* the heuristic version of the algorithm and *(b)* the biased-randomized algorithm for deterministic travel times described in Section 4. The comparison is made under three different levels of stochasticity, setting the standard deviation of travel times to 25 %, 50 %, and 75 % of the mean. For the sake of equality, the number of iterations of the simheuristic and the BRA have both been been set to 3,000. All results are reported in Table 1.

7 ANALYSIS OF RESULTS

As visible in Table 1 and reflected in Figure 3, the BRA improves with respect to the heuristic approach in terms of deterministic costs. This result is consistent, since both algorithms are built to optimize a deterministic problem and the BRA can reach solutions that the heuristic one cannot. However, this improvement may not happen under stochastic circumstances.

As shown in Figure 4, in a stochastic environment, the simheuristic algorithm improves the results with respect to the heuristic one and the BRA. The zero on the y-axis in Figure 4 represents the deterministic costs of the solution provided by the heuristic algorithm. Notice that the higher the variability in travel times, the higher are the stochastic costs of the solution. However, the simheuristic is always able to provide better solutions.

In order to further highlight the difference between a deterministic and a stochastic solution, a visual comparison is provided in Figure 5. Even if the solutions look similar, the simheuristic suggests an increased use of the third vehicle. As a matter of fact, in the deterministic solution, two vehicles are respectively used only to visit Customers 14 and 16. However, according to the solution provided by the simheuristic, this approach would have led to delays due to the dilatation in travel times.

Table 1: Results of the validation tests.

	Heuristic				Biased Randomized Algorithm				Simheuristic		
Instance	Variability 0 %	Variability 25 %	Variability 50 %	Variability 75 %	Variability 0 %	Variability 25 %	Variability 50 %	Variability 75 %	Variability 25 %	Variability 50 %	Variability 75 %
A-n32-k5	84	139	247	357	42	149	253	351	140	246	355
A-n38-k5	99	160	202	251	0	109	185	257	93	146	210
A-n45-k7	0	142	236	318	0	140	238	320	109	198	277
A-n55-k9	0	124	196	281	0	123	195	273	96	166	234
A-n60-k9	0	199	335	459	0	200	335	457	148	261	372
A-n61-k9	50	136	188	249	15	94	165	243	98	137	219
A-n65-k9	236	327	421	541	79	215	334	464	194	292	440
A-n80-k10	0	186	346	540	0	188	345	541	186	344	523
B-n50-k7	0	79	116	162	0	80	114	162	68	105	156
B-n52-k7	0	93	162	243	0	92	163	250	86	158	248
B-n57-k9	0	296	518	688	0	299	532	699	253	464	620
B-n78-k10	0	152	287	457	0	152	290	454	135	280	408
E-n22-k4	0	88	145	186	0	88	142	186	64	94	130
E-n30-k3	160	205	255	299	29	114	159	205	88	151	194
E-n33-k4	179	307	418	509	0	197	324	413	192	320	400
E-n51-k5	152	215	255	307	63	136	198	261	152	200	259
E-n76-k10	85	159	219	289	36	114	182	254	112	167	241
E-n76-k14	0	91	152	217	0	90	152	215	87	143	206
E-n76-k7	151	199	252	310	63	125	187	257	118	171	232
F-n135-k7	139	240	366	500	56	220	331	450	180	294	367
F-n45-k4	82	132	170	206	53	157	212	266	131	165	207
F-n72-k4	141	167	184	200	89	144	179	208	160	186	187
M-n101-k10	109	173	224	294	43	141	208	289	136	197	297
M-n121-k7	103	189	339	521	24	153	315	504	150	294	488
P-n101-k4	583	621	679	757	507	548	605	687	595	583	750
P-n22-k8	0	122	172	190	0	123	171	191	94	133	166
P-n40-k5	85	145	187	231	29	94	146	202	88	143	167
P-n50-k10	0	121	182	232	0	122	182	232	99	155	196
P-n55-k15	0	122	171	223	0	124	171	223	114	156	210
P-n65-k10	69	155	205	259	16	112	175	241	99	156	203
P-n70-k10	140	214	255	305	48	137	191	248	122	169	236
P-n76-k4	902	906	925	962	670	709	740	774	696	669	777
P-n76-k5	539	568	606	658	397	433	480	538	429	484	528

