Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, eds.

SOLVING AN URBAN RIDESHARING PROBLEM WITH STOCHASTIC TRAVEL TIMES: A SIMHEURISTIC APPROACH

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ABSTRACT

Ridesharing and carsharing concepts are redefining mobility practices in cities across the world. These concepts, however, also raise noticeable operational challenges that need to be efficiently addressed. In the urban ridesharing problem (URSP), a fleet of small private vehicles owned by citizens should be coordinated in order to pick up passengers on their way to work, hence maximizing the total value of their trips while not exceeding a deadline for reaching the destination points. Since this is a complex optimization problem, most of the existing literature assumes deterministic travel times. This assumption is unrealistic and, for this reason, we discuss a richer URSP variant in which travel times are modeled as random variables. Using random travel times also forces us to consider a probabilistic constraint regarding the duration of each trip. For solving this stochastic optimization problem, a simheuristic approach is proposed and tested via a series of computational experiments.

1 INTRODUCTION

During the last decades, a great increase in mobility demand has been requested worldwide, making people's travels and goods movements much more frequent (Faulin et al. 2019). However, this demand cannot be always met, originating the concept of the sharing and gig economy. This concept is based on promoting collaboration among mobility agents, which, in turn, allows for reducing mobility cost while still satisfying the initial demand level (Sawik et al. 2017). Another important benefit created by collaboration and ridesharing practices is the reduction in pollutant emissions. This is especially the case when internal combustion vehicles (ICV) are employed (Fikar et al. 2016; Aloui et al. 2021; Brand et al. 2021), as it is still the case in many urban mobility operations. There are other mobility trends, such as ride-hailing – defined as the request for a car and driver to come immediately and take the customer to a previously fixed place – that result in more comfortable trips, while also reducing parking requirements. Nevertheless, this type of mobility reduces congestion only partially. It is a mere substitute for public transportation, without reducing greenhouse gas emissions at a significant level (Tirachini 2020).

According to the Oxford English Dictionary (Pearsall et al. 2010), carpooling is defined as 'a group of car owners who take turns to drive everyone in the group to work, so that only one car is used at a time'. This concept has evolved to a broader one, in which people who might have never met before, share vehicle journeys in exchange for a fee, with no additional paybacks. Due to the social consciousness about promoting sustainability in all transportation means, which includes the need for reducing greenhouse gas emissions, carsharing has gained enormous popularity during the last years (Faulin et al. 2019). Furthermore, it has shown many social benefits associated with a positive impact on infrastructure, congestion, and energy consumption. Thus, the shared mobility for people is an advantageous approach in big cities, which usually present expensive prices and a high level of transportation demand. One of the options to implement shared mobility is carpooling. In this modality, people can make use of lower prices and achieve less pollution (Dolati Neghabadi et al. 2019). One of the most recent studies on the impact of carpooling in city logistics has been developed by Dolati Neghabadi et al. (2021), who analyze the influence of operational constraints in the use of shared cars to reach smarter mobility. If we perform an insight on the future of mobility, it is clear that collaboration and new technologies are going to assume key roles in the design of new mobility procedures. Thus, carpooling and ridesharing will be located in the core of the new transportation paradigms (Muñoz-Villamizar et al. 2017; Gansterer and Hartl 2018). Mobility is going to be part of a shared activity performed by people in an interconnected way, with a high standard of service quality. Consequently, the optimization of the trip selection and the vehicle assignment in the cases of carpooling and ridesharing is revealed as essential to improve the customer experience in these scenarios (Martins et al. 2021). In the following twenty years, the new mobility paradigm is going to be strongly based on connected autonomous vehicles (CAVs) (Lin et al. 2021), which need to have all their parameters tuned in order to reach the efficiency searched in a smart city. Thus, this profile of excellence in mobility will only be achieved by suitable optimization models that describe stochastic scenarios, such as the ones presented in this paper. Figure 1 shows the difference between ridesharing and carpooling. While in the former a vehicle is picking up different customers on its way to the destination, in the latter all passengers typically depart from a single origin.

