Optimizing Ride-Sharing Operations in Smart Sustainable Cities: Challenges and the Need for Agile Algorithms

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ABSTRACT

Mobility solutions like ride-sharing and carpooling are becoming popular in many urban and metropolitan areas around the globe. These solutions, however, create many operational challenges that need to be solved in order to make them more efficient and sustainable in time, e.g.: determining the number and location of parking slots, finding the optimal routes in terms of time or emissions, or developing synchronized schedules among ride-sharing users. This paper provides an updated review on car-sharing optimization studies (including ride-sharing and carpooling), compares different analytical approaches in this research area, and discusses the emerging concept of 'agile' algorithms as one of the approaches that might contribute to deal with the requirements of large-scale and dynamic car-sharing optimization problems.

KEYWORDS

Ride-sharing optimization, carpooling, simulation, metaheuristics, real-time optimization, smart sustainable cities.

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1. Introduction

Transport and logistics (T&L) activities represent a key sector in modern societies, and they significantly contribute to their social and economic progress. At the same time, the raise of the on-demand economy (services) and the e-commerce activity (products) has boosted the number of pick-ups and deliveries in urban, metropolitan, and peri-urban areas. Thus, there is a need for increasing the effectiveness and sustainability of T&L activities and policies (Cui et al., 2020). Due to the increasing number of people who live in urban areas, many local and regional governments realize that T&L activities will play a major role in the development of the so-called smart sustainable cities (Bibri and Krogstie, 2019). Large quantities of data are gathered in real-time via electronic devices located inside vehicles and infrastructures (computer chips, sensors, traffic cameras, drones, etc.), transmitted over the Internet, and analyzed through information and expert systems (Mehmood et al., 2017). Monetary, environmental, and social costs associated with single occupancy vehicles could be reduced by more efficient utilization of empty seats in personal transportation vehicles. This is the goal of carpooling and ride-sharing strategies, which, apart from generating substantial economic impact to users, aim at reducing the number of vehicles on the road and, as a consequence, contribute to diminishing traffic and pollution (Bistaffa et al., 2019). According to Schrank et al. (2019), the annual cost of congestion in the United States (U.S.) achieved \$ 166 billion in 2017, which caused Americans to lose around 8.8 billion hours on sitting in traffic and purchase an extra 3.3 billion gallons of fuel. Environmentally speaking, transportation counted for about 28% of total carbon dioxide-equivalent emissions (CO_2e) in the U.S. in 2018, being light-duty vehicles responsible for 59% of them (United States Environmental Protection Agency, 2020). In Europe, on the other hand, transportation was responsible for almost 30% of CO_2e in 2016, of which 72% comes from road transportation. Particularly, cars are responsible for almost 61% of these 72% of gas emissions (European Environment Agency, 2019). In an effort to minimize related problems, such as greenhouse effects and global warming, the European Union developed a strategic plan for low-emission mobility. As stated in European Commission (2016), one of the main elements on which this strategy relies on refers to increasing the efficiency of the transport system by benefiting from digital technologies, smart pricing, and further encouraging the shift to lower emission sustainable transportation modes. Therefore, the need for smarter and sustainable transportation modes is clear, whose development has been possible thanks to recent advances in communication and information technologies.

Carpooling and ride-sharing are two of the main peer-to-peer (P2P) services in car-sharing. PSP services followed the diffusion of smart-phone technology and social networking websites (Prieto et al., 2017), transforming car-sharing services into an international transportation trend. Such services rely on sharing privately owned vehicles for a particular trip in the surrounding area on an hourly or daily basis (Ballús-Armet et al., 2014).

The seminal studies regarding the use of ride-sharing systems are dated to 70s. According to Kornhauser et al. (1977), the first motivation for adopting a ride-sharing system was the fuel crisis of 1973 in the U.S., and the scarcity of federal funds for implementing new urban transport facilities. At the time, the increase of vehicles' utilization in private transport represented the most obvious target for improving the systems' efficiency without constructing new physical facilities. Since the work of Kornhauser et al. (1977), the use of ride-sharing systems has been studied and gained considerable attention from researchers. Different types of ride-sharing can be identified in the literature: *(i)* ride-sharing with static requests –in which all requests are known before the trip starts (Yu et al., 2019); *(ii)* ride-sharing with dynamic requests –where new requests can be added during the execution of the transport service (Simonetto et al., 2019); and *(iii)* ride-sharing with either deterministic or stochastic requests (Long et al., 2018). Researchers around the world have studied many variants and real-life applications in cities such as New York (Schaller, 2017), Atlanta (Agatz et al., 2011), Rome (Naoum-Sawaya et al., 2015), Beijing (Ma et al., 2013), or Tokyo (Do et al., 2016). Several optimization techniques have been used to solve ride-sharing problems, including exact and approximate methods, as well as agent-based and dynamic simulation. Also, surveys on the different variants and applications of ride-sharing problems can be found in Furuhata et al. (2013a) and, more recently, in Mourad et al. (2019). Because real-world problems are often dynamic and large-scale, car-sharing related problems are challenging. According to Borcuch (2016), a challenging task in developing car-sharing systems in real-world is the scaling of the shared-transportation problem-solving approach, in order to solve large-scale problems, like those required in real-life, where over thousands or millions of requests should be assigned.

Considering the aforementioned, the main contributions of this paper can be summarized as follows: *(i)* we provide a review of recent works on optimization problems related to ride-sharing and carpooling, classifying them according to the employed solving methodology (i.e., either exact, approximate or simulation methods); *(ii)* from the previous review, the main challenges are identified, specially in the context of smart and sustainable cities –including the increasing trend in considering self-driving and electric vehicles; and *(iii)* the concept of 'agile' optimization is discussed. Agile optimization algorithms are able to provide high-quality solutions in real-time by combining biased-randomized algorithms (Grasas et al., 2017) with parallel computing (Malapert et al., 2016). By taking advantage of these two approaches, the resulting methodology is capable of efficiently responding to every piece of new information that is being continuously incorporated into the system.

The remainder of this paper is structured as follows: Section 2 defines the car-sharing activities addressed in this work. Section 3 describes the main research questions as well as the review methodology employed in this study. Section 4 reviews the use of exact methods in ride-sharing optimization problems. Sections 5 and 6 complete a similar review for the case of metaheuristics and simulation approaches, respectively. Section 7 provides a performance analysis of ride-sharing systems by analyzing different case studies. Section 8 discusses challenges, identified in the car-sharing literature, that are related to synchronization and coordination. Section 9 do the same for those challenges related to the use of self-driving and electric vehicles. Section 10 present some research opportunities related to ride-sharing logistics and the consideration of uncertainty scenarios, while Section 11 performs a similar analysis for vehicle technical characteristics and sustainability issues. Section 12 discusses how the combination of metaheuristics with other methodologies (*x-heuristics*), such as simulation or machine learning, can be useful to deal with ride-sharing problems under uncertainty and dynamic conditions. It also discusses the concept of ‘agile’ optimization in the context of ride-sharing problems. Finally, Section 13 highlights the main findings of this work.

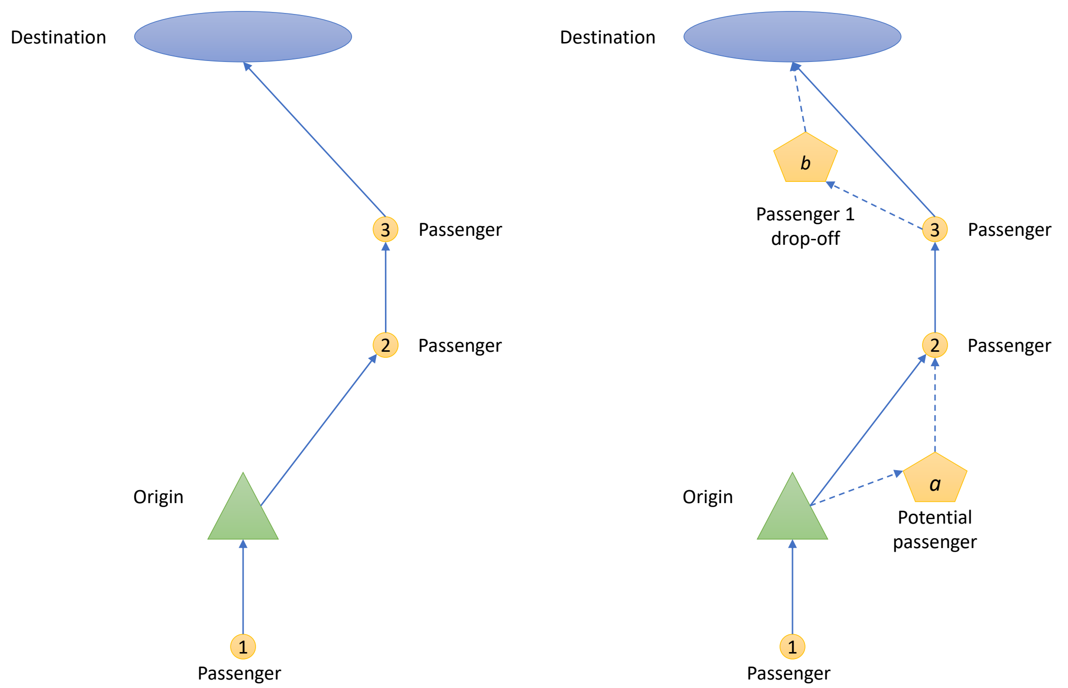
2. Car Sharing Activities

With the rise of mobile technology, car-sharing services have become an international transportation trend that holds the capability of significantly reducing congestion on the roads, diminishing traffic and pollution, and other externalities caused by the individual transportation. At the same time, these P2P systems allow users to accomplish several transportation goals, which include economic (e.g., costs reduction) and convenience interests (e.g., flexibility and speed), by allowing drivers and riders to share the associated costs (e.g., fuel, tolls, parking fees) so that each benefits from the shared ride (Stiglic et al., 2015). Although both systems allow users to travel together and share transportation costs, carpooling often limits users to consistent schedules. It also fixes riders to the same place at the same time. Consequently, the full potential of prearranged carpooling is often constrained by these operational limitations (Kornhauser et al., 1977). Ride-sharing, on the other hand, allows for more flexible schedules and locations. In both carpooling and ride-sharing services, users share rides provided by drivers, who are participating individuals that operate with their private vehicles. Both services charge passengers with a fee to share the ride. the following two sections discuss ride-sharing and carpooling services in more detail.