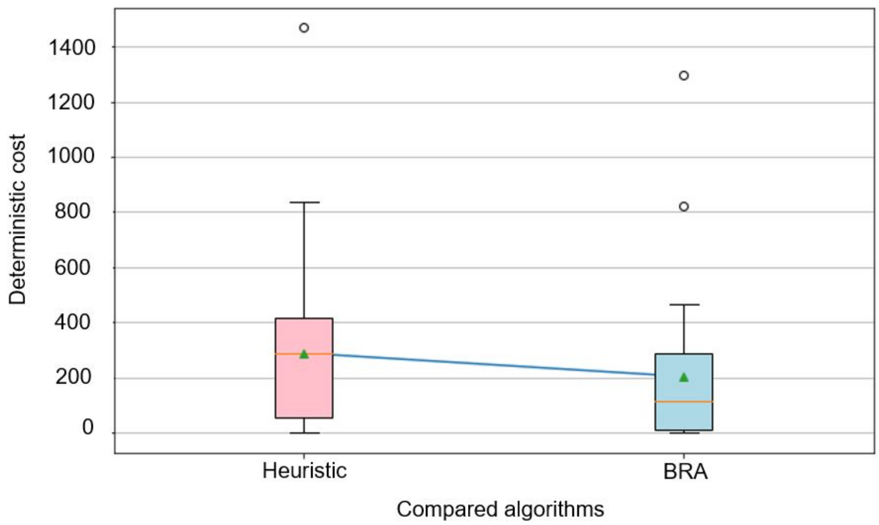

Figure 3: Deterministic costs comparison.

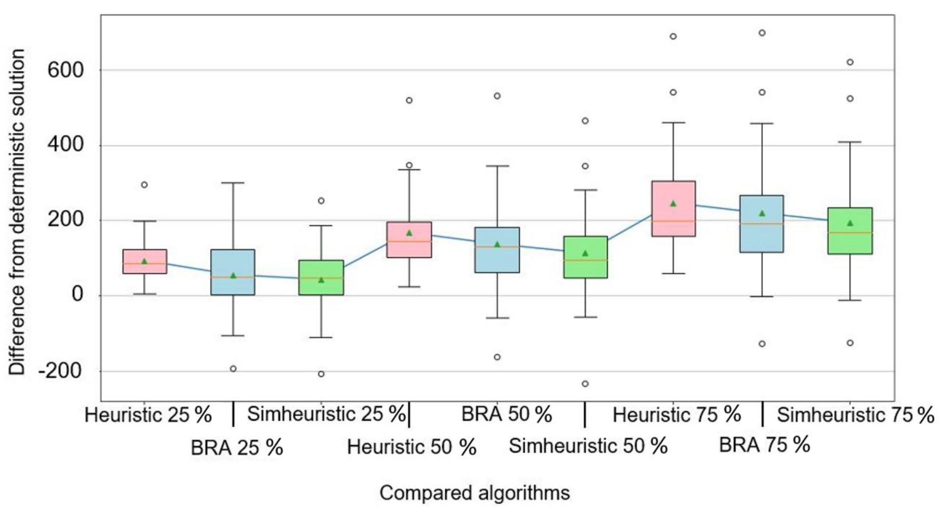

Figure 4: Stochastic costs comparison.