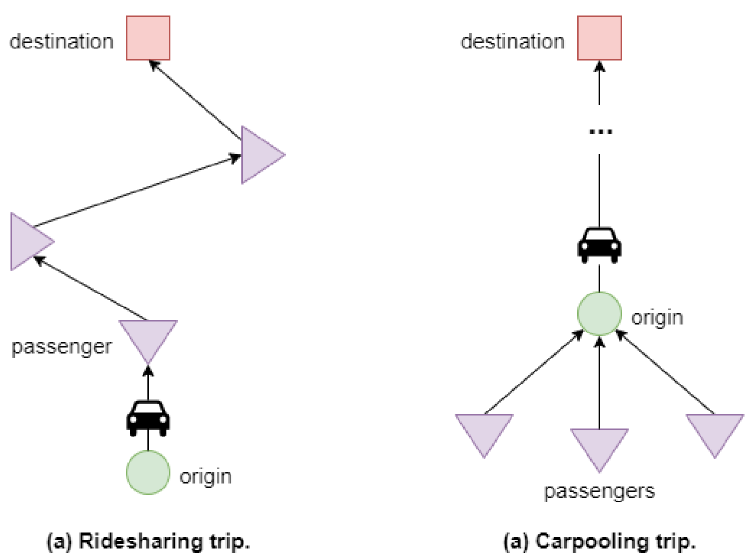

Figure 1: Illustrating the ridesharing and carpooling concepts.

In this work, we model and solve an urban ridesharing optimization problem (URSP), where a set of drivers have to select and pick up a set of passengers on their way to a destination location. Each passenger will have to pay a fee for the trip (driver's reward). Hence, the goal is to maximize the total collected reward, while taking into account constraints regarding the number of available vehicles, their loading capacities, and the target times (i.e., the maximum time at which each vehicle has to reach its destination). As a novelty, we consider random travel times, so the optimization problem becomes more realistic but also stochastic and increasingly challenging. In order to solve it, we propose a simheuristic algorithm (Chica et al. 2020), which also allows us to study the reliability of each proposed solution.

The remaining sections of the paper are structured as follows: Section 2 briefly reviews related articles, while Section 3 defines and introduces the problem to solve. Section 4 describes the proposed simheuristic algorithm and its structure. Section 5 carries out a series of computational experiments to illustrate the performance of the proposed algorithm. The results are discussed in Section 6. Finally, the main findings and future research lines are given in Section 7.

2 RELATED WORK ON RIDESHARING PROBLEMS

Ridesharing has been shown to offer several benefits including the reduction of cars on the roads and, hence, traffic congestion, better utilization of seats, and reduction in carbon dioxide emissions. Due to these benefits, ridesharing has received considerable attention in the academic community. There are mainly three different forms of ridesharing: In the first form, which is called static ridesharing, all passenger requests are known before the trip starts. In the second form, the passenger requests are dynamic, where passengers are added to the trip en-route. The final form assumes that passenger requests can be stochastic. Several realistic variants of these forms have been studied. We refer the reader to Martins et al. (2021) for a comprehensive review on ridesharing systems, their variants, and applications.

From an optimization point of view, because ridesharing problems are NP-hard, exact methods are used for smaller instances while metaheuristic methods are employed for larger instances. Agatz et al. (2011) are among the first to offer an exact method based on a rolling horizon strategy for a dynamic single-ride carsharing system, where the drivers and providers are matched with the goal of maximizing the providers' profit. Hosni et al. (2014) propose a Lagrangian decomposition method for a ridesharing system with multiple vehicles where both assignments of passengers to vehicles and the route for each vehicle are optimally determined. Later, Naoum-Sawaya et al. (2015) propose an exact integer programming model to solve a stochastic ridesharing problem where the stochasticity originates from the potential unavailability of vehicles when the request arrives. Li et al. (2018) also used a mixed-integer programming approach to solve an enhanced ridesharing system that considers meetup points for passengers and their preferable time windows. Recently, Li and Chung (2020) considered a more realistic variant with travel time uncertainties. Thus, the authors firstly presented a novel deterministic formulation for the ridesharing problem and formulated it as a mixed-integer optimization problem. Because of the long computational time needed to solve this problem even with 44 nodes, the authors proposed a hybrid heuristic method that uses an insertion algorithm in conjunction with a tabu search method. Other studies that use exact methods to solve several variants of ridesharing systems include Masoud and Jayakrishnan (2017) and Chen et al. (2019).

