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A survey on emergent trends in the optimization of car-sharing systems

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Abstract

This paper reviews the most recent literature on the optimization of car-sharing systems. Unlike other surveys, we do not focus on a single aspect of car-sharing systems, but we consider a wide range of optimization problems with a global view. Our aim is threefold. First, we revise the classic decision problems arising in car-sharing systems with conventional and electric vehicles, such as the fleet size, the station location, and the vehicle relocation. Then, we discuss some of the most recent decision problems arising in more innovative car-sharing systems, like those with autonomous vehicles, with mixed fleets, and the multi-modal and the time-dependent ones. Finally, we focus on new perspectives arising in the optimization of some innovative car-sharing services that are not yet (or little) investigated in the literature and that are worthy of attention from the operations research point of view. For each of them, we also highlight new and challenging open decision problems that deserve academic attention.

Keywords: literature review; shared mobility; multi-modal transport; autonomous vehicles; time-dependent service

1. Introduction

Implementing environmentally sustainable mobility solutions is increasingly becoming a necessity due to the recent climate changes. Along this direction, the on-demand mobility services provided by car-sharing systems (CSSs) can lead to a significant reduction in traffic congestion and then in environmental pollution. Indeed, reducing the ownership of private cars also decreases the number of parked cars (considering that a private car remains parked for more than 90% of the time, on average) and then the traffic congestion due to the search for a vacant parking lot. On the other hand, CSSs are also more advantageous for the user since they implement the so-called

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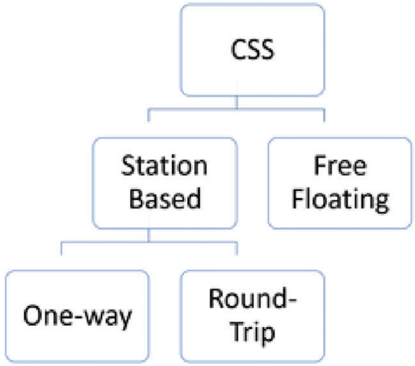

Fig. 1. A CSS classification.

pay-as-you-drive paradigm whereby a user pay for the service depending only on the effective time of use, even for a fraction of an hour, unlike the traditional car rental services. This makes cars an affordable transportation means for everyone, being free from fixed costs (e.g., taxes and assurance) or maintenance costs. For all these reasons, CSSs are receiving a big impulse. Indeed, according to Statista (https://www.statista.com/), their revenue is forecast to increase, passing from US$8.41 billion in 2017 to an expected US$16.91 billion in 2027. Of course, a great impulse to the diffusion of such systems is also given by the new technologies especially in the automotive industry and information technology, among which, is the possibility to reserve a car directly through an app and then to access and use the car without a key (a key-less service).

Moreover, in the last years, several car-sharing (CS) companies are also providing their users with a fleet of electric vehicles (EVs) rather than traditional internal combustion engine vehicles (ICEVs). Car2Go (http://www.car2go.com/), Autolib (www.autolib.eu), Autobleue (http://www.auto-bleue.org), and e-vai (https://www.e-vai.com/) are some examples of such systems. Both less harmful emissions and better traffic conditions positively impact the citizens' quality of life and, by discouraging the use of a car of one's own, people are more enticed to walk for short trips. This way, the CSSs can support *environmental*, *economic*, and *social sustainability*.

Currently, the CS services can be mainly offered either by a fleet owned by the CS company or by private cars. In the latter case, car's owners make their vehicles available to their friends/colleagues and/or to users of trusted social networks/platforms when not using them (*peer-to-peer car-sharing*). Depending on the operating model implemented, CS services can be either *station based* or *free-floating* (FF), as shown in Fig. 1. The term station based means that users pick the cars up and deliver them at stations of the system. In this case, the services offered can be either *one-way* (OW), i.e., the user can deliver the car to a station different from that of pickup, or *round-trip*, i.e., the station of delivery must coincide with that of pickup. Whereas, in FF services, there is no longer the concept of station but rather users pick the cars up and deliver them at any parking lot (Jorge and Correia, 2013). Of course, the FF CSSs are currently the most flexible but they also pose several additional management problems, among which we mention a proper vehicle relocation (VR) across the territory in order to constantly balance the supply and the demand. Moreover, the cars composing the fleet of the CSSs (also peer to peer) may be green (e.g., electric). In this case, additional management problems have to be properly addressed, e.g., the usually limited driving

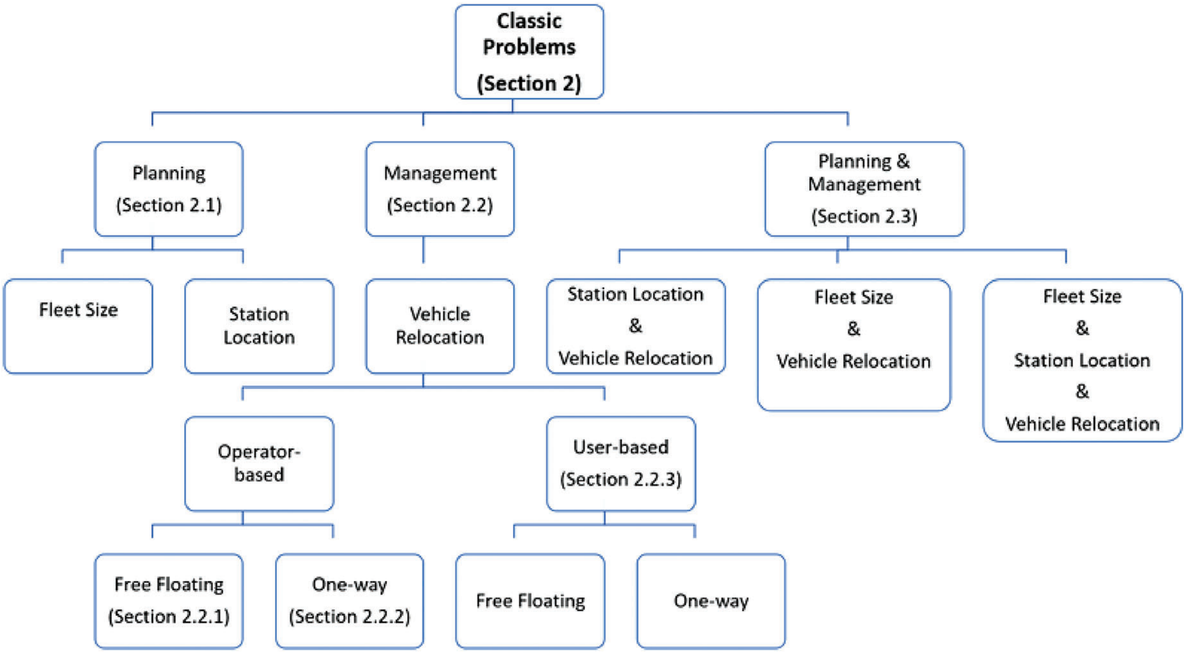

Fig. 2. A schematic representation of the classic problems reviewed.

range and, consequently, the need of being recharged. In some cases, the fleet may be mixed, e.g., comprising both EVs and ICEVs (e.g., ShareNow).

Several surveys already deal with the optimization of CSSs. For example, Jorge and Correia (2013) focus on the demand estimation, whereas Laporte et al. (2018) deal with the fleet size (FS), the station location (SL), and the inventories from a planning point of view and the VR from the management perspective. Regarding electric CSSs (ECSSs), Shen et al. (2019) describe the planning of both charging infrastructures and operations as well as the public policy and business models. Considering contributions on access-based CS, Ferrero et al. (2018) propose a taxonomy of the literature from 2001 to 2016. Illgen and Höck (2019) deal with the VR in OW CSSs, whereas Nansubuga and Kowalkowski (2021) review contributions on business models, customer behavior, user drivers, and barriers and VR, from 1996 to 2020. Golalikhani et al. (2021) discuss the current literature and the business practices towards decision support frameworks, whereas Yao et al. (2022) focus on the ECSSs from both the supply and the demand point of view

In light of the above, this survey specifically wants to answer the following questions:

1. *What are both the optimization models and methods for the most classic decision problems in CSSs?* Although our focus is mainly on new trends in the optimization of the CSSs, in our opinion, giving also an overview on some classic decision problems in CSSs (Section 2) can enable a better understanding of the new ones. Unlike the majority of the already published surveys on the optimization of CSSs, we discuss more than one classic decision problem, as shown in Fig. 2.