2.1. Ride-sharing

By being an automated process in which a service provider matches travelers with similar itineraries and time schedules to share a ride on short-notice in a personal vehicle, ride-sharing systems are naturally dynamic (Prieto et al., 2017). Their complexity relies mainly on matching individuals subject to spatiotemporal constraints, which must be specified from both parties –i.e., drivers and users– before the desired ride is established and executed. On the one hand, passengers request a ride at a specific time, from a specific origin to a specific destination. On the other hand, drivers have a fixed trajectory and departure time. Consequently, ride-sharing systems require certain sort of flexibility since deviations might be needed at different points on the trajectory in order to pick up and drop off passengers, as long as these detour distances do not exceed the driver's distance tolerance (Cici et al., 2015).

Figure 1 presents an illustration of a ride-sharing trip. In Figure 1a, solid lines represent the fixed trajectory of the driver, in which passenger 1 walks to driver's origin, and passengers 2 and 3 are picked up during the driver's trajectory to destination. Figure 1b represents an extension of the previous one, where dashed lines represent possible detour deviations that might occur, for instance, in order to: *(i)* pick up a passenger (the passenger a); and/or *(ii)* drop off a boarded passenger (the passenger 1) at a location which is different from the driver destination (location b). These two detours are done by considering a maximum threshold of locomotion. From the passengers' point of view, this process implies a wait until the driver's latest departure time.



(a) Driver trajectory with no extra detours to pick up and/or drop off passengers.

(b) Driver trajectory with possible deviations to pick up and/or drop off passengers.

Figure 1.: A visual representation of two possible ride-sharing rides.

2.2. Carpooling

Unlike ride-sharing activities, carpooling rides are less flexible activities that aim to transport simultaneously several people from a common starting point to a common end point (Nechita et al., 2016), with the main goal of saving money. These services encourage commuters who are moving in the same direction to share private vehicles (Duan et al., 2018). According to Nechita et al. (2016), the most usual situation of carpooling occurs when neighbors work at the same facility and agree to travel using only one car in order to share the travel expenses. Two variants of such carpooling exist: (a) the pools sharing a ride to work also share the same ride returning from work back home, and (b) both *to-work* and *return-from-work* are treated as different problems, and, hence, must be solved independently (Baldacci et al., 2004).

In carpooling systems, by fixing both the origin and destination locations that define the trajectories, riders are fixed to be at the same place at the same time before starting the ride. Therefore, users are limited to consistent schedules. In these systems, the origin and destination are announced by the drivers, and no deviations, pick-ups, or drop-offs are allowed during the execution of a ride. According to Stiglic et al. (2015), the use of meeting points in car-sharing, such as those from carpooling activities, increases the feasible matches between drivers and riders, apart from allowing the driver to be matched with multiple riders without increasing the number of stops the driver needs to make. In Figure 2, a carpooling ride is presented, where three passengers move to the origin, where the trip is started (i.e., the start point), and they get to the destination together with the driver.

3. Research Questions & Initial Classification

In the context of ride-sharing activities inside smart sustainable cities, this section describes the methodology adopted in carrying out a systematic literature review (Tranfield et al., 2003). Following Thornhill et al. (2009), our review is conducted using an iterative method, which consists of the definition of appropriate keywords, the search within the current literature, and its analysis. This systematic approach helps to reduce any bias and ensures the reproducibility of the process (Cook et al.,

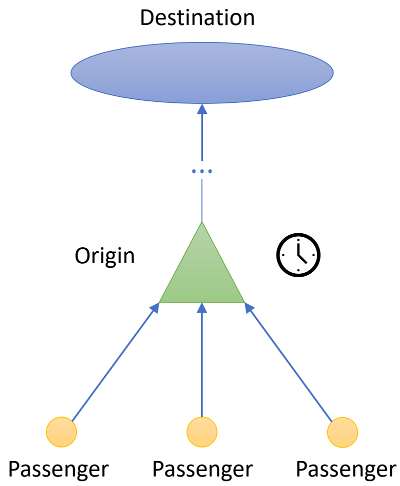


Figure 2.: A visual representation of a possible carpooling ride.

1995).

The first step includes defining the main research goals and objectives, selecting the database and the keywords, and designing the search process. We aim to answer the following research questions: *(i)* which are the main optimization challenges related to ride-sharing activities in smart and sustainable cities? and *(ii)* what optimization and simulation techniques have been employed so far in ride-sharing and carpooling optimization problems? The following keywords were proposed: ride-sharing, smart sustainable cities, carpooling, and optimization problems. We have analyzed publications included in journals indexed within the Science Citation Index (SCI) and the Social Science Citation Index (SSCI), both part of the Web of Science (WoS), which is considered to be one of the main sources of information in the academia (Newbert, 2007). Through the analysis of the literature presented in the Sections 4, 5, and 6, answers will be depicted to these questions. According to Rodríguez Bolívar et al. (2010), books (including reviews), editorials, brief communications, letters to the editor, symposiums, and articles of a professional nature, provide a limited view of the subject, and therefore, must be excluded from the analysis. However, our review does take into consideration articles published in special issues of journals, since those actually reflect a great interest in the study of any issue.

A set of inclusion/exclusion criteria have also been implemented. The first one makes reference to the inclusion of those papers related to car-sharing, ride-sharing and carpooling in smart cities. The second one deals with the consideration of works that actually apply optimization techniques and/or metaheuristics. The last criterion was based on the inclusion of those articles that explore agile optimization to solve transportation problems. From the results of the first step, a total of 1,355 papers were found. In fact, the analysis of citations of the original elements in the Web of Science collection related to "ride-sharing", "car-sharing" and "carpooling" terms, shows a growing interest (see Figure 3). Similarly, Figure 4 shows, for the terms 'ride-sharing', 'carpooling', and 'car-sharing', the time evolution of the number of articles indexed in the WoS.

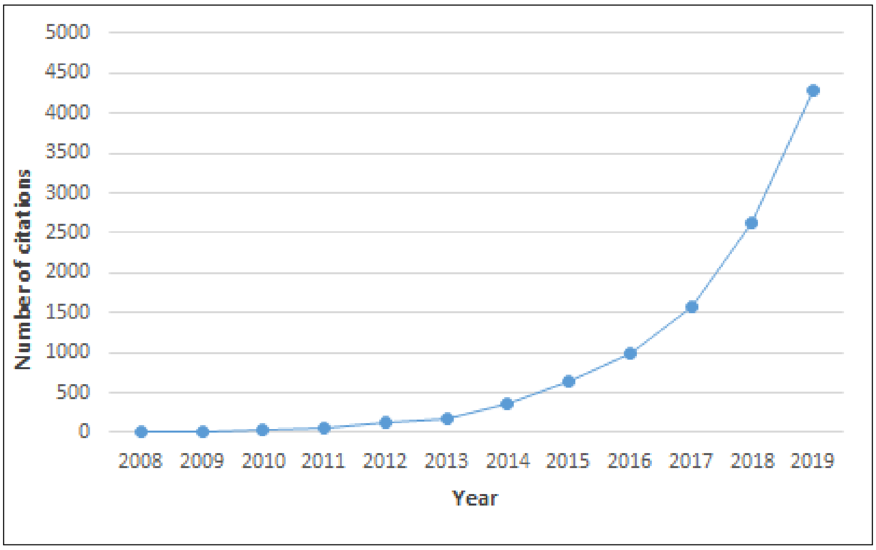


Figure 3.: Number of citations per year indexed in WoS.

The second step consists of classifying the references gathered from the performed search (Hartley and Kostoff, 2003). All in all, a total of 86 papers were selected to be analyzed. Regarding the journals in which the selected papers were published, the research reveals that the most common journals comprise a total of 32.94% (29 papers): *Transportation Research Part B: Methodological* (13 papers); *Transportation Research Part C: Emerging Technologies* (6 papers); *Computers & Industrial Engineering* (5 papers); and *European Journal of Operational Research* (4 papers). The dominant research areas are directly connected with the topics assessed in Section 2: Transportation (53.2%), Engineering (46%), Computer Science (43.2%), Business Economics (22.2%), Mathematics (15.6%), and Environmental Sciences Ecology (13.4%).

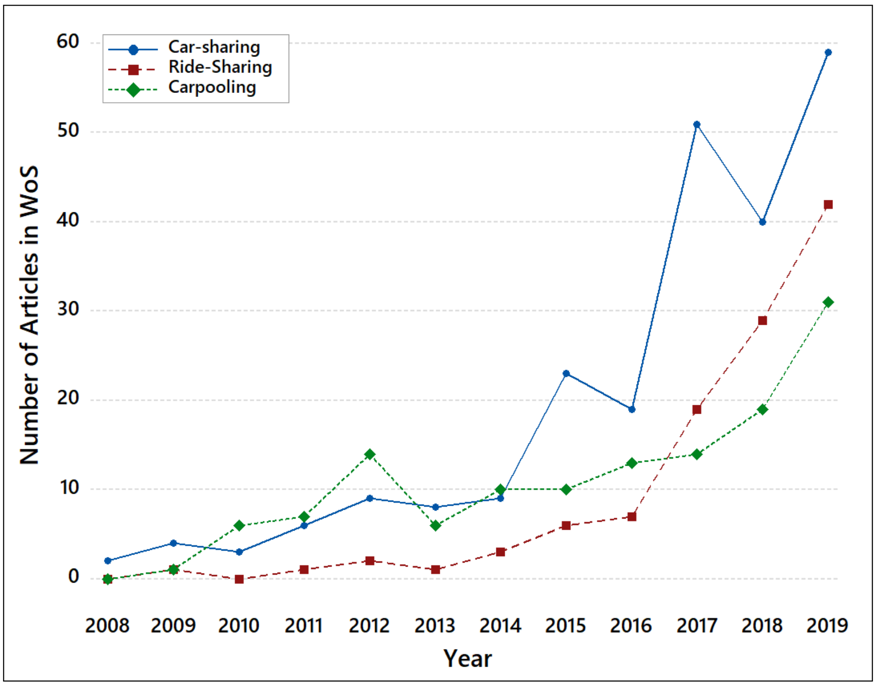


Figure 4.: Number of scientific articles per year indexed in WoS.

In the third and last step, the selected works were classified according to the analytical method used, i.e., exact, approximate or simulation approaches. Also, these works were examined to identify the addressed main challenges.

From an analytical perspective, most of the works on ride-sharing and carpooling optimization are identified as *NP-hard* problems. These problems are usually formulated as mixed-integer/integer linear programming (MILP/MIP) models, and small-sized instances are solved using exact methods. However, due to the complexity of the ride-sharing problems, approximate methodologies have been used in the literature to solve large-sized instances as well. The next sections provide a review based on the solving approach employed. Another important aspect identified in the literature refers to whether the ride-sharing system is static or dynamic. In dynamic ride-sharing systems, trip information –which includes users' origin, destination, and time schedule– is sent to the platform. Then, the solving methodology must match up drivers and riders on a very short notice, or even *en-route* (Agatz et al., 2012). Many studies are focused on developing algorithms for dynamic ride-sharing systems. Table 1 presents a classification of the reviewed articles by problem variant (static or dynamic) and solving methodology (exact or approximate). The following sections discuss in detail each of these works. In each section, we first introduce the related literature in the field of ride-sharing problems, followed by the related literature in carpooling problems.