Among the heuristics approaches employed to solve ridesharing problems are tabu search (Li et al. 2018), local search (Chen et al. 2019), genetic algorithms (Schreieck et al. 2016), greedy randomized adaptive search procedures, and their hybrid versions where two or more methods are used in conjunction with each other. For example, Jung et al. (2016) combine a nearest vehicle dispatch algorithm, a hybrid-simulated annealing, and an insertion heuristic to solve a dynamic shared taxi dispatch problem. Li and Chung (2020) combine an insertion algorithm with a tabu search method to solve a ridesharing problem with stochastic travel times. Other methods to solve ridesharing problems include dynamic simulation. Finally, Long et al. (2018) consider a ridesharing problem with time-dependent travel time uncertainty and employ Monte-Carlo simulation (MCS) to estimate the trip cost and departure time.

3 PROBLEM DESCRIPTION

We consider an urban ridesharing problem that arises in smart cities. The network of this system can be represented by a graph $G = (V, A)$, where V comprises a set of origins O, a set of destinations D, and a set of pick-up locations P. Each node $v \in V$ has a specific location defined by coordinates (x_v, y_v). The set of arcs is represented by A, where each arc $(i, j) \in A$ is associated with a transportation cost $c_{ij} > 0$, measured in distance units or transportation time. Each driver $c \in C$ and its private vehicle $v \in V$ are associated with a single origin $o \in O$ and a single destination $d \in D$. Each vehicle $v \in V$ has an initial capacity of Q_v, which is defined by the number of vacant seats. At the beginning of the plan ($t = 0$), each vehicle $v \in V$ is available at one of the origins and must reach its destination on or before a pre-established arrival time, at_v.

Each pick-up location $p \in P$ is associated with a number of passengers n_p (who are available at time $t = 0$) to be picked up, with a specific destination, and a reward r_p to be offered to the driver (driver's fee). This reward is proportional to the distance between the passenger's pick-up point and the destination point. In order to maximize the system's utilization, each driver can pick up multiple passengers, as long as the vehicle capacity and the latest allowed arrival time are not violated. A solution to the URSP consists of a set of vehicle routes R ($|V| = |R|$), each route being associated with a single vehicle, driver, origin, destination, arrival time, and, finally, with a set of passengers. The goal is to maximize the total reward collected by the set of drivers while satisfying the established deadlines and capacity constraints of each vehicle. However, delays in the destination arrival time might generate a reduction in the collected rewards. These delays might appear when considering random travel times, and might also generate route failures, which affect the reliability of the proposed routing plan. The reliability is defined as the probability that a routing plan can be implemented as designed, under a stochastic scenario, without suffering any route failure. This reliability will also be estimated using simulation.

The deterministic version of the URSP refers to the case in which travel times between nodes are predetermined and, hence, not affected by any external factor (e.g., traffic status, zone, peak times. etc.). This assumption is often employed in the literature, despite it is not realistic. To cover this gap, we model travel times as random variables, thus transforming the deterministic URSP into a stochastic one. Since travel times are now stochastic, it is not guaranteed that vehicles will be able to reach their destinations on or before a given target time. However, we can consider a probability constraint, i.e., a constraint forcing our solution to satisfy all target times in the routing plan with a certain probability α.

Figure 2 depicts a graphical presentation of a simple URSP. A set of 14 pick-up locations $(p_1, p_2, \ldots, p_{14})$, four origins (o_1, o_2, o_3, o_4), and two destinations (d_1, d_2) is considered. Each node from this network is characterized by a tuple that defines, at each time, the passenger reward, the number of passengers to be picked up, the remaining number of available seats, the total collected reward, and the accumulated travel time. For instance, vehicle v_1 departs from origin o_1 with four available seats. It travels 15 minutes to pick-up two passengers at location p_3. Each of these passengers pays 30 euros for reaching destination d_1 on or before the target time. Next, vehicle v_1 travels ten additional minutes to pick up two additional passengers at location p_2, which consume the vehicle's loading capacity. Departing from p_2 with a total of 90 euros, the vehicle heads towards destination d_1, where the boarded passengers are dropped off. A similar process can be found in the other routes of this routing plan (solution). Passengers at the locations p_1, p_8, p_9, p_{11}, and p_{12} are not collected due to the constraints in time and vehicles' capacities.