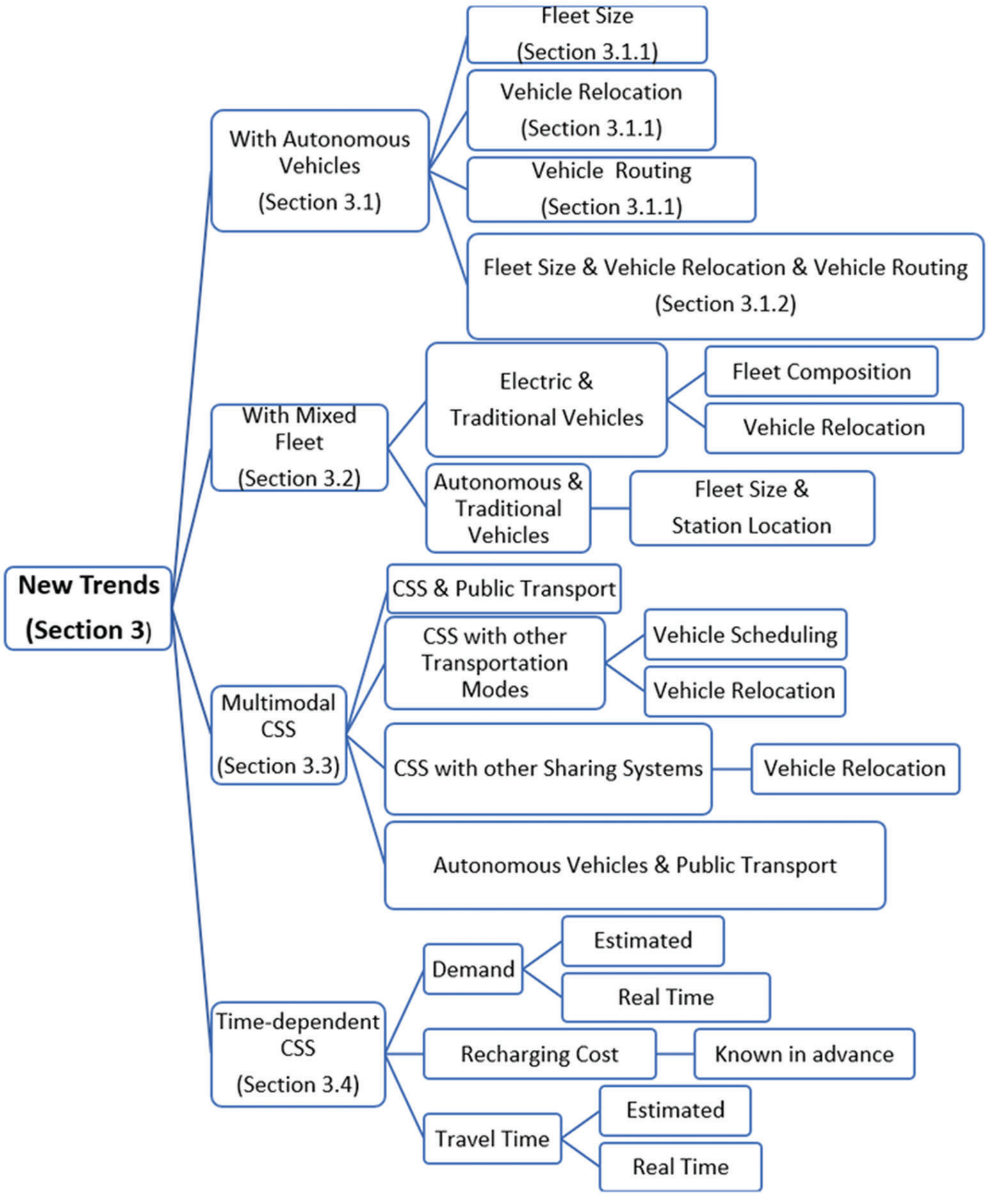

Fig. 3. A schematic representation of the new trends identified.

2. *What are the new trends in the optimization of CSSs?*
   We focus on more recent decision problems related to the introduction of autonomous vehicles (AVs) in CSSs (Section 3.1), the use of mixed fleets (Section 3.2), the integration of the CS services with other transportation modes, i.e., the multi-modal CSSs (Section 3.3), and the modeling of some time-dependent components of the CSS (Section 3.4), as depicted in Fig. 3.

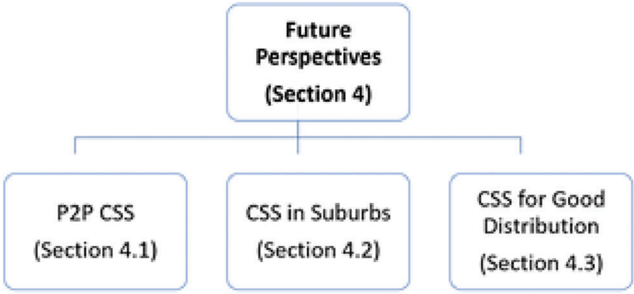

Fig. 4. A schematic representation of the future perspectives.

3. *What are the future perspectives and services worthy of being investigated from an operations research point of view?*
   To this purpose, we detected new research directions that deserve to be faced for the optimization of peer-to-peer CSSs (Section 4.1), of CS services in suburbs (Section 4.2), and of a CS service integrated with goods distribution (Section 4.3), as shown in Fig. 4. For each of them, we highlight new challenging decision problems worthy of further investigation from an operations research point of view.

The growing interest in CSSs has produced many contributions to the literature over the years. For example, since 2004 to date, more than 10,000 scientific articles have been produced (from the Scopus database, January 2023), and among them more than 1000 are in the areas of decision science and mathematics. To the sake of brevity, we limit our overview to the papers published from January 2019 to January 2023, with a few exceptions, considering the areas of decision science, computer science, and mathematics, since the previous years are already covered by the surveys that we cited above. This way, we reviewed more than 90 papers. Finally, for each research topic, the main features of the cited works were summarized in tables. In particular, in each table, for every contribution, we report the authors (column *paper*), the car-sharing type (column *CS type*, i.e., OW/FF and in some cases, also round-trip), the *fleet type* (e.g., ICEVs, EVs, and so on), the *objective function/s* to optimize, the *solution approaches* proposed, the *instance type* used (e.g., generated instances, taken from the literature, real case studies). Finally, other significant features of the problem and/or of the methodology proposed were indicated in the column *further feature(s)*. All the acronyms used in this survey are summarized in Table 1.

2. State-of-the-art of classic optimization problems in CSSs

This section describes the state-of-the-art of more classic decision problems occurring in CSSs. In particular, we analyze the contributions on both the *planning* and the *management* of a CS service. The readers are also referred to the surveys of Jorge and Correia (2013), Laporte et al. (2018), Illgen and Höck (2019), Izadi (2020), and Yao et al. (2022) already described in Section 1.

Table 1
Acronyms used in the survey

Name	Acronym	Name	Acronym
Adaptive large neighborhood search	ALNS	Autonomous vehicle	AV
Car-sharing	CS	Car-sharing system	CSS
Electric car-sharing system	ECSS	Electric vehicle	EV
Fleet size	FS	Free-floating	FF
Internal combustion engine vehicle	ICEV	Integer linear program	ILP
Mixed integer linear program	MILP	Mixed integer nonlinear program	MINLP
Not specified	NS	One-way	OW
Peer-to-peer	P2P	Station location	SL
Vehicle relocation	VR	Linear program	LP

2.1. Fleet size optimization and station location optimization

Concerning the planning, both the problem of properly sizing the fleet and that of strategically locating the stations represent issues to address. The most common objective considered is the maximization of the total number of users served. The main challenge is to consider the satisfaction of their travel requests depending on the FS and/or the SL. To this purpose, often simulation is used to emulate the users' behavior. If the fleet contains (also) EVs, there is the further decision problem of properly designing the charging infrastructure.

Monteiro et al. (2021) formulate a mixed integer linear programming (MILP) model for determining the FS such that the number of users served is maximized (i.e., indeed a measure of the quality of service). The users' flexibility, i.e., users are willing to walk to other stations if the current stations have not vehicles available, is also considered. Both round-trip and OW CSSs are taken into account, and the dynamics related to users looking for available resources are also simulated via agent-based simulation. Different scenarios are considered by taking data from São Paulo, Brazil. Both a nonlinear integer programming model and a genetic algorithm are proposed in Sai et al. (2020) for locating the stations of a CSS, maximizing the number of users served. The proposed approach is tested on a real-life case study taken from Lanzhou (China). Stochastic programming is applied in Wang et al. (2021b) to determine the optimal stations location and also the type of each charging facility, in ECSSs. The aim is to minimize the route distances, the driver delivery times, the electricity procurement costs, and the downside risk costs, under uncertainties on users' demands, itineraries, traffic flow, and electricity prices. The proposed approach is tested on a transportation network from https://github.com/KexingLai/EVCS-Planning-for-Car-Sharing. Su et al. (2022) propose a dynamic optimization method based on a Mixed Integer Programming model to address the SL in OW CSSs, maximizing the system manager's total profit (i.e., the total revenue due to the users satisfied minus the costs related to station construction, parking slot operations, vehicle maintenance, and rescheduling). Their solution method is tested on a real-life scenario taken from Vancouver (Canada).

Other literature contributions address both the FS and the SL problem. Zhang et al. (2021) focus on solving the two problems in OW station-based CSSs, under uncertain demands, maximizing the profit and minimizing the risk. The profit is the difference between the total revenue and the operating costs due to both parking spaces and purchased vehicles. Both a branch-and-cut algorithm and a scenario decomposition approach are developed and tested on a case study from Ha:mo RIDE (Toyota). A data-driven MILP model is recently formulated in Chen et al. (2022) to determine the number, the size, and the location of the stations as well as the FS in OW ECSSs, minimizing the total daily cost paid by the system manager (for station investments, parking lots, vehicles, and power consumption). The spatial demand distribution as well as the interactions among stations is also considered. The proposed MILP model is solved via an extension of the Benders decomposition algorithm and tested on a real-life case study taken from Beijing (China).

Lu et al. (2021a) address the problem of allocating EVs at the stations in OW CSSs to maximize the total profit, considering both uncertain and stochastic demands, as described more in detail in Section 3.4.

The contributions described in this section are summarized in Table 2.