Table 1.: Classification of ride-sharing articles by version (static or dynamic) and solution methodology.

Study	***Car-Sharing Problem***		***Methodology***		
	Static	Dynamic	Exact	Heuristic or Metaheuristic	Other
Kornhauser et al. (1977)		•			•
Baldacci et al. (2004)	•		•	•	
Agatz et al. (2011)		•	•		
Yan and Chen (2011)	•			•	•
Herbawi and Weber (2012)		•		•	
Hosni et al. (2014)	•	•	•	•	
He et al. (2014)	•				•
Lee and Savelsbergh (2015)		•	•	•	
Fagnant and Kockelman (2015)		•		•	•
Santos and Xavier (2015)	•	•		•	
Huang et al. (2015)	•		•	•	
Naoum-Sawaya et al. (2015)	•		•		
Stiglic et al. (2015)	•		•		
Schreieck et al. (2016)		•			•
Jung et al. (2016)		•		•	
Alonso-Mora et al. (2017)		•	•	•	
Levin et al. (2017)	•	•		•	
Masoud and Jayakrishnan (2017)	•		•		
Najmi et al. (2017)	•	•		•	
Wang et al. (2017)		•	•	•	
Li et al. (2018b)	•		•	•	
Long et al. (2018)	•				•
Ma et al. (2018)	•			•	
Lokhandwala and Cai (2018)	•			•	•
Yu et al. (2019)	•		•		
Chen et al. (2019)	•		•	•	
Simonetto et al. (2019)		•		•	
Li and Chung (2020)	•		•	•	
Cheikh-Graiet et al. (2020)		•		•	

4. Exact Methods for Car Sharing Optimization

Despite their limitations for solving large-sized *NP-hard* optimization problems in short computing times, the use of exact methods is still relevant since they can be utilized to validate approximate methods in small-sized instances, as well as to provide lower and upper bounds to optimal solutions.

4.1. Ride-sharing

Ride-sharing systems are naturally dynamic because they require matching of travelers with similar itineraries and time schedules on short-notice (Prieto et al., 2017). Consequently, exact approaches for solving this class of problems must be flexible enough to deal with such particularities, since most of them require solutions in real-time. Considering a dynamic single-trip ride-sharing problem, Agatz et al. (2011) proposed an optimization procedure to match up drivers and riders on a very short notice and to determine the best set of proposed ride-share matches. In the addressed environment, new drivers and riders continuously enter and leave the system. The objective is to minimize the total-wide vehicles-miles and the total travel cost, i.e., to maximize the total revenues of the provider. The proposed methodology is based on a rolling-horizon strategy, which incorporates an optimization procedure to determine the best set of ride-sharing matches by using the CPLEX commercial optimization software. To test their methodology, the authors performed a simulation based on travel demand data for the Atlanta metropolitan area. For cases in which the instances cannot be solved to optimality quickly, the authors defined a maximum solution time limit or an optimality gap which guarantees the finding of high-quality solutions. As expected, the simulation results improved basic greedy matching rules and suggested that the use of dynamic ride-sharing systems is able to reduce the overall travel cost of the system, as well as travel times of passengers. Likewise, Hosni et al. (2014) proposed a Lagrangian decomposition approach to maximize the total profit in a ride-sharing problem –i.e., their goal was to minimize the vacant seats, taxi fares to passenger, and number of vehicles. In this problem, customers request rides from specific pick-up locations to specific drop-off locations. Therefore, the optimal assignment of passengers to taxis must be determined, as well as the optimal route for each taxi. The Lagrangian approach decomposes the problem into sub-problems that are independently solved. Recently, Li and Chung (2020) introduced a novel deterministic model for the ride-sharing under travel time uncertainty, which addresses different origins and destinations of drivers and riders. Similar to the previous study, the objective aims to find optimal matches between riders and drivers, besides finding the optimal routes for drivers in which multiple drivers and multiple riders are considered. The model was solved through a MIP model using the *Gurobi* solver (Optimization, 2014). Apart from being able to find optimal solutions, several hours to several days were needed to solve problems of up to 44 nodes. In order to overcome this shortcoming, same authors have proposed a hybrid method. Similarly, Naoum-Sawaya et al. (2015) studied a stochastic ride-sharing scenario by considering the unforeseen event of the car unavailability. They proposed an exact integer programming (IP) model to solve the problem. Lee and Savelsbergh (2015) focused on understanding the required budget to achieve a certain service level, in terms of serving a minimum percentage of riders, in a dynamic ride-sharing system. This budget is related to the cost of employing dedicated drivers, who are only addressed when the number of passengers increases to a certain level. Similar to previous authors, they formulated the problem as an IP model, which was solved by commercial IP solvers in order to validate a proposed metaheuristic approach. Li et al. (2018b) also proposed a mixed-integer linear program (MILP) to solve a ride-sharing problem, resolved by the CPLEX, and to validate a metaheuristic approach. Another example of dynamic ride-sharing can be found in Wang et al. (2017), in which the passenger has the option of accepting or declining the assigned vehicle. They also proposed different mathematical programming approaches to find the best stable solution.

In the context of autonomous vehicles, Alonso-Mora et al. (2017) presented a mathematical model for solving, in real-time, high-capacity ride-sharing problems via dynamic trip-to-vehicle assignments. The authors proposed a reactive-anytime-optimal algorithm. Based on a greedy assignment, this algorithm returns a valid assignment of travel requests to vehicles. Then, refines it over time, converging to an optimal solution. The optimal routes are dynamically generated with respect to online demands and vehicle locations by solving an ILP model. Later stages aim to balance the remaining idle vehicles, which are in areas far away from the one with an active request. The authors concluded that the using the ride-sharing concept can provide a substantial improvement in urban transportation systems by reducing the fleet size substantially. They also conclude that system parameters –such as vehicle capacity and fleet size– have a direct influence on the service quality and demand. Masoud and Jayakrishnan (2017) proposed an exact method, based on a decomposition algorithm, to solve a multi-hop ride-sharing problem. The objective is to minimize the total traveling cost, which also includes the fixed cost of the vehicles and the penalty cost of the non-serviced passengers. Chen et al. (2019) proposed an ILP formulation to solve the ride-sharing problem considering return restrictions to satisfy the business needs, meeting points, and the option for riders to transfer between drivers. However, the efficiency of this method was limited by the size of the instances, which were optimally solved just for cases with up to 80 participants –the computational time was set to a maximum of two hours. Finally, Yu et al. (2019) investigated a green ride-sharing problem whose multi-objective function consists in maximizing the average ride profit of the drivers and minimizing the carbon emissions. An exact method –based on cutting the non-Pareto-optimal solutions using a decomposition approach– was developed to solve this problem. The method was tested on benchmark instances for the pick-up and delivery problem with time windows, which were initially proposed by Li and Lim (2003).

4.2. Carpooling

Baldacci et al. (2004) proposed both an exact and heuristic method for solving a single way, referred to as a *to-work*, carpooling problem. The exact approach is based on a bounding procedure that combines three lower bounds derived from different relaxations of the problem. Two different problem formulations were presented. The first one is based on three-index decision variables specifying the arcs traversed by each car while the second one uses a set-partitioning (SP) formulation whose variables correspond to feasible paths for the cars. The paths were generated by dynamic programming, and for solving the formulations, the CPLEX solver was employed as the integer programming solver in the exact method. The authors tested the approaches to VRP derived instances, where the majority of the problems could be solved by the exact approach in reasonable computing times. Moreover, the proposed bounding procedure showed to be competitive with other column generation methods. Years later, Stiglic et al. (2015) introduced an IP formulation to formulate a single driver, multiple riders ride-share matching problem, in order to maximize the number of matched participants in large-scale ride-sharing systems with meeting points. The authors designed and implemented an algorithm that optimally matches drivers and riders, in which each driver has the possibility of having at most only one place to pick-up passengers, and one place to drop-off them, which characterizes a carpooling service. In other words, passengers will be taken at the same time in a common node, and they will also be dropped off at the same time in another common node. The pick-up and drop-off nodes are set at strategic locations or transit points –such as bus stops, refueling stations, etc. This allows passengers to be picked up by other drivers on their way to their final destination. The CPLEX was shown to solve the integer programs –i.e., the matching process– in a few seconds in all tested settings, which suggests that the algorithm is appropriate for use in practice. This concept has been also studied by other researchers, such as Li et al. (2018b), Stiglic et al. (2018), and Khademi Zareh et al. (2019).

5. Metaheuristic Methods for Car Sharing Optimization

Regarding the use of approximate methods, both metaheuristics (Duarte et al., 2018; Glover and Kochenberger, 2006) as well as modeling and simulation methods (Law and Kelton, 2000; Macal, 2016) have been employed to deal with ride-sharing and carpooling problems. Among the former, different metaheuristic frameworks have been tested, including: genetic algorithms (GAs), tabu search (TS) local search (LS), greedy randomized adaptive search procedures (GRASP), and hybrid methods that aim to combine a few heuristics.

5.1. Ride-sharing

Genetic Algorithms (GAs): The GAs consist of one of the main approximate methods to solve ride-sharing problems. For example, Herbawi and Weber (2012) studied the dynamic ride-sharing problem. Their objective function includes several dimensions, such as total travel time, distances of the drivers' journeys, total travel time of the passengers, and number of matches. Schreieck et al. (2016) proposed an automated matching algorithm in order to minimize the time to matching rides in a dynamic ride-sharing problem. The proposed methodology is based on matching ride offers and requests. It also uses a smart data structure to increase the calculation speed of matches. The shortest path between request points is created by utilizing the *GraphHopper* open source library (`https://www.graphhopper.com/`).