4 SIMHEURISTIC APPROACH

To solve the urban ridesharing problem with stochastic travel times, we propose an 'agile' two-stage simheuristic algorithm capable of providing good-quality solutions in a few minutes even for large-scale URSP instances. Agile optimization techniques are crucial for real-time decision-making problems. They combine the use of biased-randomized heuristics (Belloso et al. 2019) with parallel computing in order to cope with large-sized dynamic combinatorial optimization problems. These algorithms are designed to be fast in execution, simple in implementation, easy to tune, and flexible. In addition, simheuristics are a special type of simulation-optimization algorithms that combine simulation techniques with metaheuristics to tackle stochastic combinatorial optimization problems (Ferone et al. 2019). Depending on the characteristics of the system under consideration, simheuristics include a MCS (Gruler et al. 2020) or a discrete-event simulation

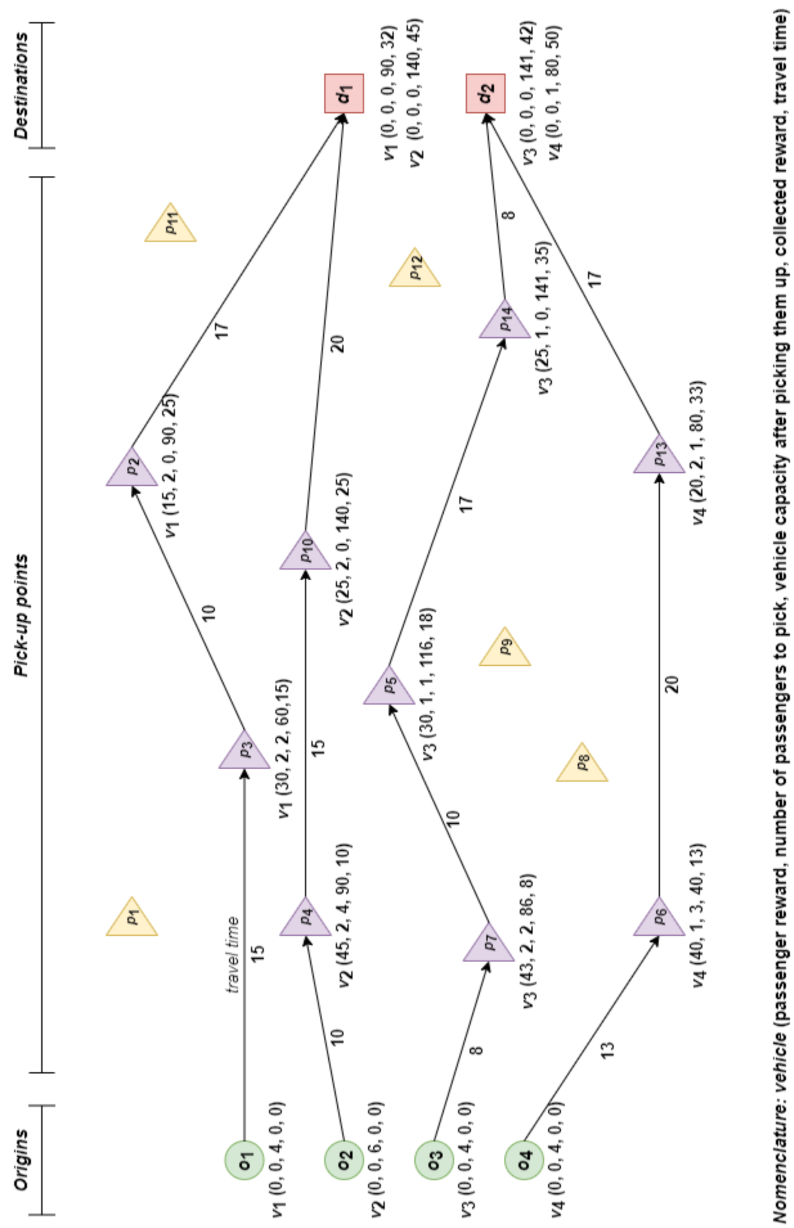

Figure 2: A visual representation of the URSP.