2.2. *Vehicle relocation optimization*

Regarding the management of CSSs, one very crucial issue concerns VR optimization. As said in Section 1, both OW and FF CSSs guarantee a flexibility higher than that of the round-trip ones. However, the main challenge is to balance the supply and the demand of vehicles moving them where they are requested. The main objective optimized is the difference between the total revenue associated with the user requests satisfied and the costs, among which, those due to the relocation tasks. According to Barth and Todd (1999), VR can be performed considering the immediate demands of a particular parking lot (*static relocation*) or by estimating the requests considering either historical data or via techniques for forecasting travel demand (*historical predictive relocation*) or with an exact knowledge of the demand, e.g., in CSSs with reservation (*exact predictive relocation*). In addition, the relocation tasks can be performed directly by users (i.e., *user-based relocation*) or by the service provider (Barth et al., 2004). In the first case, the relocation is performed by users who are incentivized to delivery a car at a station/parking lot through the leverage of price. In this case, an additional level of risk has to be considered since the user may not accept. Otherwise, the service provider may be either use a truck or a team of operators. However, with the aim of reducing both the traffic congestion and the pollution, trucks are no longer used. Indeed, relocation tasks performed by operators are the most widely implemented (*operator-based relocation*) according to which, the route of each operator is a sequence alternating a pickup of a vehicle and its delivery.

In the following, the main contributions on operator-based VR in both FF (Section 2.2.1) and OW CSSs (Section 2.2.2) are described. Finally, contributions on user-based VR are described in Section 2.2.3, whereas Section 2.3 discusses the main literature works in which several of the aforementioned decision problems are addressed simultaneously. The contributions discussed in this section are summarized in Tables 3 and 4.

2.2.1. *Operator-based vehicle relocation in free-floating CSSs*

Concerning the VR tasks in FF CSSs, the main challenge consists in determining the zones with more vehicles than necessary and, on the other hand, those with a shortage. This usually requires referring to historical data. If the fleet is also made up of EVs, the additional challenge consists in determining which recharging station an EV is recharged at. In Folkestad et al. (2020), for example,

Table 2
Main features of the papers cited in Section 2.1

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Chen et al. (2022)	OW	EVs	Station investment cost Parking space cost Vehicle cost Power consumption cost	MILP Benders decomposition	Case study from Beijing	Spatial demand distribution
Lu et al. (2021a)	OW	EVs	Revenues-supply costs-travel costs-holding costs-penalties	MILP Robust optimization Chance-constrained technique Network decomposition math-heuristic	Case study from Sun Moon Lake National Park	Multi-layer time–space network
Monteiro et al. (2021)	OW	ICEVs	Users satisfied	Simulation-based optimization	Case study from São Paulo	Walk to nearby stations Also round-trip
Sai et al. (2020)	OW	EVs	Users satisfied	Nonlinear integer programming Genetic algorithm	Case study from Lanzhou	Budget constraints
Su et al. (2022)	OW	ICEVs	Revenues-construction costs-parking slot operation costs-vehicle maintenance costs-rescheduling costs	Dynamic optimization method	Case study from Vancouver	Construction costs Parking slot operation costs Vehicle maintenance costs Rescheduling costs
Wang et al. (2021b)	OW	EVs	Route distances + driver delivery times + electricity procurement costs + downside risk costs	Stochastic programming	Taken from literature	Uncertain users' requirements Uncertain itineraries Uncertain traffic congestion Uncertain electricity prices
Zhang et al. (2021)	OW	ICEVs	Profit Risk	Branch-and-cut algorithm Scenario decomposition algorithm	Case study from Ha:mo RIDE	Demand uncertainty

Table 3
Main features of the papers discussed in Section 2.2 (Part I)

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Bogyrbayeva et al. (2021)	FF	EVs	Relocation time	Reinforcement learning	Case study from Car2go	Operators use shuttle VR overnight
Boyacı and Zografos (2019)	OW	EVs	Revenues- VR and operator hiring costs	Simulation-based optimization	Case study from Nice	Operator-based VR
Bruglieri et al. (2019)	OW	EVs	Renevues- salaries of workers	ALNS Tabu search	Case study from Milan	Operators use folding bikes Bounding procedures
Cai et al. (2022)	OW	EVs	Renevues- salaries of workers	Hybrid ALNS Tabu search	Simulated data	Triangle inequality may not hold
Folkestad et al. (2020)	FF	EVs	VR costs	Mixed integer programming Genetic search and adaptive diversity control	Simulated data	Operators use service cars Routing of operators and of service cars
Hellem et al. (2021)	FF	EVs	Revenues- VR, toll, wear costs	Rolling horizon optimization ALNS	Case study from Oslo	Operators use public transport or folding bikes
Huang et al. (2020b)	OW	EVs	Revenues- VR, electricity, worker costs Revenues- electricity costs	MINLP	Case study from EVCARD	Operator-based VR User-based VR
Kypriadis et al. (2020)	FF	EVs	VR walking times	Algorithmic techniques	Case study from Rome Case study from Florence	Operator-based VR overnight
Lai et al. (2022)	OW	EVs	Revenues- fare discounts to users- staff movement costs- charging costs	Iterated local search	Data from network of GoFun	Car and staff relocation User flexibility EV charging
Li et al. (2022a)	OW	EVs	Budget allocation	Simulation-based optimization	Case study from Chengdu	Stochasticity and road congestion
Li et al. (2022b)	OW	ICEVs	Revenues- holding and moving/ transferring costs	Stochastic programming	Case study from NY taxicab trip record dataset	Stochastic demands

Table 4
Main features of the papers discussed in Section 2.2 (Part II)

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Lin and Kuo (2021)	FF	EVs	Revenues-purchasing costs + expected profit Expected profit	L-shaped method	Simulated data	Operator-based VR Demand stochasticity Parking space stochasticity
Prencipe et al. (2022)	OW	EVs	Revenues Profits for energy sale/purchase	MILP	Case study from Delft	Vehicle-to-Grid technology
Qin et al. (2022)	OW	EVs	Revenues- staff costs Route duration	Branch-and-price-and-cut method	Generated data	Set-packing reformulation
Santos and de Almeida Correia (2019)	OW	ICEVs	Costs due to vehicle movements for VR Costs for staff movements by public transport Costs for potential profit losses for unserved users Penalties for unserved maintenance requests	Simulation-based optimization	Case study from Lisbon	Operator-based VR Penalties for requests unserved Carpooling among operators
Schiffer et al. (2021)	FF	ICEVs	Users served	Exact algorithm	Case study from Car2go	User-based VR k-disjoint Shortest Paths Problem
Soppert et al. (2023)	FF	ICEVs	Users' maximum walking distances Zone sizes	MILP	Case study from ShareNow	More profitable pricing decisions
Stokkink and Geroliminis (2021)	OW	EVs	Weighted omitted demand loss-cost for offered discount	Markov chain-based model Learning algorithm	Case study from Grenoble	User-based VR
Wang et al. (2019)	OW	EVs	Inventories-thresholds after VR	ILP Simulation	Case study from EVCARD	Upper and lower thresholds Operator-based VR

Continued

Table 4
(Continued)

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Wang et al. (2021a)	FF	EVs	Revenues due to users satisfied Revenues generated by losing incentives or gaining surcharges	Two-level logit model Heuristic	Case study from EVCARD	User-based VR Incentives and surcharges
Yang et al. (2022)	OW	ICEVs	Revenues- vehicle depreciation and VR costs Monetary + travel time + discomfort costs	Multi-leader–follower framework	Case study from Quanzhou	Operator-based VR Competitive market

a mathematical model for both charging EVs and relocating them by operators is formulated, minimizing the relocation costs plus the costs of deviating from the ideal state at each station and for postponing charging tasks. Each operator directly drives an EV to relocate and reaches the next EV to relocate by a service vehicle. The problem complexity is further increased considering the dependencies between the routing of both the operators and the service vehicle. A hybrid genetic search with an adaptive diversity control algorithm is also designed. Hellem et al. (2021) address also both the operator-based relocation problem and the EV recharging problem but with a real-time users' demand, as detailed in Section 3.4. Alike Folkestad et al. (2020), in Kypriadis et al. (2020) EV relocation is performed overnight by one operator, primarily minimizing the relocation walking time. The resulting *minimum walking car repositioning problem* is solved via algorithmic techniques, also extended to the case with more operators, tested on a real CS service operating in Rome and Florence. Also, Bogyrbayeva et al. (2021) consider EV relocation tasks overnight by using a shuttle that picks the drivers up and drops them off. The proposed reinforcement learning approach is tested on a Car2go CSS in Amsterdam (The Netherlands). Finally, Soppert et al. (2023) propose two analytical matching functions, considering also the customers' maximum walking distance and zone sizes. Numerical results are carried out on a case study based on data of ShareNow.

2.2.2. *Operator-based vehicle relocation in one-way car-sharing systems*

Concerning the operator-based VR, in one-way CSSs, one challenge regards how to properly balance the supply and the demand of vehicles among the stations. To this aim, each operator usually picks a vehicle up at a station and deliveries it at another station, thus alternating a pickup with a delivery. Determining the sequence of pickups and deliveries, for each operator, respecting several constraints (e.g., the time window within each car has to be delivered at the station where it is required) is another challenge to address as well as determining the appropriate number of vehicles initially available at each station. For example, Li et al. (2022b) design a data-driven optimization-based approach for both determining the initial number of cars at each station and relocating the vehicles, considering stochastic demands. The proposed approach combines the non-parametric learning algorithm and the two-stage stochastic programming, and it is tested on instances taken from the New York taxicab trip record data set. The aim is the maximization of the expected total profit, i.e., the total revenue minus the holding and transferring costs. In some papers, these decision problems are also addressed in a competitive CS market like in Yang et al. (2022). In particular, the authors address both a pricing and operator-based relocation problem. To this aim, they propose a multi-leader–follower framework, maximizing the profit of each company and minimizing the users' disutility. The profit is represented as the total revenue due to the users served minus the vehicle depreciation and relocation costs. On the other hand, the disutility is defined in terms of monetary, travel time, and discomfort costs.