8 CONCLUSIONS

In this paper, a distribution problem related to a pharmaceutical supplier in Spain is considered, and an efficient algorithm able to deal with multiple vehicles, delivery time windows, and stochastic travel times is proposed. The time windows, as usual in real life, have not been considered as rigid constraints, although, their violation was involving an additional costs to be minimized. One of the novelties introduced by this paper consists in the way the delay costs are calculated. Indeed, the additional costs occurring every time a customer is visited outside its delivery time window depend on both the extent of the delay and the importance of the customer; in other words, the same delay involves greater costs when it takes place in correspondence of a more-important customer. The algorithm proposed has been validated over well-affirmed benchmark problems frequently used by the research community and has proven to be efficient and reliable. There are still several possible chances for improvement, and, in our opinion, the most promising

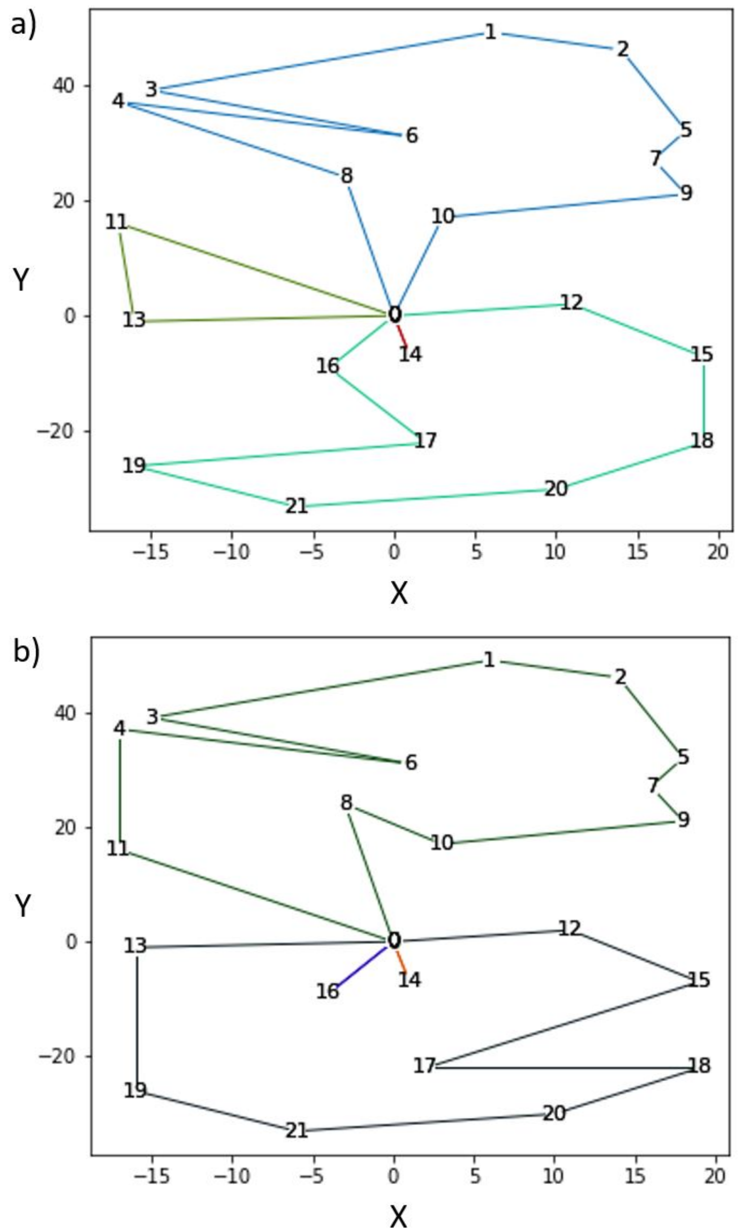

Figure 5: Visual comparison of a) a stochastic solution and b) a deterministic one.

ones are the following: *(i)* the extension of the analysis to more complex stochastic optimization problems and additional sources of uncertainty; *(ii)* the improvement of the algorithm incorporating the constructive procedure in a more complex meta-heuristic or improving the neighborhood search; *(iii)* the consideration of additional aspects in the comparison of stochastic solutions, such as the standard deviation, the quantiles, or the full probability distribution; and *(iv)* the application of the algorithm to a problem that resembles the real one for number of vehicles, time windows, and number of customers.

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