(Rabe et al. 2020). The algorithm employed in this case to solve the URSP with stochastic traveling time is described in two steps: First, the complete problem instance is divided into small sub-problems (clusters of nodes). Each of these sub-problems includes all customers associated with a given destination point. Different sub-problems might share some of the pick-up locations. Second, for each sub-problem an extended savings heuristic is applied (Panadero et al. 2020). This heuristic relies on the following steps:

- Generate a dummy solution, where one feasible route is created for each pick-up point, i.e., the vehicle departs from the origin, visits the pick-up node, and then travels to the destination.
- Build a savings list of edges, where the savings associated with an edge connecting locations i and j is computed as $savings_{ij} = \alpha(c_{in} + c_{0j} - c_{ij}) + (1-\alpha)(u_i + u_j)$, being $\alpha \in (0,1)$ an algorithm parameter, c_{ij} the traveling time between i and j, n the destination node, 0 the origin, and u_i, u_j the associated rewards at each node. Therefore, these savings consider both travel times as well as the aggregated reward obtained by visiting both locations.
- Sort the list of edges in descending order of savings value.
- While the list is not empty, start an iterative merging process; in this process, the edge at the top of the list (i.e., the one offering the highest savings) is chosen, and the two associated routes are merged as far as the resulting route reaches the destination on or before the deadline and the vehicle capacity is not exceeded.

The described heuristic is deterministic, i.e., the top element of the savings list is always selected for the next possible merge. In order to introduce a non-uniform randomization process, we extend this heuristic into a biased-randomized approach (Quintero-Araujo et al. 2017). Biased-randomized algorithms transform a deterministic strategy into a probabilistic one without losing the logic behind the original heuristic. This is achieved by employing a skewed probability distribution instead of a uniform one. In our case, we have employed the geometric distribution, which makes use of a single parameter $\beta \in (1,0)$. While values of β close to 0 emulate a uniform random selection, values of β close to 1 perform in a greedy way. Of course, intermediate values are capable of generating selection mechanisms that are nor greedy nor uniform. Consequently, different alternative solutions might be generated whenever the biased-randomized heuristic is utilized (Juan et al. 2009). In this way, the biased-randomized heuristic is repeated for a pre-defined number of iterations or computational time, resulting in a multi-start approach (Martí et al. 2013). Thus, several feasible and 'good' solutions are generated, and the one with the highest collected reward is returned.

The simulation layer is incorporated into the previous biased-randomized multi-start (BRMS) approach. By doing so, the extended algorithm becomes able to cope with the existence of random travel times. In particular, we combine the BRMS metaheuristic with MCS to deal with the stochastic nature of the problem. For each vehicle route generated by the biased-randomized savings heuristic, a series of calculations are performed in order to replace the given (deterministic) travel times with the calculated (random) stochastic ones. In our numerical experiments, the given deterministic travel times are replaced by random values following a log-normal probability distribution whose expected value is given by the deterministic traveling time. In this way, the simulated travel times between a pair of nodes can be smaller or greater than the deterministic ones. Based on these new values, whenever a vehicle reaches its destination point with a delay, a penalty cost is applied to the collected rewards. The simulation process also allows us to measure the estimated reliability of a given solution, i.e., the probability that a proposed solution can be satisfactorily implemented in a real-life scenario without suffering from delays in the arrival times of its routes.

5 COMPUTATIONAL RESULTS

Our simheuristic algorithm was implemented as a Python application. The experiments were conducted on a personal computer with an Intel Core i7-8550U processor and 16 GB of RAM. Since there are no publicly available benchmark instances for the URSP with random travel times, we generated a new set of instances for testing the proposed approach. These instances are composed of a set of different origins, different destinations, and several locations where passengers can be picked up. The coordinates for each pick-up location, the driver's fee, and the number of passengers to be picked up, follow uniform distributions in the range $[1,85]$, $[10,40]$ and $[1,2]$, respectively. Each instance is composed of six origins, two destinations, and 64 pick-up locations. Each origin is associated with a vehicle, which has a maximum number of available seats. For each instance, there are two vehicles of four, six, and eight empty seats. Each origin and pick-up location is characterized by one of the destinations. Likewise, each pick-up location is associated with different passengers that have applied for a ride from there to their destination point. The maximum traveling time is set as 100 time units.