If, on the one hand, the advent of electric mobility can help to significantly reduce the harmful emissions and thus to increase the citizens' quality of life; on the other hand, the introduction of EVs into sharing systems poses further challenges, particularly due to the charging operations (Mounce and Nelson, 2019). In particular, recharging the vehicles (also during the working day of the system) and returning them with the sufficient battery level are both issues to properly address. Moreover, especially in CSSs with operator-based relocation, EVs must have the sufficient battery level for moving them to the recharging stations. Bruglieri et al. (2019) propose both an adaptive large neighborhood search (ALNS) and a tabu search meta-heuristic to efficiently address the EV relocation problem, maximizing the total profit (i.e., the difference between the total revenue due to the users served and the total cost due to the operators employed), under the hypothesis that operators move from a station of delivery to that of pickup by folding bicycles. In addition, each relocated car must satisfy not only a time window but also a desired state of charge within a given time. Figure 5 shows a small instance of their problem with five parking stations, framed by large squares, each one including two chargers. Each operator starts from a common depot (represented by a triangle) and moves towards a station of pickup with a folding bicycle, whereas to a station of delivery, with the EV to relocate. The distance between adjacent parking stations is 5 km as well as their distance from the depot. Since the bike speed and the EV speed are assumed to be 15 and 25 km/h, respectively, this implies that traveling from a node of pickup to one of delivery, between adjacent parking stations, takes 12 minutes whereas 20 minutes for vice versa. We also assume that one minute is necessary both to take the EV to relocate (including also the time to load the folding bicycle in the trunk of the EV) and also to park it and retrieve the folding bicycle. The driving range of each EV is 150 km, and the recharging time is 240 minutes. Finally, the duty time of each operator is five hours. The arrival time at each station of pickup/delivery is reported below each visited node, whereas the time window each EV is requested at is indicated between square brackets. In addition, each recharging station reports the battery level requested by a user. The example shows that not all the requests can be satisfied due to their time windows and also due to the battery constraints. The results obtained by the two meta-heuristics are compared with those found by the ruin and recreate meta-heuristic of Bruglieri et al. (2017) and with the optimal results obtained via MILP. The authors also propose some bounding procedures to evaluate the results of the meta-heuristics when the optimal solutions are not available. An integrated modeling and solution framework also based on simulation is proposed by Boyacı and Zografos (2019) for the problem of relocating EVs in OW CSSs maximizing the total profit. Wang et al. (2019) optimize the EV relocation, in systems without reservation, considering upper and lower thresholds for inventories and dynamic demand, as explained more in detail in Section 3.4. A simulation-optimization

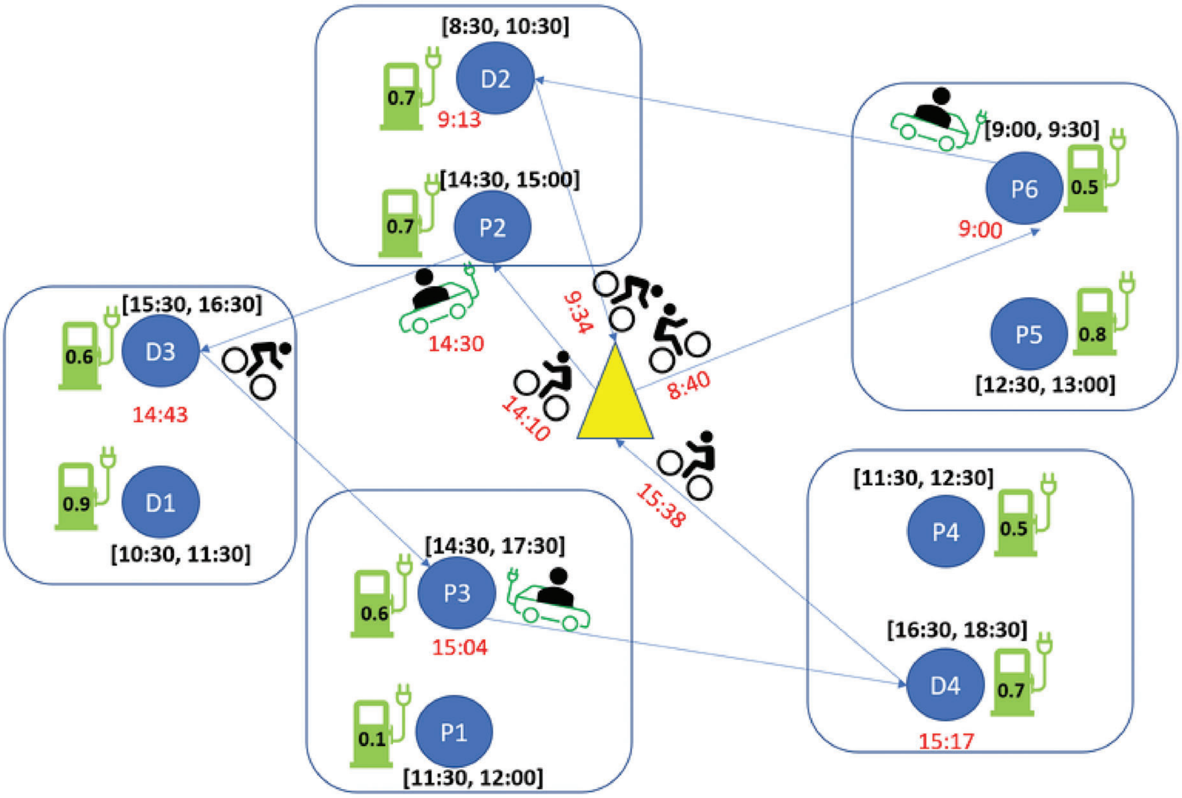

Fig. 5. An application example of vehicle relocation.

approach is described in Li et al. (2022a), where the simulation model considers the stochasticity and the EV-dependent road congestion, whereas the optimization part deals with the relocation problem. Cai et al. (2022) maximize the total profit due to the served requests, through both a hybrid ALNS and a tabu search algorithm. Qin et al. (2022) propose a branch-and-price-and-cut method for relocating EVs, maximizing the overall operational profit, i.e., the total revenue minus the total cost due to the staff employed. Inside a rolling-horizon decision framework, an iterated local search is proposed by Lai et al. (2022), considering a real-time setting and integrating the operators' movement with their possible relocation, the users' spatial flexibility, and the charging tasks, to maximize the total profit (i.e., the total revenue minus costs due to fare discounts for users, staff movement, and EV recharges). In electric CS services, one of the most significant issues to address refers to the charging tasks. Prencipe et al. (2022) deal with the relocation problem of EVs by introducing the vehicle-to-grid technology that allows transferring energy from EVs to the main grid. Such a problem is then formulated via MILP, maximizing the total profit due to the requests served and due to the energy sales/purchases.

Finally, in some papers, carpooling among operators is also allowed. If on the one hand, it may increase the number of relocation tasks performed by the operators, on the other hand, it poses a further challenge regarding the synchronization among them. To the best of our knowledge,

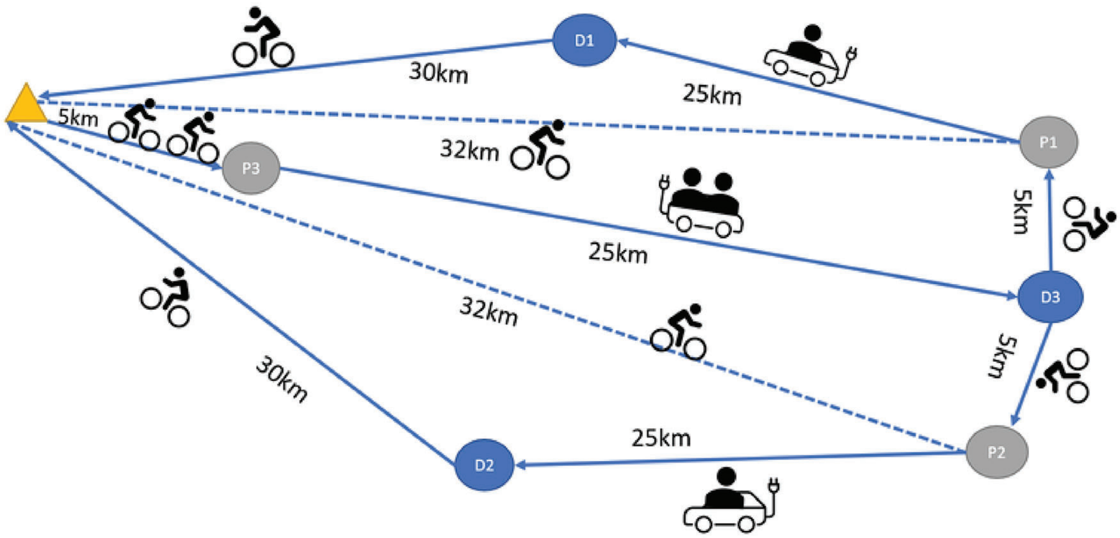

Fig. 6. An illustrative example of collaboration among operators.

collaborative CS was introduced in Bruglieri et al. (2018). The idea proposed consists in allowing operators to carpool when moving from a pickup station to a delivery station. The authors formulate a MILP model and design a column generation based heuristic to solve large-sized instances of the problem. Preliminary results have shown that this collaborative approach allows operators decreasing distances traveled by bike (when moving from a delivery station to a pickup station) but also increasing total profit (by being able to serve more requests in time). Figure 6 shows an illustrative example of the problem. In particular, it is assumed the presence of two operators, an average speed by bike and by car equal to 15 and 25 km/h, respectively, an average time for picking up and delivering the cars equal to one minute and a total duty time of five hours. If the collaboration between the two operators is allowed, they move by bike from the depot to P3, then they can pick a car up and go together to the delivery station D3 where each one continues the respective trip. This way, each of them travels 40 km by bike. On the other hand, if collaboration is not allowed, only one of them can travel 40 km by bike (e.g., through the route depot–P3–D3–P1–D1–depot) and the other one 62 km (through the route depot–P2–D2–depot). Carpooling among operators is also proposed in Santos and de Almeida Correia (2019) in which a real-time decision support tool, made up of a forecasting model, an assignment model, and a filter, is designed. The assignment model aims at minimizing the total cost due to vehicle movements for VR, staff movements by public transport, potential profit losses for unserved users, and penalties for unserved maintenance requests.