Local Search Algorithms (LS): Regarding the use of LS, Simonetto et al. (2019) studied the dynamic ride-sharing in order to minimize the duration time of trips. In their work, they recast the ride-sharing problem into a succession of batch processes that combine a linear assignment algorithm, a context-mapping algorithm, and a capacitated vehicle routing problem with pick-up, delivery, and time-windows. The authors used an insertion heuristic to insert new passengers into live rides and developed a local neighborhood search (LNS) to solve this complex variant. Two real-life data-sets are used in order to test their LNS: the New York City taxi data-set and the Melbourne metropolitan area data-set. Apart from proposing an exact approach for solving the ride-sharing problem, Hosni et al. (2014) also introduced an incremental cost heuristic to solve the dynamic version of the problem. In this version, the location of the seekers appears in real-time. For each taxi vehicle, whenever a new request arrives, a minimization problem is solved. This allows to compute the additional cost when including it into the route. The objective is to maximize the total profit –i.e., minimizing the vacant seats, taxi fares to passengers, and the number of vehicles. For solving large instances, Chen et al. (2019) also proposed a savings-based constructive heuristic, which combines the use of ride-sharing with external mobility service providers. Among the positive conclusions regarding the reduced number of trips and vehicle miles, the authors showed that ride-sharing creates more benefits when the participation is high and when the origins and the destinations of the trips are more spatially concentrated. They achieve up to 31.3% savings in distance-based cost and up to 28.7% reduction in the number of vehicles needed to fulfill the users' travel schedules. Apart from solving a dynamic ride-sharing problem exactly, Lee and Savelsbergh (2015) also proposed a metaheuristic based on neighborhood search and shaking procedures, in order to solve the large-scale instances that the IP model was not able to. Similarly, Naoum-Sawaya et al. (2015) also developed a heuristic to solve real-life instances related to the city of Rome.

Hybrid Methods: Hybridization of metaheuristics has also been employed in the ride-sharing literature. For example, Jung et al. (2016) proposed three different algorithms to solve the dynamic shared-taxi-dispatch problem: a nearest vehicle dispatch (NVD) algorithm, an insertion heuristic (IS), and a hybrid-simulated annealing (HSA). In this problem, passengers on demand are dynamically assigned to empty seats in passenger cars. The NVD simply assigns a passenger to its nearest geographically available vehicle, which is the most commonly used in real-life applications given the need for quick response times. The IS handles real-time passenger requests by considering all feasible vehicles and finds the best available vehicle to assign to a new passenger (which does not have to be the nearest one). Finally, the HSA assigns efficiently and dynamically passengers on-demand to available vehicles. This is done by systematically re-optimizing the assignment of new requests, as well as updating existing schedules in real-time. Two objectives were addressed: *(i)* minimizing total travel time of passengers, and *(ii)* maximizing system profit from selectively accepting passengers based on the current schedule. Simulations were conducted to investigate how a shared-taxi system can improve passenger travel –compared to conventional taxi services– by utilizing vehicle resources more efficiently. Apart from proposing an exact approach for solving a ride-sharing problem under travel time uncertainty, Li and Chung (2020) also proposed a hybrid algorithm that combines an extended insertion algorithm with a TS method. The insertion algorithm finds initial feasible routes, which are iteratively improved by the TS. The hybrid TS was able to find near-optimal solutions in shorter computational time, when compared with the exact approach, and to overcome other heuristics' solutions.

Other heuristic methods: Wang et al. (2017) studied a dynamic ride-sharing problem in which the passenger has the option of accepting or declining the assigned vehicle. They proposed a heuristic algorithm to find stable matches –i.e., those in which no rider and driver, currently matched to others or unmatched, would prefer to be matched together. Similar to Agatz et al. (2011), they used the rolling horizon strategy for dealing with cases in which new trip announcements continuously arrive. Similarly, Najmi et al. (2017) also developed a clustering heuristic to solve a static and dynamic ride-sharing problem to minimize the total traveling distance. They presented a novel clustering heuristic based on both the origin and the destination of users, to solve a large-scale dynamic ride-sharing problem. This algorithm was previously introduced in a static context, being then posteriorly embedded within the rolling horizon strategy, to periodically solve the matching problem as new announcements enter the system. A year later, Li et al. (2018b) have proposed a TS algorithm for solving an enhanced ride-sharing system with meet points and users' preferable time windows.

5.2. Carpooling

Genetic Algorithms (GA): Huang et al. (2015) proposed a genetic-based carpooling matching and routing algorithm to solve a carpooling problem for online systems. In this version of the problem, the driver may pick-up more than one passenger during the trip, respecting capacity constraints, i.e., the number of seats. Then, an efficient matching of drivers and passengers should be provided by the online system. Each passenger is taken by a single driver. The algorithm determines carpooling matches and it is divided into two modules: evolution initialization and genetic evolution. The former transforms the solutions into chromosomes, and the initial population is generated by a distance-based greedy heuristic. The chromosomes are made up of segments, which represent the passengers assigned to each driver. The latter aims to find the optimum carpool route and matching results. In the crossover operator, the segments are combined. The mutation is based on insertions (applied at the segment with the worst sub-fitness) and multiple swaps. A chromosome repair is called when an invalid chromosome is generated. Another use of a GA for solving a taxi carpooling path optimization model was proposed by Ma et al. (2018), where a single objective model was extended to a model with multiple objectives. Apart from minimizing the taxi travel distance, the proposed models aimed to reduce detour distance and cost of passengers, as well to increase the passengers' satisfaction and taxi drivers' income.

GRASP Algorithms: Using a GRASP framework, Santos and Xavier (2015) studied the problem of taxi-sharing combined with carpooling. Carpooling drivers specify their departure point, destination, time departure, and the maximum delay tolerated by the latter. As for taxi drivers, they indicate their current locations as well as the start and end time of their service. The drivers must also fix the price per kilometer, as well as the maximum capacity of their vehicles. Each passenger has a maximum cost that he/she is willing to pay for the trip. The authors' strategy is to solve this dynamic problem by transforming it into a series of static problems.

Tabu Search Algorithms (TS): Recently, Cheikh-Graiet et al. (2020) proposed a TS algorithm for solving a dynamic carpooling problem. This dynamic system supports the automatic and optimal ride-matching process between users on very short notice or even en-route, and includes the possibility to drop off passengers at a given walking distance from his destination, in order to increase users' satisfaction. For doing that, the proposed TS employs several original searching strategies developed to make optimal decisions automatically, while allowing transfers and detours. A simulation environment was developed based on actual carpooling demand data from the metropolitan area of Lille, in France. The proposed methodology was able to satisfy a maximum of carpool requests by involving a minimum number of vehicles. This satisfactory performance was achieved by allowing detour and transfer processes.

Other heuristic methods: Yan and Chen (2011) addressed a carpooling problem with pre-matching information (PMI), modeled as an integer multiple commodity network flow problem (IMCNFP), and solved by a solution method, based on Lagrangian relaxation and a heuristic for generating the upper bound solution, since the IMCNFP is characterized as *NP-hard*. The authors were the first to consider the PIM into this problem, which is obtained from previous matching results and can include valuable information, such as carpool partners, the remaining vehicle capacity, and the route/schedule for each previously participating vehicle. The use of PIM aims to reduce inconveniences among commuters since most of the previous users from the same matching would expect similar carpool partners, and drivers would expect any change of their schedule/route to fall within a tolerable range. To test the proposed methodologies, the authors generated a set of 30 instances, based upon data reported from a past study carried out in Taiwan, and they concluded that both the model and solution algorithm were efficient on solving the problem. With the goal of minimizing CO_2 emissions, Bruck et al. (2017) studied the static carpooling and provided two mathematical models and two heuristic-based methods to solve a real application. Su et al. (2019) developed a new hybrid method that combines an artificial bee colony algorithm (Karaboga et al., 2014) with a variable neighborhood search (Hansen and Mladenović, 2014) and a tabu list (Gendreau and Potvin, 2005) to minimize the total distances of all passengers.

6. Simulation Methods for Car Sharing Management

The use of simulation for car-sharing management dates back to 70s. For example, motivated by the fuel crisis of 1973 in the U.S., and the scarcity of federal funds for implementing new urban transport facilities, Kornhauser et al. (1977) developed a simulation for assessing the productivity potential of dynamic ride-sharing systems on a hypothetical automated guideway transit network designed for Trenton, New Jersey. Different policies were tested, based on the number of specific origins and destinations that can be served by a vehicle at any one time. For the single-origin to single-destination, the daily average vehicle occupancy improved by 60-120% over the purely non-shared-ride operation. Since then, simulation approaches have been used widely to study car-sharing problems. Among simulation approaches, agent-based and dynamic simulation have been the most frequently used methods to deal with car-sharing issues.

6.1. Ridesharing

Agent-based modeling: Regarding agent-based modeling, the taxi ride-sharing problem was addressed in Lokhandwala and Cai (2018) using the New York city fleet as a case study. These authors employed the following implicit objectives: decrease the fleet size, increase the occupancy rate, decrease the total travel distance, and reduce the carbon emissions. The main findings of the paper are that ride-sharing may reduce the service level in suburban areas and that the ride-sharing combining autonomous driving with autonomous vehicles can potentially decrease the fleet size by up to 59%. In their simulations, the total travel distance was decreased by up to 55%. Due to the possibility of full-day operations and the absence of drivers, the use of autonomous vehicles in a ride-sharing system has received increasing attention during the last years. Fagnant and Kockelman (2015) dealt with using shared autonomous vehicles (SAVs) in urban areas. In their work, dynamic ride-sharing opportunities were included in order to optimize fleet sizing, improve the model's capabilities, and deliver a benefit-cost analysis for fleet operators. These opportunities allow two or more independent travelers to share a single SAV. An agent-based micro-simulation model was proposed to build an SAV fleet to transport those trip-makers from their origins to destinations over a day, which was then modified to allow travelers to access SAVs that are currently occupied or claimed by other trip-makers –i.e., the dynamic ride-sharing system. The proposed model is composed of four modules: *(i)* the SAV location and trip assignment module; *(ii)* the SAV fleet generation module; *(iii)* the SAV movement module; and *(iv)* the SAV relocation module. The first module assigns waiting travelers to the nearest SAV, prioritizing those who have been waiting longest. In the second module, SAV paths are computed using a Dijkstra-based algorithm to determine the shortest time-dependent route for a SAV to reach each assigned traveler –and his/her final destination. The third module tracks SAV movements of picking-up and dropping-off travelers. Finally, the last module is used to balance the supply-demand over space and time. As expected, the use of ride-sharing mobility is able to improve the model capabilities, hence reducing the average total service time.