Regarding the algorithm parameters, we have set β to be randomly selected in the interval $(0.1, 0.3)$, following the methodology proposed by Calvet et al. (2016) for parameter fine-tuning of metaheuristics. The number of simulation runs executed for each route is set to 100. For penalizing rewards when a delay occurs, we have defined the following rules: For delays greater than 5, 15, and 30 minutes, a reduction of 20 %, 40 %, and 100 % of the collected rewards is applied, respectively. Of course, these are only experimental values for testing our approach, and other values could also be defined by the manager depending on the particular conditions of each real-life case. Regarding the α parameter for the savings calculation, we have first executed the deterministic heuristic with all α values in the set $\{0.00, 0.05, 0.10, .., 0.90, 0.95, 1.00\}$. Then, we have selected the one providing the best solution and used it for the biased-randomized algorithm as well as for the simheuristic one. For each sub-problem, the simheuristic is executed during ten seconds. In order to generate the stochastic and positive travel times, we have employed a log-normal probability distribution with mean $E[C_{ij}] = c_{ij}$ and variance $Var[C_{ij}] = 50$, respectively.

Table 1 presents the results obtained by our simheuristic. For each instance, the following information is offered: the vehicle (route) identification, the total collected reward of the best-found solution under a deterministic scenario *(bestDet - d)* as well as the collected reward provided by this solution when it is executed in a stochastic scenario *(bestDet - s)*, and the solution obtained by our simheuristic for the stochastic scenario *(bestStoch - s)*. Finally, for each solution type, we also provide its associated reliability level.

For Instance 3, Figure 3 depicts the routes sequence for both the deterministic and stochastic solutions. The origins are shown in black, while destinations are presented in red. The locations in 'ghost white' represent the passengers who are not picked up by the drivers due to a lack of vehicle capacity or lack of time in the current route.

6 ANALYSIS OF RESULTS

As it can be observed in Table 1 and Figure 4, the solutions obtained for the deterministic version of the URSP, *(bestDet - d)*, offer the best overall behavior, achieving an accumulated reward of 3362 when considering all four instances. However, when these routing plans are executed in a scenario under uncertainty (i.e., one with random travel times), they are clearly sub-optimal solutions, since they are outperformed by our simheuristic approach, both in aggregated reward (2768.0 versus 2947.7) as well as in terms of reliability level (0.66 versus 0.74). As one can suspect from Figure 4, there are no statistically significant differences among the three solutions (actually, an ANOVA test returns a p-value of 0.270). Still, this is frequent when comparing solving approaches in many optimization problems, where relatively small differences might be measured between a near-optimal solution and a sub-optimal one. Of course, as the level of uncertainty considered is increased, these differences will tend to grow larger, and eventually, they might easily become statistically significant.

7 CONCLUSIONS AND FUTURE WORK

This paper analyzes the urban ridesharing problem with random travel times. In this problem, a given set of vehicles, departing from different origins (e.g., drivers' homes in the metropolitan area), are employed