2.2.3. *User-based vehicle relocation*

According to the user-based VR, incentives are usually proposed to the users in order to pick a vehicle up or delivery a vehicle at a specific station/place. This way, users directly relocate vehicles. One main challenge consists in how to determine the incentives to propose since they represent a significant discriminating factor according to which the users may decide to collaborate or not. Moreover, the possible influence of other transportation modes on the user's choice is another challenge. Indeed, as demonstrated by Wang and Liao (2021), in which the dynamics related to the supply and the demand in OW CSSs are analyzed, considering a user-based policy, several different factors may affect the users' choices, e.g., the traffic conditions as well as the availability of alternative transportation modes. To this aim, they analyze four different first-come-first-served queuing mechanisms, showing that two of them are more efficient. However, as observed by Schiffer et al. (2021), an open issue is understanding if the sole user-based VR policy is sufficient to cover the imbalance between the supply and the demand of vehicles. The authors observe that to this aim the majority of the papers in the literature proposes simulation-based approaches. Instead, their work proposes an optimization-based method for maximizing the number of users satisfied under a user-based VR policy in FF CSSs. The problem is reformulated as a *k-disjoint shortest path problem*, solved by an exact algorithm, and a real case study is taken from Car2go in Vancouver (Canada). Moreover, the success of a user-based VR policy also depends on the availability of the vehicles, for example, close to the origin/destination of a trip as observed in Stokkink and Geroliminis (2021). To properly address this aspect, in an OW ECSS, they propose a predictive user-based VR policy, i.e., a Markov chain-based model for predicting user-based relocation tasks, maximizing the expected additional profit due to the incentives offered to users. A learning algorithm is developed for both estimating the expected future demands and determining the best discounts. Wang et al. (2021a) propose a method to determine both the incentives and the surcharges according to the demand patterns, in OW CSSs, maximizing the total revenue due to the users satisfied and the losing incentives or gaining surcharges. The proposed approach is tested by using the database of EVCARD (a Chinese CS company in Shanghai).

A comparison between user-based and operator-based VR policies is also investigated. For example, Huang et al. (2020b) present a comparative study in OW ECSSs, with the time-varying EV state of charge. For the operator-based VR strategy, a mixed integer nonlinear program (MINLP) model is formulated, maximizing the revenues minus costs due to relocation, electricity consumption, staff movement, and hiring. For the user-based VR policy, they formulate an MINLP model for setting the price of each trip and a second MINLP model to determine a fixed penalty for those trips leaving the same zone. Results show that VR can be efficiently performed by both the policies.

2.3. Integrated frameworks for several decision problems

This section describes some literature papers, summarized in Table 5, dealing with several of the aforementioned decision problems, simultaneously. To this purpose, Deza et al. (2022) show how it is possible to balance the supply and the demand of EVs at the stations by properly managing the SL problem. Indeed, they formulate the first problem via MILP, maximizing the number of users satisfied and solve the SL by column generation. Bekli et al. (2021) propose an integer programming model to determine the number and the location of fast charges, VR, and battery availability in OW ECSSs, maximizing the total revenue minus the total cost (i.e., the infrastructure upgrade costs, the expected relocation personnel costs, and the VR costs). The authors also design a variable reduction heuristic for relocation and a three-stage station aggregation heuristic for locating fast chargers. An integrated framework is proposed in He et al. (2021) to determine both the size and

Table 5
Main features of the papers discussed in Section 2.3

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Bekli et al. (2021)	OW	EVs	Revenues- infrastructure upgrade costs- expected relocation personnel costs- VR costs	Integer programming Heuristic	Case study from Nice	SL VR
Deza et al. (2022)	OW	EVs	Users satisfied	MILP Column generation	Case study from Ontario	SL VR
He et al. (2021)	OW	EVs	Revenue- staff costs for VR- charging infrastructure costs	Nonlinear optimization Heuristic	Case study from Car2go	SL VR
Huang et al. (2020a)	OW	EVs	Revenues- electricity consumption costs- parking space rental costs- vehicle fixed costs- energy costs- staff costs- penalties for unsatisfied users	MINLP Golden section line search Shadow price algorithm	Case study from Suzhou Industrial Park	SL FS VR
Lu et al. (2021b)	OW	ICEVs	Revenues- fuel costs- VR costs- parking space costs- vehicle depreciation costs- vehicle maintenance costs	Bi-level optimization Genetic algorithm	Case study from Rotterdam	FS Prices VR

the location of the charging stations as well as the VR and charging operations with full recharges, in OW ECSSs. For such a decision problem, the authors formulate a nonlinear optimization model, maximizing the total profit, given by the total revenue minus the total cost (including staff costs for relocation and charging infrastructure costs). They also design a second-order cone programming-based heuristic to efficiently solve the problem.

A bi-level nonlinear mathematical programming formulation is proposed in Lu et al. (2021b), in OW CSSs. At the upper level, the decisions concern the FS, the prices, and the relocation tasks, maximizing the total profit and taking into account also the potential reaction of travelers. At the lower level, instead, the decisions concern the selection of the travel modes made by the travelers, minimizing the travel costs. Indeed, the travelers can choose between private and shared cars. By applying the Karush–Kuhn–Tucker conditions, the authors transform the bi-level optimization model into a single one. Then it is solved by a genetic algorithm and tested on a real-case study from Rotterdam (The Netherlands).

In OW CSSs, the problems of FS, SL, and EV relocation are solved by Huang et al. (2020a), maximizing the difference between the revenues and the costs due to electricity consumption, parking space rental, vehicle fixed costs, relocation operation (i.e., energy and staff costs), and penalties for unsatisfied users. A rolling horizon approach is designed to solve the resulting MINLP model.

Moreover, they design both a golden section line search method and a shadow price algorithm for the problem of fleet and station sizing. Finally, vehicle deployment and relocation are addressed in Lin and Kuo (2021) considering both demand and parking space stochasticity, as described more in detail in Section 3.4.

3. New trends in the optimization of car-sharing systems

This section aims at presenting some new trends in the more recent literature about the optimization of CSSs. To this purpose, Section 3.1 describes the most frequently faced decision problems in CSSs with AVs, Section 3.2 considers the optimization of CSSs with a mixed fleet, Section 3.3 analyzes the papers concerning the optimization of multi-modal CSSs, and, finally, Section 3.4 analyzes the papers where the influence of time in the optimization process is taken into account (e.g., for the demand, the recharge costs, and the travel times).

3.1. Car-sharing with autonomous vehicles

The advent of AVs can significantly support the design of smarter cities. Among several advantages, their ability of parking themselves may lead to an overall decrease in parking demand. A benefit that may become more significant especially if AVs are integrated into shared mobility services, e.g., car/ride-sharing systems (Liu et al., 2022). Moreover, users are usually likely to ask for a CS service with AVs. For example, Curtale et al. (2022) show promising results obtained by applying structural equation models to 2154 respondents coming from France, Italy, The Netherlands, and Spain. In fact, the users of ECSSs are likely to use CS services with AVs. Moreover, thanks to the capability of forming platoons, AVs can improve traffic efficiency, thus reducing travel times and energy consumption (Wang et al., 2022c). However, platoons require coordination among AVs with possible delays for travelers. To this end, Wang et al. (2022c) design an agent-based model to simulate on-demand mobility services with AVs in an urban context. The simulation study, carried out on the road network of The Hague (The Netherlands), remarks that platoons may guarantee a system-wide energy consumption saving of 9.6%, depending on vehicle type and platoon strategy. In addition, their study highlights that platoons can also reduce the travel times in cases of delays due to vehicle coordination.

The advantages due to the introduction of autonomous vehicles (AVs) into shared mobility services are also analyzed in the literature. For example, Cremer et al. (2021) show how CS services with electric AVs (EAVs) can decrease the traffic congestion, the total cost due to the relocation operations, and, finally, the energy consumption through smarter driving modes. In addition, people with disabilities are willing to use AVs (Etminani-Ghasrodashti et al., 2021) and their diffusion could be further increased by making more efficient public transport (Haboucha et al., 2017). Despite all these advantages, the absence of a driver poses new further challenges to the researchers. Indeed, the decision problems posed by the introduction of AVs in CSSs may also be very different from those addressed in CS services with ICEVs and/or EVs. For this reason, in the following subsections, we discuss the introduction of AVs in shared mobility services, from both a planning and a management perspective.