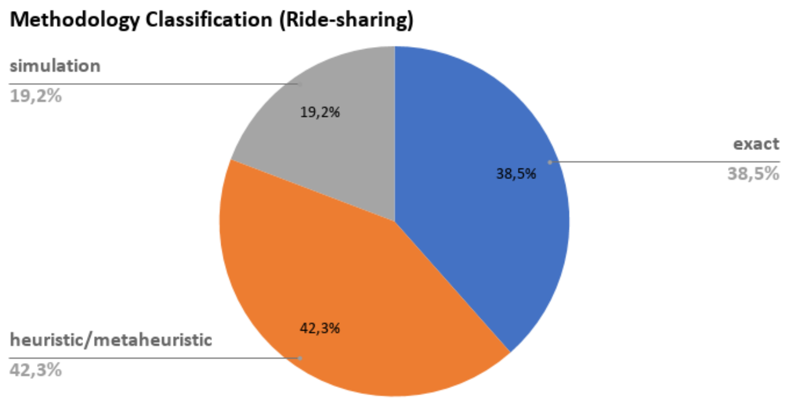
The approach by Levin et al. (2017) applied shared autonomous vehicles to ride-sharing and dynamic ride-sharing. There are two main objectives to be minimized: the travel time and the number of SAVs. They also consider a constraint on waiting times. Despite this work does not propose an optimization model itself, a heuristic was created together with an event-based simulator using existing traffic models. The proposed heuristic for dynamic ride-sharing was applied in downtown Austin city, and compared with personal vehicles results from dynamic traffic assignment. A central SAV dispatcher was used to make routes and passenger assignments using centroids as destinations of AVs. The paper concludes that some SAV scenarios also increased congestion because there are additional trips made to reach travelers' origins, but the total number of vehicles on the road may be reduced.

Dynamic simulation: Long et al. (2018) were the first authors to propose a stochastic ride-sharing model that addresses stochastic travel times following a time-independent distribution with a positive lower bound. This model was then extended to formulate a stochastic ride-sharing model with time-dependent travel time uncertainty. The model aims to maximize both the total generalized trip cost-saving and the number of matches between drivers and riders. The authors employed Monte Carlo simulation in order to estimate the departure time and the minimum trip cost associated with each driving-alone trip and ride-sharing trip. In their work, the time interval is divided into smaller sub-intervals (discredited into many planning horizons), which transforms the dynamic ride-sharing problem into a sequence of static ride-sharing problems. The authors concluded that the travelers' values of time, the unit variable cost of driving, the travel time uncertainty, and the selection of the weights in the objective function have a significant impact on the performance of the ride-sharing systems. Also, a feasible ride-sharing match, based on deterministic travel times, can become infeasible in a stochastic ride-sharing system. Interest readers are referred to the recent survey by Narayanan et al. (2020) for more SAVs applications.

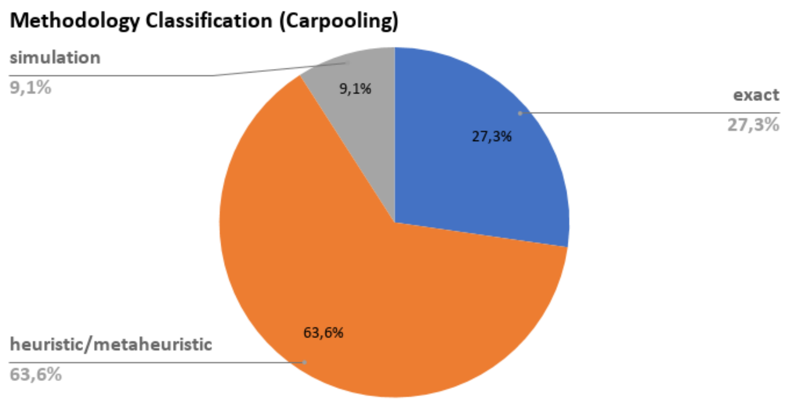
6.2. Carpooling

An intelligent route scheme, based on mining GPS trajectories from shared riders to support a carpool service in heavy urban traffic conditions, was proposed by He et al. (2014). In this case, riders with similar preferred routes are grouped by using a GPS-assisted mining approach in order to minimize the driving distance, reduce commute costs, protect the environment, and alleviate urban traffic problems. Drivers' preferences (such as minimizing the total travel costs, the walking distance to make connections, the detour distance to pick-up riders, the social distance, etc.), and the dynamic join-and-leave policy are taken into account. The proposed approach consists of two major subsystems: trajectory mining and carpool routing. The first subsystem processes each user's trajectory log recorded at a rider's GPS device, while the second one runs on the database of extracted (mined) frequent routes. The final route is generated by a pairwise merging process. The authors concluded that increasing walking and detour distance leads to a higher success rate, while excessive detouring will lose carpooling service efficiency. Moreover, the efficiency of the ride-sharing increases with the carpooling size and the response time of finding a candidate driver is unrelated to the total distance of the route, although the decision time of searching qualified passengers is quite related to the route distance.

As we could notice, since the first motivation for adopting a ride-sharing system, addressed by Kornhauser et al. (1977), this problem has become even more complex thanks to new advances in telecommunication and the emergence of mobile technology. Consequently, several solving approaches have been proposed in the literature for solving different variants of these car-sharing problems, which are often enriched by new constraints and objectives. In conjunction with Table 1, Figure 5 depicts the rate of used solving approaches for each car-sharing activity, according to the previous classification.



(a) Ride-sharing.

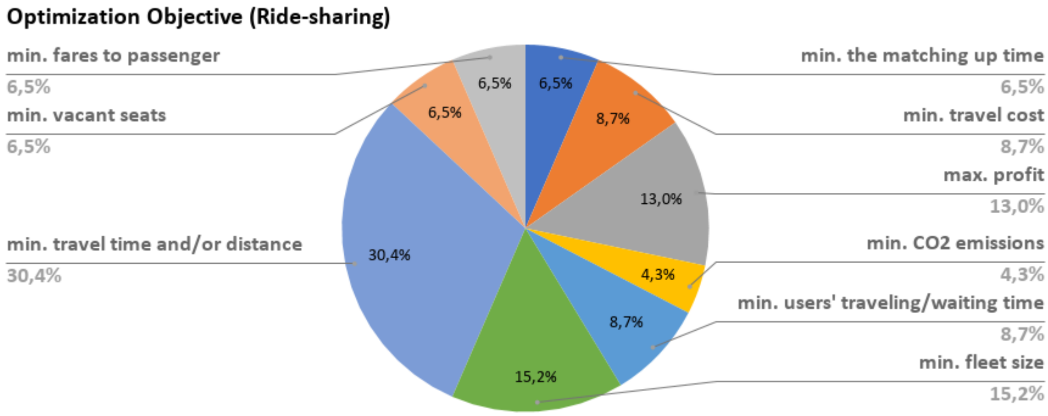


(b) Carpooling.

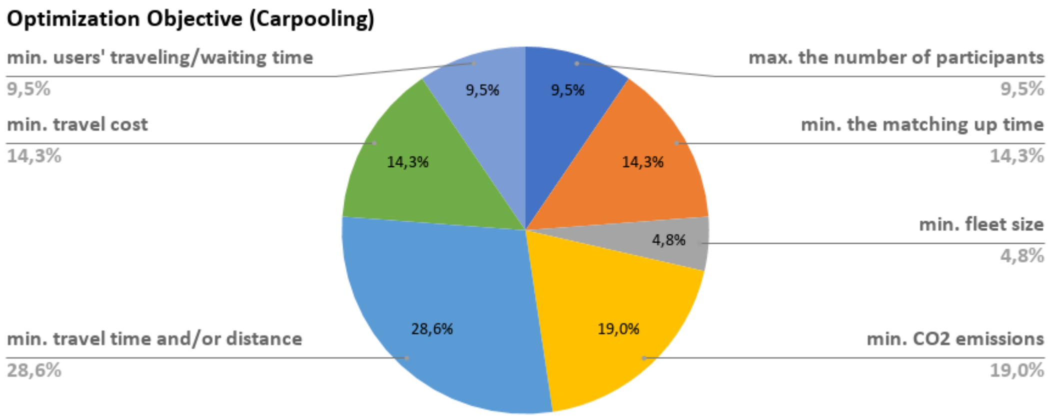
Figure 5.: The percentage of reviewed papers per solving methodology classification.

When analyzing Figure 5, it is noticeable the use of approximated methodologies to solve both the problems related to ride-sharing and carpooling systems. Specifically, for ride-sharing activities, the use of exact approaches is also substantial. However, as mentioned, their use is often limited due to the size of the problem instances, whose particularity transforms its employment unsuitable for solving real-life and large problem instances. On the other hand, the use of heuristics and metaheuristics approaches is the most significant in both cases, being them able to provide high-quality solutions in short computational time as required by such systems.

Apart from the prior classification provided in Table 1 and Figure 5, we have performed, in Figure 6, a new categorization of these studies, including a deeper analysis regarding the addressed optimization objectives for each car-sharing activity.



(a) Ride-sharing.



(b) Carpooling.

Figure 6.: The percentage of reviewed papers regarding the addressed optimization objectives.

Among the objectives highlighted in Figure 5, minimizing the travel time and/or distance represents the main objective when solving these models. For ride-sharing activities, it is also noticeable the interest in increasing the provider's profit and reducing their respective travel costs. From an operational perspective, several papers aim to reduce the fleet size, which is directly related to other objectives, such as reducing the number of vacant seats and CO2e. Regarding the latter objective, reducing CO2e has been considerably established as one of the model objectives in carpooling studies, followed by the minimization of the match-up process between drivers and riders, which is frequently required dynamically and in real-time.

7. Performance Analysis of Ride-Sharing Systems

The use of shared transportation systems has led to the improvement of several associated activities in the context of urban transportation. Despite the practical challenges associated with their implementation in real life (such as coordination and synchronization of users, uncertainty, and dynamism of the real-world), ride-sharing and carpooling systems showed to hold the capability of reducing several problems caused by the individual transportation. Among them, we can highlight the reduction of congestion on the roads, reduction of vehicle miles traveled, increase of occupancy on vehicles, diminishing both traffic and pollution, reduction of operating costs and fares, and so on.

In the literature, there exist several studies that address real-cases of ride-sharing and carpooling activities around the world. Some recent studies show how efficient car-sharing systems are able to achieve the goals previously introduced. Most of them depict gains on fleet reduction and its related attainments. For instance, Li et al. (2018a) studied the effects on traffic conditions in the city of Langfang, China, by considering a carpooling system for the existing traffic demand. The proposed system was able to achieve 49% of trip reduction rate and it alleviated the traffic condition in 82.5% of the congested road segments. Moreover, by reducing and alleviating congestion of roads, the carpooling was able to increase the travel speed during peak-hours on most road segments by 5–40%. By analyzing this work, it can be noticed the potential of this system on reducing congestion and, consequently, on improving the locomotion on the roads.