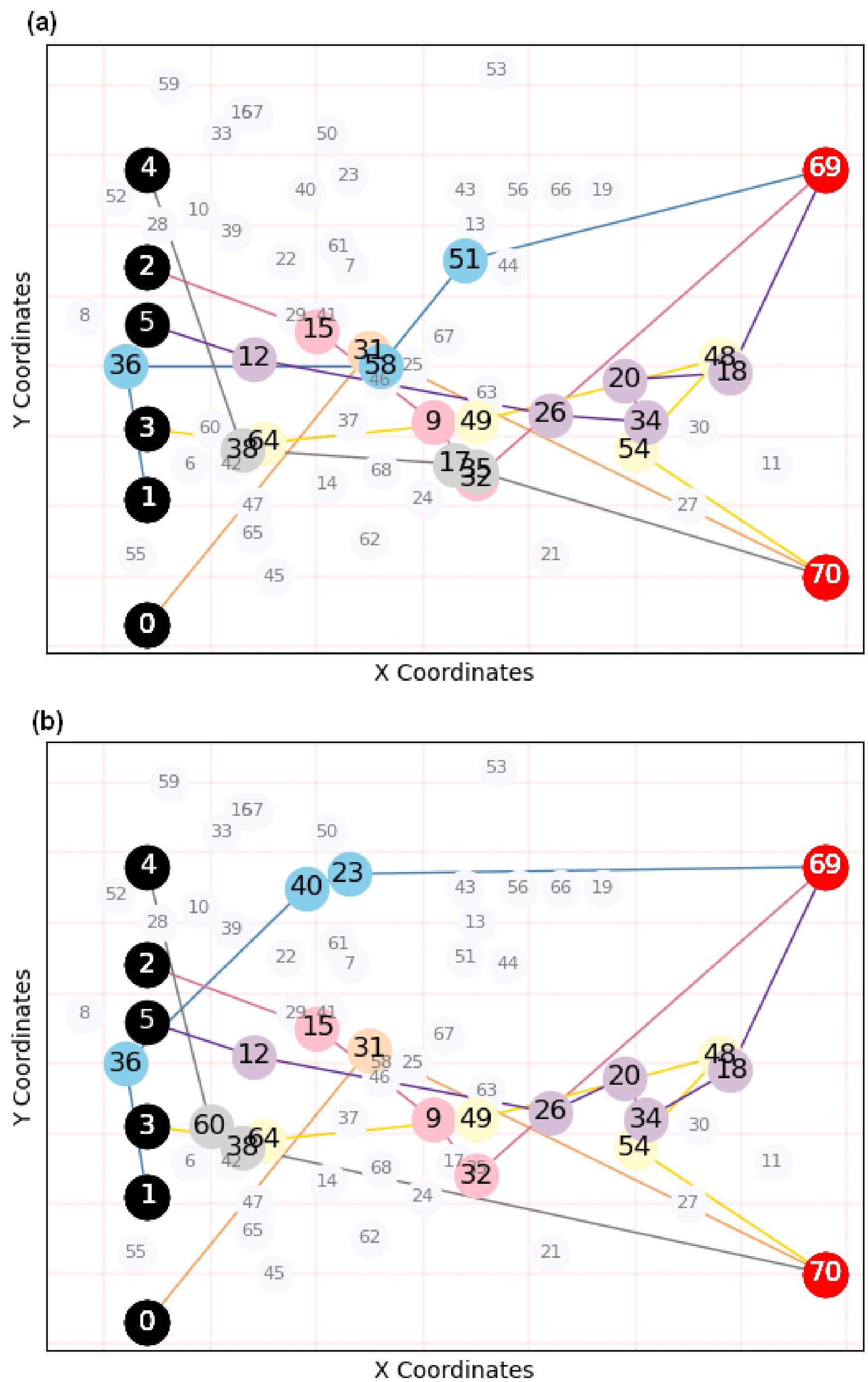

Figure 3: Solution routes: a) Best deterministic solution; b) Best stochastic solution.

Table 1: Solution cost per shared vehicle.

		Collected Reward			*Reliability (%)*	
		bestDet (d)	**bestDet (s)**	**bestStoch (s)**	**bestDet**	**bestStoch**
Instance 1	**vehicle 0**	158	137.8	141.7	99	100
	vehicle 1	126	101.7	107.9	77	84
	vehicle 2	181	143.2	156.8	48	64
	vehicle 3	176	150.7	155.8	78	78
	vehicle 4	171	141.7	151.3	50	67
	vehicle 5	133	110.2	116.9	58	62
Instance 2	**vehicle 0**	145	121.3	125.9	59	69
	vehicle 1	128	107.1	114.3	90	93
	vehicle 2	84	69.0	75.6	67	80
	vehicle 3	132	106.6	107.1	59	66
	vehicle 4	65	55.6	58.8	66	76
	vehicle 5	234	186.0	201.7	64	69
Instance 3	**vehicle 0**	22	18.8	20.2	65	72
	vehicle 1	112	92.8	94.8	62	62
	vehicle 2	154	124.3	140.3	54	73
	vehicle 3	151	120.0	132.5	59	67
	vehicle 4	84	71.2	75.9	58	64
	vehicle 5	244	193.6	212.3	62	72
Instance 4	**vehicle 0**	154	131.6	138.3	76	76
	vehicle 1	133	107.9	118.8	68	80
	vehicle 2	212	174.7	186.0	79	88
	vehicle 3	28	23.2	25.5	62	73
	vehicle 4	88	73.2	79.8	54	67
	vehicle 5	247	205.9	209.6	64	68
			Total		**Average**	
		3362	2768.0	2947.7	66	74