As already anticipated in Section 1, to the best of our knowledge, in this context the most recent surveys are those of Narayanan et al. (2020), Esfandabadi et al. (2022), and Zhao and Malikopoulos (2020). In particular, Narayanan et al. (2020) focus on some of the most relevant expected impacts, e.g., regarding traffic and safety, travel behavior, economy, transport supply, land use, environment, and governance. Then, the AV topology is described together with the main components involved in modeling AV services. However, they highlight that such a system is usually classified according to their operation (i.e., *booking time frame* and *sharing system*). According to the *booking time frame*, the system is further classified into *on-demand* and *reservation based*. Although very few literature contributions exist, the latter allows a better route planning and scheduling that may also lead to higher efficiency, less operating cost, and higher resource utilization. According to the *sharing system*, Narayanan et al. (2020) consider the classification into ride-sharing, CS (which is also the focus of our survey) and mixed systems. Although the number of contributions analyzed by Narayanan et al. (2020) covers a large time horizon, i.e., from 1950 to January 2019, we believe that many interesting works, mainly concerning the planning and the management of CSSs with AVs, have been published from 2019 to date. Indeed, about 73% of the papers analyzed by us fall into the period 2019–2023. Therefore, we believe that discussing also these recent papers represents another contribution of our work. Moreover, we find that very few papers (about 15%) are also cited in Narayanan et al. (2020), leading to the conclusion that our focus may be considered different from theirs. Esfandabadi et al. (2022) focus on collaborative consumption and CS business models, user behavior, intention, and preferences and also on CS operational challenges (i.e., infrastructure and fleet management). Moreover, the authors describe some technological advancements and cite few works related to the use of AVs in the context of the mobility as a service. In fact, considering the time horizon from 2019 to 2021 that is in common with us, only 5% of our references are also cited by them, thus confirming a different focus. Finally, Zhao and Malikopoulos (2020) analyze the research efforts in shared systems with AVs until 2019, focusing also on specific technological issues and discuss potential future research directions. Considering the time horizon in common with us, we find that 15% of our references are also cited by them.

In the following, we detect some research topics that, according to us, are worthy of a detailed analysis in the context of CSSs with AVs: the FS problem, the AV relocation, and the routing problem (Section 3.1.1). Finally, some optimization-based frameworks dealing with several decision problems simultaneously are described in Section 3.1.2. All the works cited are summarized in Table 6 where the columns *CS type* and *fleet type* are not included since we believe they are less significant due to the AV peculiarities.

3.1.1. The fleet size, the AV relocation, and routing

Determining the FS may have several implications on the vehicle replacement rates, on the system-wide vehicle miles traveled, on the traveler wait times, and also on the life-cycle environmental impacts. In this context, Allahviranloo and Chow (2019) design a bi-level optimization approach where at the upper level optimize by LP the FS considering the space-time demand distribution. At the lower level, the vehicles availability, possible variations in the ownership cost, and the demand of other users are taken into account since they may affect the actual users' preferences.

Relocating AVs is in general simpler than the case of conventional vehicles thanks to their peculiarities of being self-driving and then, self-rebalancing. This means that usually relocating AVs

Table 6
Main features of the papers discussed in Section 3.1

Paper	Objective(s)	Solution approaches	Instance type	Further feature(s)
Allahviranloo and Chow (2019)	Vehicle costs Relocation costs Deviation costs	Bi-level optimization heuristic	Case study from NY	FS Time slot pricing mechanism
Babicheva and Burghout (2019)	Average and maximum user waiting time Unserved users	Index-based redistribution algorithm	Case study from Palaiseau	VR Expected users' arrivals Predicted waiting times
Charkhgard et al. (2020)	Unserved users Operating costs	MILP Chance-constraint programming	Simulated data	VR Stochastic travel times New reformulations
Dai et al. (2021)	Users' waiting times	Reinforcement learning	Case study from Cambridge	VR Random and first-mile demand patterns
Iacobucci et al. (2019)	Waiting times Electricity costs	MILP	Case study from Tokyo	VR Also charging decisions
Iacobucci et al. (2021)	Waiting times Charging costs	Simulation-based optimization	Data from NY	Time-varying electricity costs EAV routing, charging and relocation
Iacobucci et al. (2022)	Users served Operating costs	Multi-stage optimization	Case study from taxi trips in NY	VR Stackable cars
Lee et al. (2020)	Fleet and electricity costs Charging station operating costs	Reliability-based design optimization	Simulated data	SL Station capacity
Li and Liao (2020)	Revenues- operational costs- individual activity- travel costs	Bi-level optimization Lagrangian relaxation-based heuristic	Data from Nguyen–Dupuis network	Hub location FS Initial AVs location Travel and relocation tasks
Li et al. (2021)	Total operational cost Monetary value of the trip travel times Penalties of schedule delay early and late	MILP Diving heuristic	Data from Ziliaskopoulos network X-shape network Nguyen–Dupuis network Sioux-Falls network	FS Parking lot design Daily operation managment

Continued

Table 6
(Continued)

Paper	Objective(s)	Solution approaches	Instance type	Further feature(s)
Ma et al. (2021a)	Travel distances and times Energy consumption	MILP ALNS	Data taken from the literature	Vehicle routing Speed optimization
Ma et al. (2021b)	Construction costs of parking spaces + installation costs of charging facilities + vehicle purchase costs + vehicle charging costs + distance costs	MINLP Genetic algorithm	Data taken from the literature	SL Vehicle routing
Miao et al. (2019)	Total travel distance VR and parking costs Satisfied charging needs Charging infrastructure allocation costs	Two-stage multi-objective optimization NSGA-II	Data from Changchun	VR SL
Mo et al. (2021)	Revenues	Agent-based simulation Game theory	Data from Tampines	Competition between AVs and public transport
Narayanan et al. (2022)	Users' perceived utility System manager's profit	Dynamic user equilibrium model Linear Programming	Data from the Braess network	Vehicle routing Conventional private vehicles and AVs
Tian et al. (2022)	Revenues- daily operating costs	MINLP Particle swarm optimization	Data from the Sioux Falls Network	Number of stations and parking spaces FS VR Pricing strategies
Wang and Guo (2021)	Instant and single-step reward Accumulative and multi-step reward	Kuhn–Munkres algorithm Kuhn–Munkres algorithm and Q-learning algorithm	Simulated data	Vehicle assignment Parking and recharging assignment Vehicle relocation
Wang et al. (2022a)	Served users Operating profits	Deep reinforcement learning	Data from Beijing	VR Recharging operations

does not require employing operators and in fact, most of the literature focuses on the presence of a central operator who remotely dispatches them. In Iacobucci et al. (2019), an optimization-based method is proposed for relocating and charging EAVs. In particular, the charging decisions are taken for minimizing the overall waiting time and the electricity cost, whereas the relocation ones are for minimizing the waiting times. A MILP model is formulated, and numerical results are carried out on data taken from Tokyo (Japan). Babicheva and Burghout (2019) address the problem of relocating AVs, minimizing the average and the maximum passenger waiting time and the number of unserved users. Then, they propose an index-based relocation algorithm, incorporating expected passenger arrivals and predicted waiting times, tested on a real scenario taken from Palaiseau, Saclay, France. In Charkhgard et al. (2020), the problem of relocating AVs in FF CS services is addressed to simultaneously optimize the number of unserved users and the total operating cost. A deterministic scenario and a stochastic scenario with uncertain travel times are both described. For the former, a MILP model is formulated that is then extended to the stochastic case via chance-constraint programming. A reinforcement learning–based approach is developed in Dai et al. (2021), minimizing the total users' waiting time, tested on a real scenario taken from Cambridge (Massachusetts). Iacobucci et al. (2022) introduce the use of stackable cars that can be coupled together when parking but also driven together during relocation. Thus, a relocation task may also refer to transfer more vehicles together from a zone with a surplus of vehicles to a zone with a shortage of them. Therefore, they consider operator-based relocation, user-based relocation, and autonomous relocation in the case of a self-driving fleet. They propose a multi-stage solution approach, maximizing the users served while minimizing the total operating cost. The VR problem is addressed by decomposing it into three sub-problems: predicting the maximum inventory imbalance, determining the number of vehicles to move, and, finally, assigning the relocation tasks (with both operator-based and user-based strategies).

Ma et al. (2021a) propose a MILP model for the problem of routing EAVs in a CSS. The novelty of their work is to introduce also the speed optimization on each arc of the network traveled by EAVs, minimizing a weighted objective function that includes the total travel distance, the total travel time, and the total energy consumption. An ALNS integrated with a speed optimization subroutine is developed and tested on instances taken from the literature. Narayanan et al. (2022) propose a dynamic user equilibrium model to determine the path choice and the departure time of road users, assuming that conventional private and shared AVs co-exist. Users are assumed to select paths and departure times, maximizing a perceived utility, whereas system managers aim at maximizing the profit. They solve the dynamic user equilibrium model through a fixed point algorithm, whereas the AV chain is formed by a linear program. To solve the resulting bi-level model, an iterative optimization and assignment method is developed. Case studies are inspired by the Braess network (https://github.com/bstabler/TransportationNetworks).