Another example was conducted by Lokhandwala and Cai (2018), for New York City, U.S. This study revealed that autonomous driving in ride-sharing can potentially decrease the fleet size by up to 59%, without a significant increase in waiting time and additional travel distance. The total travel distance can be decreased by up to 55%, and about 725 metric tonnes of carbon emissions can be reduced per day. Apart from reinforcing previous conclusions about alleviating congestion and reducing vehicles' travel distance, this study further shows how shared-transportation modes can be environmentally beneficial to the population. Similarly, Cai et al. (2019) presented a real case study for quantifying the environmental benefits of ride-sharing taxis in Beijing, China, where the trip information from 12,083 taxis in Beijing was used to identify shareable trips and quantify the potential energy savings and emission reduction. Like previous studies, the use of taxi-sharing throughout the entire day can reduce, annually, fleet vehicle miles-traveled by 33%, save approximately 28.3 million gallons of gasoline and reduce 2,392 tons of CO_2e, among other emissions. However, according to Simonetto et al. (2019), the total number of vehicles employed for ride-sharing services must be limited as a function of the demand, in order to achieve both the traffic and environmental benefits. The latter authors showed how real-time ride-sharing offers clear benefits in terms of the service level, compared to traditional taxi fleets, even considering a partial adoption of the system. In their study, they concluded that approximately only 10% of the current taxi fleet would be needed to meet 96% of the demand in the Melbourne Metropolitan Area, Australia. Accordingly, we can notice how this work supports the efficient use of vacant seats of conventional taxis, being, consequently, able to substantially decrease the number of operating vehicles in metropolitan areas.

In another recent study, Zhang et al. (2020) analyzed the taxi data of Lanzhou City, China. Similar to the previous examples, the use of ride-sharing strategies could reduce the number of taxis by 57% and the travel distance by 44%. Another valuable conclusion is related to the total revenue of each taxi, which is significantly improved when compared to the driving efficiency of the non-sharing mode. Therefore, apart from improving the taxi operation efficiency and save drivers' travel distance, the use of ride-sharing strategies can reduce the passengers' travel expenses and, hence, increase the drivers' travel efficiency. Another example of travel distance reduction is depicted by Wang et al. (2018), which addressed a taxi-sharing case study in Singapore City, Singapore. In their work, the proposed framework was able to achieve not only a reduction in time but also a reduction in travel distance from 20% to 30%.

Based on these studies, we can conclude noticeable environmental benefits, economic impacts, and, especially, transportation issues that can be partially solved when car-sharing activities are employed in big cities. As stated in Simonetto et al. (2019), such shared-transportation modes are also useful in the case of non-monopolistic economies and partial adoption of vehicles, which allows start-ups, small-medium enterprises, and city authorities to embrace their employment for potentially improving transportation and life quality of citizens.

8. Challenges Related to Synchronization & Coordination

The following sections will review the main challenges and research opportunities related to the optimization of ride-sharing operations in smart sustainable cities. Figure 7 offers a conceptual map including some of the main keywords that will be further analyzed in Sections 8–11.

When dealing with ride-sharing systems, one of the most challenging tasks is how to efficiently match-up a driver offer and a demand from a rider. In a dynamic environment, this matching has to be done in real-time. In general, besides minimizing the driver-passenger matching processing time, the objectives when solving the ride-sharing problem are: *(i)* to minimize the driving distance, detour distance, commute costs, vacant seats, taxi fares to passengers, and the number of vehicles; and *(ii)* to maximize the total profit obtained from serving the involved riders –possibly including parcel requests (e.g., Li et al. (2014))– while indirectly protecting the environment and reducing fuel consumption as well as traffic in urban areas.

As stated by Agatz et al. (2011), this driver-passenger matching process should be largely automated in a dynamic setting. This would allow establishing ride shares in a way that requires minimal effort from the participants. Usually, this process is supported by predetermined conditions from both the system itself and its users

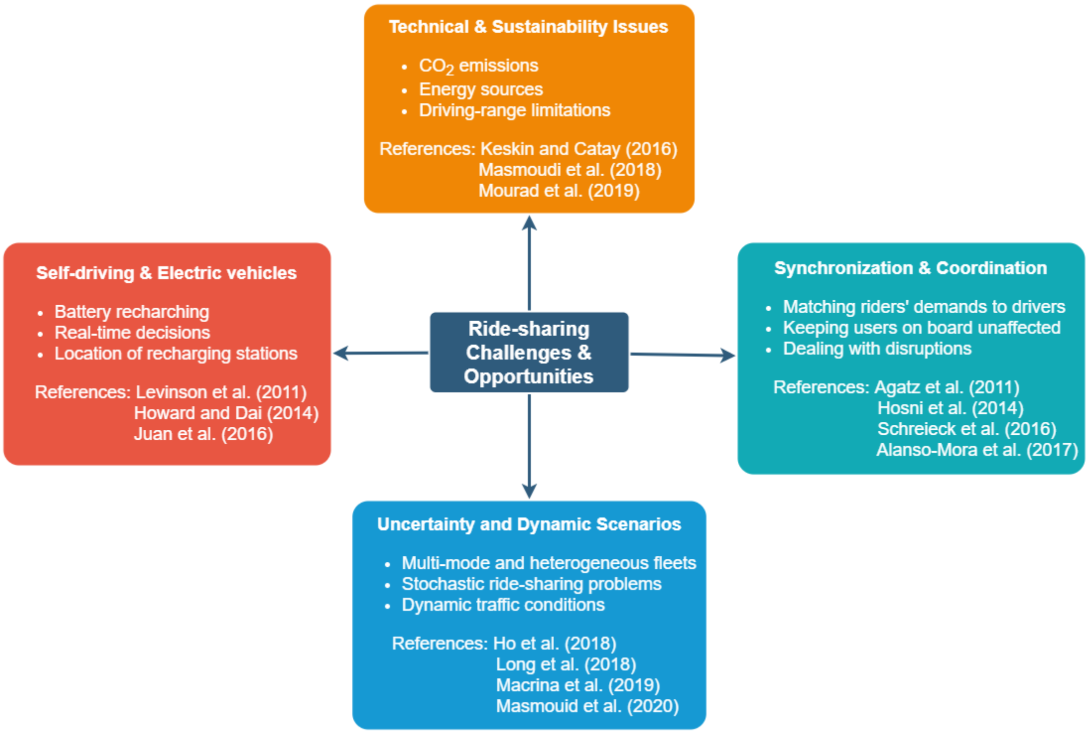


Figure 7.: Main challenges and research opportunities related to ride-sharing operations.

in order to ensure their convenience and satisfaction. It includes, for instance, the consideration of a maximum detour distance, number of available seats, departure time-range, etc. (Schreieck et al., 2016). Accordingly, several papers regarding the use of ride-sharing systems are focused on proposing a solving methodology to match-up drivers and riders on very short notice, or even *en-route*. Most of these methodologies are based on approximate techniques, which are suitable in the considered application context for being able to provide high-quality solutions in a short computational time. However, some of the studies break the overall problem into sub-problems, which can be exactly solved in a reasonable amount of time. This is the case, for instance, of Hosni et al. (2014). Others make use of simulation approaches for dealing with the dynamism and uncertainty involved in the process (Long et al., 2018). Finally, some works are focused on proposing efficient data structures that allow increasing the matching-up speed (Schreieck et al., 2016).

Once an efficient matching procedure is generated for solving the drivers and riders matching, the resulting routing stage, which considers the newly updated schedules must be resolved. Consequently, when dealing with coordination and synchronization of riders' requests and drivers' offers, the routing stage is transformed into a fully riders-dependent process. Hence, this stage consists in designing optimized routes for attending different riders' demands, expectations, and objectives without causing any disturbances or interruptions to the drivers who are already on board. Besides the general goal of minimizing the overall transportation costs, this process includes the minimization of waiting times and walking distance for riders, as well as the detour distance for drivers (and, indirectly, for riders who are already on the trip). Since the related routing problem can be seen not only as a vehicle routing problem but also as the dynamic pickup-and-delivery problem (Alonso-Mora et al., 2017), the routing process incorporates different constraints beyond those traditionally considered in the classical vehicle routing problem. Therefore, a significant challenge when addressing the routing stage in ride-sharing systems is the need to generate good solutions fast enough to provide the users with a quality service. In this context, the proposing methodology must be able to incorporate information on trips provided by new users during the planning execution and then maintain the quality service by generating high-quality routes for both the passengers previously assigned in the vehicle and the ones to be incorporated.

From the users' perspective, the challenges vary, for instance, from how to combine ride-sharing with other types of transportation, when ride-sharing is only a part of the users' full trip (Furuhata et al., 2013b), to data privacy and trust between drivers and passengers (Svangren et al., 2018). According to the latter study, 80% of the participants had trust issues towards drivers that were materialized as concerns about reliability and privacy. Despite being interested in having some earlier information concerning the other passengers and drivers, most users are still unwilling to give much information about themselves while sharing rides. Therefore, this trade-off between the need for prior information and the reluctant behavior of users to provide them is one additional particularity that makes the use of such systems challenging nowadays. One way to overcome this difficulty is to understand people's attitudes, beliefs, and travel behavior, which can be gathered thanks to the emergence of social media. According to Tang et al. (2019), this valuable information can be used for improving the ride-sharing decisions taken by participants, e.g., by generating dynamic shared-ride plans, improving group queries, optimizing ride matches, and for up to date information notices or other purposes involved in ride-sharing. However, this is one more challenging task due to the need of gathering techniques to extract specific types of travel-related information.

9. Challenges Related to Self-Driving and Electric Vehicles

Figure 7 identifies some key challenges in regards to self-driving and electric vehicles. The first challenge is related to the real applicability of AVs. Although the use of AVs represents a breakthrough with the power of changing the modern transportation by transforming it into a more sustainable, safer, and convenient one, self-driving vehicles also bring issues of safety, congestion, fuel, efficiency, and equity (Howard and Dai, 2014). From the human point of view, the use of AVs in public spaces remains an unconvincing way of safe transportation, due to its incapability of dealing and reacting to unexpected or unusual events as a human driver. When considering a real-world application, AVs-related issues are affected by a lot of external factors that change the standard and expected behavior of the involved variables (Levin et al., 2017). For instance, when immersed in a realistic scenario, such as the city centers –in which pedestrians and vehicles share a shared space– decisions must be taken in real-time and dynamically. It might be the case when a pedestrian crosses the road at the wrong time, or when a traffic accident happens. Another example can be described as a road that is blocked off, or even when obstacles are found in the roads. Therefore, in order to solve the resulting problem dynamically and efficiently, the solving methodology must be able to deal with uncertainty, dynamism, and unexpected events during the execution of the planning routes.

When combining the use of autonomous vehicles with an electric-based engine, the ride-sharing problem results in an even more complex scenario to deal with. As pointed out by Juan et al. (2016), the use of electric vehicles (EVs) in smart cities is somehow limited by different strategic and operational challenges. Hence, the second challenge is associated with their ability to cope with the strategic planning point of view.