to pick up passengers at certain pre-established locations along the road and ride them to their destination points (e.g., different city areas). The destination points need to be reached before a target time, and the vehicles' capacity has to be respected at any time. Each passenger pays a fee for the service, which constitutes the driver's reward. Hence, the goal is to maximize the total collected reward subject to the previously mentioned constraints. To make the problem more realistic, we consider its stochastic version, where travel times are modeled as random variables. By introducing these uncertainty factors, delays might occur in the planned routes. Depending on their magnitude, these delays might cause partial or total loss of the collected reward.

To deal with this stochastic urban ridesharing problem, we first propose a heuristic for the deterministic version. This heuristic is then extended into a biased-randomized algorithm and, finally, into a simheuristic. The latter is capable of taking into account the uncertainty conditions in the system. A series of computational experiments shows how the deterministic routing plan might become easily sub-optimal when it is employed in a stochastic scenario. Hence, the simheuristic is needed in order to provide good-quality and more-reliable solutions in relatively short computing times. Although our solution method being applied in a few small- or medium-sized instances, their use showed the potential of not only providing drivers with efficient operating plans, but also passengers with better services when applied to real-world scenarios, which opens up many possibilities for future work.

This work can be extended in different ways. To start with, we could also consider larger instances, random pick-up times, or changes in the routing plans generated by unexpected disruption in the city traffic network. Under these dynamic environments, it might become necessary to frequently re-optimize the trajectories of each driver, which might require an even more agile and distributed approach than the one presented here. Another aspect to be considered refers to minimizing the difference between the

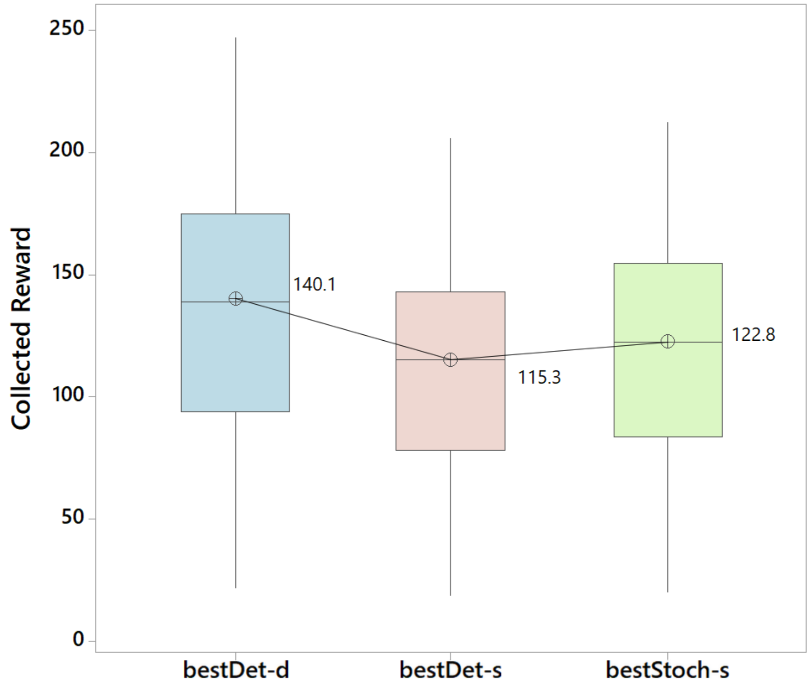

Figure 4: Rewards provided by each solution under deterministic and stochastic scenarios.

less and more profitable vehicle routes of the solution. In other words, apart from maximizing the total rewards collected by all vehicles, promoting the balance between the routes would generate satisfactorily good working environments for drivers. Further future lines of research include the enhancement of our simulation model, for instance, by considering different probability distributions to model the stochastic variables, as well as increasing the number of simulations to be performed.

ACKNOWLEDGEMENTS

This work has been partially funded by the Spanish Ministry of Science (PID2019-111100RB-C21-C22 /AEI/ 10.13039/501100011033 and RED2018-102642-T), and the Erasmus+ Program (2019-I-ES01-KA103-062602).

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