3.1.2. *Integrated frameworks for several decision problems*

This section investigates contributions in which several decision problems are addressed simultaneously, in the context of CS services by AVs. For example, in FF EAV sharing systems, Lee et al. (2020) propose a new framework for the problem of both locating and sizing the charging stations, including system's uncertainty. The proposed reliability-based design optimization approach aims at minimizing the total system cost due to the fleet, electricity, and charging station operations. Huang et al. (2022) propose an optimization framework for dealing with the EAV routing and charging decisions. The activities of both relocating and charging EAVs are considered in the integrated system, Safari, proposed by Wang et al. (2022a) in which a dynamic deadline-based deep reinforcement learning algorithm is developed. Miao et al. (2019) formulate a two-stage multi-objective optimization model. The first stage aims at maximizing the total distance due to the served users and at minimizing the total cost simultaneously. The total cost is due to both the

VR fee and the parking fee. On the other hand, the second stage aims at maximizing the satisfied charging needs and at minimizing the total cost related to the charging infrastructure allocation simultaneously. Then, they develop a non-dominated sorting genetic algorithm-II (NSGA-II) tested on a real scenario from a metropolitan region of Changchun (China). Li and Liao (2020) propose a hub-based relocation strategy for FF AV sharing services. Therefore, they design a bi-level deployment model in which, at the upper-level, the hub location problem, the FS, and the initial location of AVs are optimized. On the other hand, the travel and the relocation tasks are managed at the lower level. They develop a Lagrangian relaxation-based heuristic tested on a real case study derived from the Nguyen–Dupuis network. Li et al. (2021) formulate a MILP model in order to address the FS, the parking lot design, and the daily system operation management, minimizing the daily system cost including the total operational cost, the monetary value of the trip travel time, and the penalty cost due to schedule delay both early and late. A diving heuristic is also designed to efficiently solve the problem on large-sized instances. Iacobucci et al. (2021) propose a simulation-based optimization approach to route, relocate, and charge a fleet of EAVs to provide the lowest waiting times to the users while minimizing the charging costs in which the time-varying electricity costs are also considered. Real data are taken from New York City. We refer the readers to other details on this work in Section 3.4. Tian et al. (2022) formalize a Logit model to capture the mode choice behavior in multi-modal networks, considering the minimum customer service rate for the system's reliability. First, they formulate an MINLP model to jointly determine the number of stations and parking lots, the FS, the AV relocation, and the pricing strategies, maximizing the total profit computed as the difference between the total revenue due to the served customers and total daily operation cost. Then they combine particle swarm optimization with an optimization solver as a solution approach, tested on the Sioux Falls network. Ma et al. (2021b) address the problem of both locating the stations and routing EAVs in OW sharing services, minimizing a total cost given by the total construction cost due to the parking spaces, the total installation cost due to the charging facilities, the total vehicle purchase cost, the total vehicle charging cost, and, finally, the total distance cost. For such a decision problem, an MINLP model is formulated and a genetic algorithm is developed, tested on instances taken from the literature. Wang and Guo (2021) model three decision problems concerning the vehicle assignment, the charging, and the parking assignment, and the VR in a FF sharing system with AVs, maximizing the total revenue. In particular, they model the EAVs dispatching problem through a Markov decision process. Then, an ILP formulation models the multi-task dispatching optimization problem, maximizing the instant and single-step reward. For such a problem, a Kuhn–Munkres algorithm is developed. On the other hand, through stochastic programming, the authors model the multi-task dispatching optimization problem, maximizing the accumulative and multi-step reward.

3.2. *Car-sharing with a mixed fleet*

Selecting the vehicle types that may compose the fleet is a very crucial challenge when designing CS services. Turoń et al. (2022), for example, show that a fleet with only EVs may decrease the system performance due to both their longer recharging times and their high purchasing costs. In particular, the research is carried out on the Polish market of CS services, considering different vehicle types, i.e., conventional, electric, hybrid, and hydrogen. Among the most significant criteria to consider, they use the purchasing costs and the energy/fuel consumption per 100 km. Their results highlight the predominance of the hydrogen vehicles compared to the others. If, on the one hand, having a mixed fleet may help to overcome specific issues related to the use of only one type, on the other hand, it may add more complexity to the already described decision problems. Therefore, this section describes some contributions dealing with decision problems in a sharing service with a mixed fleet.

A fleet of battery, plugin hybrid, and hybrid EVs are considered by Lemme et al. (2019) in an OW CSS. An ILP model is formulated with the aim of analyzing the actual benefits of the EVs compared to the conventional ones and also of determining the fleet composition. Two objective functions are minimized: one models the overall cost (i.e., maintenance, acquisition, and infrastructure), whereas the other takes into account the sustainability through local pollutants costs. A tailored pricing strategy is developed in Lu et al. (2022) for the FS and for the station size in OW CSSs with both AVs and conventional vehicles. One objective function, to maximize, represents the overall profit (i.e., the revenues minus the costs due to the driving, the maintenance, and the deprecation), whereas the other objective function, to minimize, represents the users' costs (i.e., the rental fees and the walking costs). The resulting bi-objective problem is formulated via NonLinear Programming. In addition, a genetic algorithm is designed and tested on a case study taken from Lanzhou (China).

Zhang et al. (2022) consider a heterogeneous fleet of EVs in OW CSSs with the aim of determining how many EVs of each type to use, which requests serve, by which EV and managing the recharging and the relocation issues. An example of the advantage of having EVs with different cost and driving range is shown in Fig. 7, where a fleet composed of one EV (in red) with a driving range of 100 km and daily cost of 50 euros and one EV (in green) with a driving range of 60 km and daily cost of 35 euros are used. They can serve in a feasible way the seven car-sharing requests each one with origin and destination located in nodes P_i and D_i, for $i = 1, \dots, 7$, respectively. The numbers in square brackets beside the nodes represent the time windows associated with the pickup requests. We assume an average speed of 25 km/h for both the kind of EVs. Moreover, we assume that the battery level never must go below 0.2, for safety reasons. In a scenario in which only EVs of the second type are used, the total cost would be 105 euros since three of them are necessary. Indeed, due to their driving range of 60 km, the route on the right cannot be performed by a second type EV without recharging, but the time windows of the users do not allow any recharge (also starting from P_1 at 8, the earliest arrival times in the next pickup nodes are 8.48, 9.12 and 10, respectively, and then the time window of P_4 is tight). Instead, in a scenario in which only first type EVs are used, the total cost would be 100 euros since in any case two EVs are necessary due to the time windows. Therefore, the scenario depicted in Fig. 7, where one EV per type is used, with a total cost of 85 euros, is the less expensive. The objective function to maximize is modeled as the total revenue minus the penalties due to unsatisfied users, the fixed EV costs, and the relocation costs. For such a problem, a MILP model is formulated, whereas large-sized instances are solved via Dantzig–Wolfe decomposition. An approach combining ant colony optimization into a column generation framework is developed to efficiently solve the pricing sub-problems. A fleet of both EVs and ICEVs is considered instead in the CSS studied by Samie and Rezaee (2022), considering the users who want to rent EVs and those who are indifferent. The problem of relocating the fleet for maximizing the profit is then addressed through both a MILP formulation and a rolling-horizon approach.

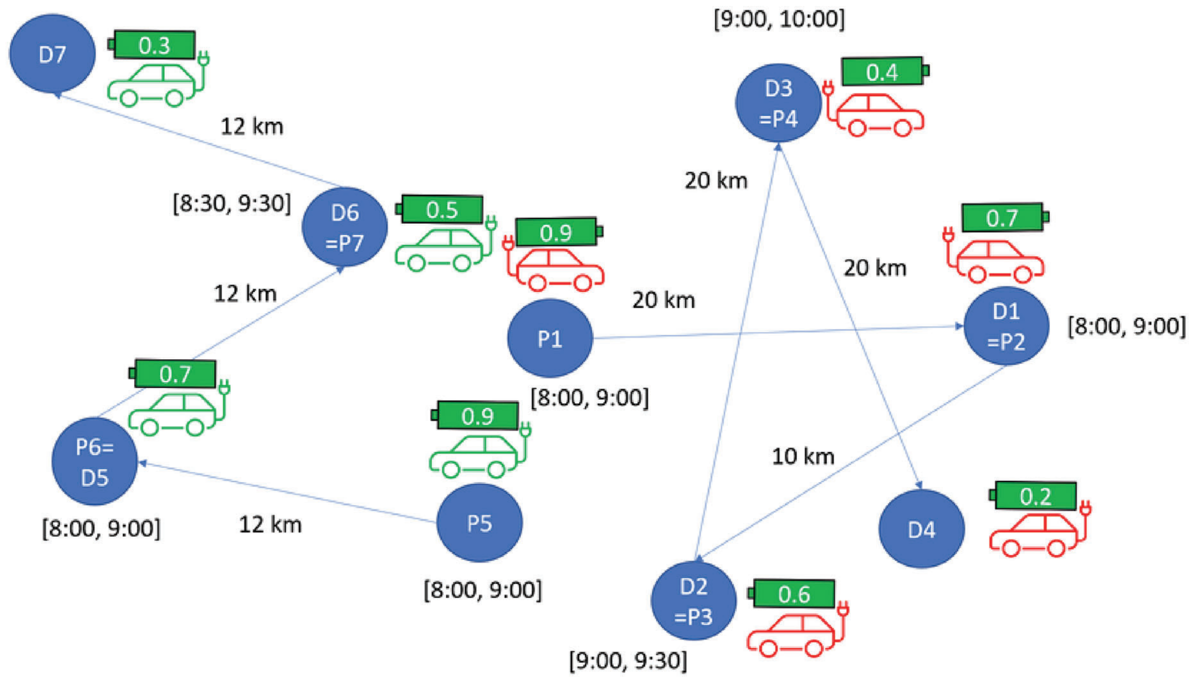

Fig. 7. An illustrative example of a CS with the mixed fleet.