The incorporation and use of EVs in logistics and transportation problems require the consideration of several limitations. For instance, EVs have limited driving-range capabilities, which brings the necessity of installing recharging stations in order to ensure their operation and then to provide an efficient operational plan (Bongiovanni et al., 2019). Consequently, questions such as *how many* recharging stations and *where* they should be installed are raised and must be taken into account.

The last challenge is related to the inclusion of decisions within the operational level. Another implication related to the introduction of EVs in the operational plan is the definition of the best fleet size and their combination (mixed fleet) with conventional vehicles to provide a compelling experience to the market. From the operational planning point of view, we can cite economic (Mourad et al., 2019), charging network (Levin et al., 2017); and (Corlu et al., 2020). Regarding economic aspects, the replacement of conventional vehicles with electric ones is an investment that should be carefully studied by the companies. Subsidies are becoming a usual effort from the government to reduce the acquisition cost of these zero-emission vehicles (Ma et al., 2017; Rudolph, 2016). Moreover, the installation of recharging stations is another costly investment needed to enable their operation. Regarding charging network issues, they are mainly related to the installation of refueling stations, including how many of them and in which locations. Finally, routing plays a vital role in transportation. In this way, an efficient route-planning, which takes into account the specific mentioned features of EVs, should be provided. This includes the incorporation of recharging stations in the working plan of the routes. Therefore, it is notable that, apart from the advantages of using EVs, their use in smart sustainable cities brings the necessity of redesigning the whole transportation system in order to get its benefits properly.

10. Logistics Issues and Uncertainty Scenarios

Figure 7 presents some key challenges in relation to logistics and uncertainty scenarios. The majority of ride-sharing studies assume only one mode of transportation, which is based on a homogeneous fleet of vehicles. However, transportation of people or freight is generally carried out by a heterogeneous fleet of vehicles –e.g., vehicles with different capacities, sizes, or energy sources, such as EVs or internal combustion engine vehicles (ICEVs). As indicated by Masmoudi et al. (2020), some alternative fuel vehicles (AFVs), such as flexible fuel vehicles or fuel cell vehicles, use different types of alternative combustibles (e.g., hydrogen propane, ethanol, bio-diesel, liquid natural gas, etc.). Therefore, one crucial feature research in ride-sharing consists of using a heterogeneous fleet of both autonomous and non-autonomous vehicles (EVs, ICEVs, AFVs, etc.), either under static, dynamic, or stochastic scenarios.

It is also possible to use mixed-mode operations, such as the combination of a private transportation fleet with a public one (buses, metro, etc.). In fact, operations that use mixed modes of transportation are quite usual in ride-sharing practices (Macrina et al., 2019). Again, a major challenge of the mixed operations mode is the synchronization of ride-sharing systems with public transit. Cooperation among public and private transportation modes is necessary to complete the requests of users in urban, peri-urban, and metropolitan areas. Thus, for example, when travel times are stochastic a user may be left behind at the transfer point due to a delay in the drop-off time. This will be even more common and critical for an integrated ride-sharing service with the use of public transit that has infrequent service (Ho et al., 2018). Hence, the schedule planner needs to develop robust plans. This can be achieved, for example, by reserving sufficient waiting times at the transfer points. In case of transfers not being realized as planned, it is essential to recover the plan by deploying additional vehicles or making adjustments in the plans of other vehicles. Therefore, several challenges can be found regarding the use of AVs: *(i)* how to design robust plans involving AVs; *(ii)* how AVs will interact with the existing modes of transportation; *(iii)* to what extent will AVs improve transportation efficiency; and *(iv)* how AVs will benefit from the public/private transportation modes. An interesting research direction is to develop and analyze the impact of using mixed transport modes in a dynamic and stochastic environment. The main challenge is to plan a set of routes by providing the best fleet composed of two different modes of transport (private and public transit) to satisfy the requests of passengers, where these requests are dynamic and stochastic –including the risk of suffering service disruptions. Some passengers may be transferred from a vehicle to another one on the way to their destination. The main challenge here is that the arrival and departure vehicles should be synchronized A few papers have considered synchronization aspects (Aissat and Oulamara, 2014; Stiglic et al., 2015). More research could be developed to extend the ride-sharing models by introducing other synchronization aspects, for instance: load synchronization, resource synchronization, and operation synchronization (Drexl, 2012). Another example is to provide flexible driver-to-vehicle systems and multi-depot settings in which the vehicles and the drivers should be synchronized (Ho et al., 2018).

Based on the earlier analysis of the literature, we have observed that only very few studies have been reported for the stochastic ride-sharing problems. More specifically, out of the 29 papers reported in Table 1, only a few including Naoum-Sawaya et al. (2015) and Long et al. (2018) consider stochastic elements. The most studied travel times of ride-sharing passengers are assumed to be deterministic (Xu et al., 2015). In real cases, however, there is usually some uncertain information related to travel time. Note that real-world ride-sharing activities are mostly stochastic because the processes are often unpredictable due to changing circumstances, which remain unknown until the process is under execution (Agatz et al., 2012). Similarly, most traditional ride-sharing papers consider only new user requests under a dynamic environment. These studies do not consider other types of events (e.g., accidents, traffic conditions, etc.), which require modifications of existing plans or affect the synchronization of vehicles. As suggested by Ho et al. (2018), disruption management is an important and realistic aspect that should be taken into consideration for any company while planning a set of routes to service its users. In such cases, the already existing routes should be modified to manage the disruption. Hence, the need for developing new models and frameworks to capture these factors of disruption management in the field of ride-sharing. Furthermore, SAVs could set up an interesting mobility option for the passengers (Farhan and Chen, 2018), i.e., SAVs essentially provide a ride-sharing service to travelers. Studying how the SAVs can be managed in such disruption situations can be considered a promising research direction.

11. Vehicle Technical Characteristics and Sustainability Issues

Figure 7 identifies some key challenges related to vehicle characteristics and sustainability issues. For example, traditional ride-sharing models assume that the service of people is performed by a fleet of ICEVs (Yu et al., 2019) or SAVs/AVs with similar characteristics (Levin et al., 2017): engine speeds, engine displacement, curb weight, frontal surface area, etc. As discussed in Masmoudi et al. (2018), the special characteristics of the vehicle may affect the fuel consumption as well as the CO_2 emissions. Also, the vehicle identification varies according to many physical features, such as curb-weight and vehicle size. Adding to these specifications, we also find variations based on combustion technology. These include engine speed, engine displacement, aerodynamic drag, and engine friction aspects. If these vehicle aspects are modified or transformed, this may have a remarkable impact on fleet emissions. Additionally, one of the critical aspects that might affect fuel consumption is vehicle aerodynamic durability (Fontaras et al., 2017). Therefore, different vehicle characteristics should be incorporated into the optimization models.

Using a fleet of AVs has received a great deal of attention by researchers until now, due to the importance of this new technology. However, there are some variations in which AV-based systems need to be considered differently. For instance, some privately-owned AVs might be used while their owners do not use them. Therefore, these AVs can be employed on a specific road, which can help to minimize their traffic-related issues compared to ICVEs. In addition, planning recharging stations and maintenance services may need different strategies and techniques, especially as they have multiple charging technologies (Keskin and Çatay, 2016) and the battery may need several hours to be recharged. This can be time-consuming at some re-charging stations (Mourad et al., 2019). Future research considerations in this area include the identification of using a fleet of AVs for people transportation, how AVs respond to passenger mobility needs, and how shared AVs could affect existing routes.

One challenge that arises in most realistic applications of electric AVs in routing problems is that a vehicle of this type may need to frequently recharge its battery to be able to continue the service route, due to their limited battery capacity (Bongiovanni et al., 2019). In addition, the inadequate infrastructure for recharging AVs makes it very difficult to plan the routes of these vehicles. There is a scarcity of recharging stations needed for these vehicles. Also, they are usually not evenly distributed across a certain region, especially when compared to the widely available gas stations on the roads to refuel the ICEVs (Levin et al., 2017). In this regard, effective transportation planning should take into consideration the visits of users, as well as stops in these stations. The need to recharge the battery is frequently encountered during the customary working day. In the context of the ride-sharing problem, not taking the recharging requirements beforehand in planning the service route may cause service disruption due to a shortage in energy, and possible violation of the problem constraints –e.g., the visiting time windows and/or the maximum ride time of users. Such violations can largely lead to the dissatisfaction of customers, which impacts on the overall service quality and breaks one of the main conditions of the ride-sharing. Moreover, to decide when the AVs should be recharged during the planning of routes it is necessary to develop a new realistic energy-consumption function that takes into consideration the characteristics of these vehicles (Corlu et al., 2020). This can be based on the consumption model function developed for the ICEVs or EVs with drivers developed in several works (Masmoudi et al., 2020).

A recent trend in vehicle routing and green logistics is considering environmentally friendly processes in all aspects of the transportation process. Specifically, the reduction of CO_2e is a major concern. In this context, a relevant challenge in the field of green vehicle routing problem (GVRP) is the pollution routing problem (PRP), in which the minimization of energy and CO_2e emissions are widely studied (Demir et al., 2012, 2014). Unlike the traditional objective function for ride-sharing that tries to minimize the total traveling distance (Wang et al., 2019), operational cost (Alonso-Mora et al., 2017), travel time (Jung et al., 2016), or maximizing the total profit (Yu et al., 2018), future research can consider minimizing the total required energy based on the vehicle characteristics, the environment, the speed of the vehicle, and the traveling distance. In addition, existing ride-sharing models can be extended into multiple-objective ones by introducing dimensions related to profit, operational costs, environmental impacts, etc. So far, the most studied ride-sharing problems consider a single objective function (Wang et al., 2019), while only a few multi-objective ride-sharing studies have been reported (Yu et al., 2019).

12. Hybrid *x-Heuristics* and Agile Algorithms for Ride-Sharing Problems

Regarding the existing approaches for solving ride-sharing problems, we observed that the choice of metaheuristics is becoming increasingly popular. For example, out of the 29 studies presented in Table 1, only 5 of them focus on proposing only an exact approach, whereas 9 of them propose a heuristic method in conjunction with an exact method, and 14 of them provide a heuristic/metaheuristic method and/or other solving approaches (e.g., simulation techniques). Despite the importance of using exact solution methods for solving these problems to optimality, the use of such methodologies is often limited by the size of the problem instances or proposed only for validation purposes. This is due to the fact that most ride-sharing problems are *NP-hard*, large-scale, and contain difficult constraints imposed by real-life operations. In our view, future strategies for ride-sharing optimization should consider the following aspects: *(i)* the development of solving methods that use updated information to cope with stochastic and dynamic ride-sharing variants; *(ii)* the development of new dynamic and stochastic frameworks and techniques to capture different events (e.g., accidents, failures, etc.) that can happen in the existing route planning; *(iii)* the development of *agile optimization* (AO) algorithms able to provide real-time solutions.

Regarding stochastic variants of the ride-sharing problem, the combination of metaheuristics with simulation, also known as *simheuristics* (Juan et al., 2018), can be an effective methodology. Some recent applications of simheuristics can be found in areas as diverse as waste collection management under uncertainty (Gruler et al., 2017), arc routing problems with random demands (Gonzalez-Martin et al., 2018), flow-shop scheduling problems with stochastic processing times (Gonzalez-Neira et al., 2017), project portfolio management under uncertainty (Panadero et al., 2018), or inventory routing problems with stochastic demands (Gruler et al., 2020). Similarly, when dealing with ride-sharing variants under dynamic conditions (e.g., traffic conditions that evolve over time), one promising approach is the hybridization of metaheuristics with machine learning methods, also called *learnheuristics* (Calvet et al., 2017). Recent applications of learnheuristics to different vehicle routing problems under dynamic conditions can be found in Calvet et al. (2016) and Arnau et al. (2018).

Despite being able to generate high-quality solutions for a range of optimization problems, traditional solving methodologies, such as exact methods, metaheuristics, and simulation techniques, might not represent the most suitable approach when a real-time solving limit is imposed as a hard operational constraint of the associated *NP-hard* problem. In order to deal with this limitation, the concept of agile optimization has arisen as a new optimization and decision-making tool for solving optimization problems in real-time. As mentioned, dynamic ride-sharing requires the dealing of new information dynamically in real-time, often during the plan in execution, i.e., *en-route*. This information includes the trip information, which leads to the necessity for several taking real-time decision making. Hence, due to these likely continuous changes, a re-optimization of the system is required each time new data should be incorporated into the model.

AO refers to the massive parallelization of biased-randomized (BR) algorithms, which are extremely fast in execution, easily parallelizable, flexible, and require the fine-tuning of a few, or even just a single parameter. In the BR techniques, a biased (non-symmetric) randomization effect is introduced into a heuristic procedure by using a skewed probability distribution. This simple mechanism extends a deterministic heuristic –which is extremely fast in execution, even for large-scale optimization problems– into a probabilistic algorithm without losing the logic behind the original heuristic (Ferone et al., 2019). The core idea of AO is to run several hundred or even thousands of threads in a concurrent way, being each one an execution of a BR heuristic. As a result, many alternative solutions are generated in the same wall-clock time as the one employed by the original heuristic –some of them outperforming the one generated by the original heuristic– and the best solution is chosen. Therefore, in addition to the advantage of finding reasonably good solutions in real-time, the use of AO algorithms for solving (dynamic) ride-sharing problems can be seen as a useful approach for solving this type of problems in which new information arrives all the time. In summary, AO algorithms represent a new paradigm in the design of optimization algorithms, which follows the following principles: *(i)* extremely fast execution, thus providing real-time decision support; *(ii)* easy to implement and run using parallelization techniques; *(iii)* flexibility to deal with different T&L problems and variants; *(iv)* parameter-less, hence avoiding complex and time-costly fine-tuning processes; and *(v)* specifically designed to run iteratively every few seconds or minutes –hence allowing for high-frequency re-optimization– as new streams of data arrive in a dynamic and connected environment. This novel AO approach represents a breakthrough with respect to traditional optimization, simulation, and machine learning methods, which typically require long computation times –and, therefore, cannot deal with present and future T&L scenarios using unmanned and self-driving vehicles, which are characterized by their dynamism and uncertainty. Notice that AO works in an environment of dynamic (constantly changing) conditions, whereas traditional optimization tends to oversimplify these important aspects of the real world. Traditional optimization frameworks are limited when dealing with real-time coordination and optimization needs in current and future T&L applications in smart sustainable cities. This is especially the case when electric, unmanned, and connected/self-driving vehicles are considered in ride-sharing and carpooling activities. Using a scale from 1 (low performance) to 5 (high performance), Figure 8 shows a comparison of multiple analytical methodologies in terms of dimensions such as: *(i)* capacity to provide optimal values (exact methods excel here); *(ii)* computational time required (both heuristics and agile algorithms show the highest speed levels, offering real-time solutions); *(iii)* flexibility to model real-life situations (simulation excels here); *(iv)* capacity to deal with uncertainty scenarios (simulation and simheuristics show a superior performance here); *(v)* capacity to deal with large-scale problems (heuristics, metaheuristics, and agile algorithms surpass the others); and *(vi)* capacity to deal with dynamic environments (learnheuristics, heuristics, and agile algorithms excel in this one).

13. Conclusions

From the trends analyzed in this work, ride-sharing operations in smart and sustainable cities are expected to continue growing over the next few years. Therefore, policy-

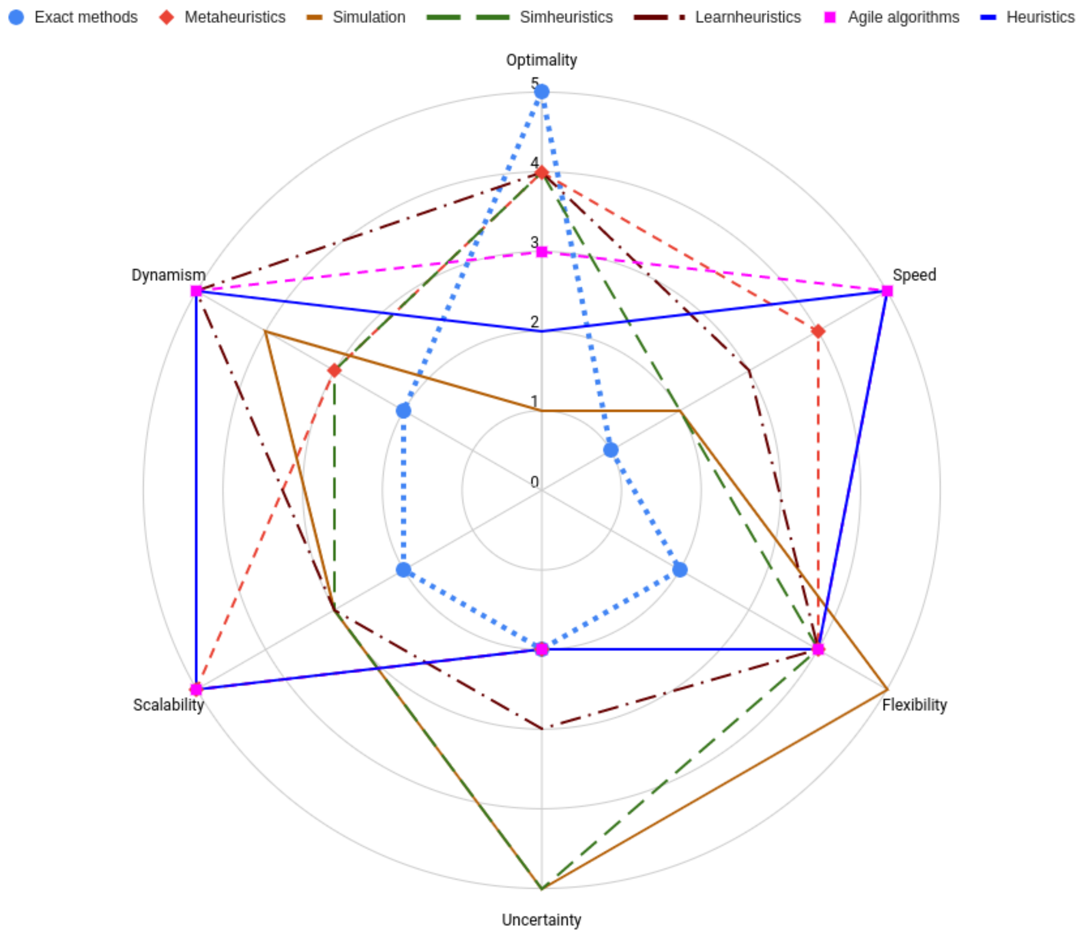


Figure 8.: Multi-dimensional comparison of different analytical approaches.

makers should consider how to optimize these operations to provide timely and efficient service to citizens and, at the same time, minimize important aspects such as the impact of the mobility of people in the environment and social activity inside the city. In this regard, our review confirms the existence of studies that show clear benefits of ride-sharing and carpooling practices in urban areas, such as: *(i)* a reduction in the overall cost of mobility systems, measured in travel time and in energy consumption; and *(ii)* a notable reduction in the volume of vehicles circulating in the city, which could also lead to lower levels of CO_2e.

However, there are still several aspects that must be taken into account by authorities when designing, developing, and, especially, implementing these systems for real-life applications. In this regard, we hope that this article sheds light on these issues. For this purpose, a review of the existing literature on the ride-sharing and carpooling optimization problems has been presented. We expect to facilitate the identification of problems and the analysis of alternatives based on experiences in other urban areas. Likewise, the most relevant studies in the field have been classified according to the analytical methodology used, that is, exact methods, metaheuristics, or simulation, which can help with the decision-making process considering different environments (including uncertainty). The particularity and dynamism in real-time of these problems make them especially difficult to adapt to real cases. In this case, some authors, for example, Borcuch (2016), point out that, from a government point of view, the biggest challenge for any city in adopting these shared modes of transport is how to find a balance between adopting these platforms and regulating them in the name of safety and responsibility.

In order to reinforce the analysis of alternatives and the decision-making process, our study has also identified the main challenges and research opportunities related to the optimization of shared trips. In this way, it is also expected to serve as a handbook for policy-makers that helps navigate towards a more sustainable (environmentally, socially, and economically) city paradigm. This may include the analysis of the vehicles' capacity, the boosting of multiple charging technologies, the creation of charging stations, or the design and planning of more sustainable routes, among others. In terms of main challenges, this paper illustrates those challenges related to synchronization and coordination issues, as well as the increasing inclusion of electric and autonomous vehicles in our modern urban, peri-urban, and metropolitan areas. In terms of research opportunities, the paper analyzes the research opportunities associated with the inclusion of heterogeneous vehicle fleets, dynamic scenarios, conditions of uncertainty, technical characteristics of the vehicle, and energy and sustainability issues (for example, type of fuel required and level of emissions carbon), etc. With all this, it is intended that the managers of these areas are aware of the changes that the incorporation of these practices in their cities implies, the improvements it will bring, as well as the resources that will be necessary for their implementation.

Finally, the document goes a step further and presents new approaches to deal with resource optimization problems in carpooling in real life, which must take into account random events and dynamic traffic conditions. To address these issues, the need to develop new hybrid approaches that combine metaheuristics with simulation and/or machine learning methods is analyzed. Also, the article highlights the concept of agile optimization algorithms, which allow generating good quality solutions in real-time (even less than a second) and recalculating them every few minutes as new data becomes available.

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