The problem faced by Smet (2021) consists in the possibility of replacing a vehicle type in heterogeneous round-trip CSSs. It means that when a user asks for a vehicle type not available, a different type can be proposed. Since stochastic demands are also considered, a two-stage stochastic integer programming model is formulated. At the first stage, the number of vehicles of each type and their location are determined, maximizing the total profit, i.e., the trip revenues minus the maintenance costs. In the recourse problem, the objective function to maximize represents the total trip revenue. A sample average approximation approach is also developed to find solutions in reasonable amount of time.

The contributions cited in this section are summarized in Table 7.

3.3. *Multi-modal car-sharing*

Integrating different transportation services (i.e., private and public) into a unique system can contribute to especially transform the urban public mobility (e.g., Terrien et al., 2016; Ting et al., 2021) and to support the development of smart cities. For example, a holistic approach for integrating renewable mobility services in smart cities is the outcome of the EU-funded project MOVESMART (Gavalas et al., 2020).

In particular, integrating CS services and public transport contributes to increase the efficiency of the latter. In this context, a challenge concerns how to orchestrate these services to provide users with well-organized travel plans (*collaboration-as-a-service*; Merkert et al., 2020). This poses new

Table 7
Main features of the papers discussed in Section 3.2

Paper	CS type	Fleet type	Objective(s)	Solution approaches	Instance type	Further feature(s)
Lemme et al. (2019)	OW	Battery EVs Plugin hybrid EVs Hybrid EVs	Maintenance costs Acquisition costs Infrastructure costs Local pollutants Greenhouse gas emissions	ILP	Case study from Fortaleza	Analysis of benefits of EVs Fleet composition
Lu et al. (2022)	OW	AVs ICEVs	Manager's profit Users' costs	Bi-objective nonlinear programming Genetic algorithm	Case study from Lanzhou	FS Station sizing Pricing strategies
Samie and Rezaee (2022)	OW	ICEVs EVs	Revenues-relocation costs	MILP Rolling-horizon approach	Generated instances	User-based relocation Operator-based relocation Two user groups Dynamic discriminatory prices Freelance driver wages
Smet (2021)	Round-trip	Types of ICEVs	Revenues-maintenance costs Total revenue	Stochastic programming Sample average approximation approach	Generated instances	Determining number of vehicles per type Vehicle location
Zhang et al. (2022)	OW	Types of EVs	Revenues-penalties-relocation costs-vehicle costs	MILP Dantzig–Wolfe decomposition	Generated instances	Ant colony optimization Column generation

challenging decision problems, with the aim of usually minimizing the total costs while maximizing the users' satisfaction. To this purpose, a bi-objective multi-modal CS problem is addressed in Enzi et al. (2022), minimizing the total cost and maximizing the user satisfaction, simultaneously. User's satisfaction is evaluated according to the preferences towards trips, for assigning trips to different transportation modes and for routing both cars and users throughout the day in a closed community. The authors also consider a variant with time-dependent both preferences and travel times and, then, variable task and trip sequences. For efficiently solving this last variant, a branch-and-cut algorithm integrated into bi-objective approaches, i.e., the ϵ-constraint method and a weighting binary search method, is proposed and tested on a real case study from Vienna, Austria.

The integration of several and different transportation modes with CS is analyzed in Enzi et al. (2021) for a company and its employees. In particular, the company owns some vehicles but it also allows using other modalities (i.e., public transport, bikes, taxis, or walk). Each employee specifies the mode to use and interchanges can occur only at depots. Moreover, only the employees with a driving license can be a driver in ride-sharing mode. The resulting decision problem is formulated as a *vehicle-scheduling problem* for assigning the transportation modes to the trips and for routing the cars on a time-space graph. A two-layer decomposition algorithm based on the column generation approach is designed and tested on data taken from Vienna. Nguyen et al. (2022) analyze the integration of OW CS services in a multi-modal network (private cars and public transport) through a bi-level Stackelberg game, maximizing the total profit (i.e., the total revenue minus costs that include those for VR, maintenance, and depreciation as well as for parking lot maintenance). First, the system managers decide the price of the service offered and the relocation strategies. Then, the travelers take decisions according to the equilibrium choice of routes and of transportation modes. A link-based method is developed and tested also on the Fort-Worth network with 182 nodes and 441 links.

Some contributions also propose the integration of CSSs with other shared mobility systems. For example, Warrington and Ruchti (2019) propose a two-stage stochastic programming–based approach for managing the relocation in shared mobility systems where different modes coexist (e.g., bikes, electric scooters, cars), considering stochastic demands, as detailed in Section 3.4. Yu and Shen (2020) propose a two-phase optimization approach for combining CS and ride-sharing services. Since random travel times are considered, also this work is described more in detail in Section 3.4. Wang et al. (2022b) study the integration of electric CS services with those of bike-sharing, under a user-based relocation policy. Regarding bike relocation, in the case in which a station has more vehicles than it needs, the system encourages users to deliver the bikes to another point of interest selected randomly. Instead, when a station has less vehicles than it needs, the system encourages users to deliver bikes at this station. Also, in this case, the total subsidy to users is minimized. A genetic algorithm is then developed for the joint relocation activities, tested on a real case study taken from an EV-sharing company in Shanghai. Georgakis et al. (2020) propose a scenario-based heuristic in order to compose routes made up of different transportation modes (i.e., private cars, public transport, and shared vehicles) offered via several service types (bike-sharing, CS, and ride-sharing). The proposed methodology is tested on two real case studies, respectively, from Budapest and Manchester.

Integrating AVs into public transportation networks is another new promising research direction worthy of investigation. For example, Levin et al. (2019) study the problem of optimally integrating shared AVs into a transportation network. In particular, passengers may stop at intermediate places (e.g., bus stops) that do not necessarily correspond to an origin or a destination. The aim is to minimize the total travel time, i.e., the total waiting time plus the total in-vehicle travel time. An LP model is formulated, and a heuristic rolling-horizon approach is developed and tested on the Sioux Falls network. Although the authors demonstrate that integrating AVs with transits can reduce the waiting times, passengers experience higher in-vehicle travel times due to the fact that they do not have a direct trip. Moreover, the use of transit becomes significant when the AV FS is small and/or the transit frequency is high. Pinto et al. (2020) propose both a bi-level optimization model and a heuristic for allocating resources between transit patterns and AVs in shared mobility systems operating in a large metropolitan area, minimizing the overall waiting times and the number of unserved users. The proposed approaches are tested on real data taken from the multi-modal transit network in Chicago. A MILP model and valid inequalities are proposed in Lee et al. (2022) to minimize the overall time given by the total waiting time, the total in-vehicle time, and by both the early arrival and the latest arrival times. Also, time-dependent travel times are considered. Their approach is tested on data taken from Copenhagen (Denmark).

Some studies analyze the competitive perspective in which both AV and public transport are profit-oriented. To this aim, for example, Mo et al. (2021) propose an approach coupling agent-based simulation with game theory, tested on a real scenario taken from Tampines (Singapore).

Table 8 summarizes the contributions cited in this section in which some column headers were changed in order to better emphasize some peculiarities of the multi-modal CSSs. In particular, we replaced the column header *"CS type"* with *"Integrated with"* that indicates the other transportation modes combined with CS. In addition, we added a new column entitled *"Other service type(s)"* reporting other possible transportation services (e.g., carpooling, ride-sharing etc.) offered together with the CS one.

3.4. Time-dependent car-sharing

A recent trend in the optimization of CSS consists in modeling the influence of time. This has been addressed in three main different ways: by considering the time-varying demand, the time-varying recharge cost (for EVs), or the time-varying travel time.

Inside the first research direction, we can find two main research threads: the one where the variation of the demand over time is estimated and the one where the real-time demand is taken into account in a dynamic way. Concerning the first thread, Li et al. (2021) propose a time-dependent shared AV system design by jointly determining the FS, parking lot assignment, and daily system operation. Unlike previous works in this field, they consider the time-varying features of travel demand in the long run and develop a diving heuristic algorithm capable of finding nearly optimal solutions. Wang et al. (2019) develop an optimization-based approach for optimizing the EV relocation operations, in systems without reservation, with stochastic demand, considering upper and lower thresholds for inventories. An ILP model is formulated to determine the routes for the operators, minimizing the total difference between inventories and thresholds after executing relocation tasks. The database of EVCARD (see Section 2.2.2) is used for testing the proposed approach. Babicheva and Burghout (2019) consider expected passenger arrivals and predicted waiting times for the problem of relocating AVs as described in Section 3.1.1.

Table 8
Main features of the papers discussed in Section 3.3

Paper	Integrated with	Other service type(s)	Objective(s)	Solution approaches	Instance type	Further feature(s)
Enzi et al. (2021)	Bikes Taxi Public transport	Ride-sharing	Total travel distance Total travel time	Column generation	Case study from Vienna	Interchanges only at depots No VR
Enzi et al. (2022)	Other transportation modes		Total cost Users' preferences	Branch-and-cut algorithm $\epsilon-$constraint method Weighting binary search method	Case study from Vienna	Trips assignment to transportation modes User routes
Georgakis et al. (2020)	Private cars Public transport Bikes	Ride-sharing Bike-sharing	Total travel time	Scenario-based heuristic	Case study from Budapest and Manchester	Dynamic journey planning
Lee et al. (2022)	Public transport		Total waiting and in-vehicle time Early and late arrival times	MILP	Case study from Copenhagen	Path-oriented scheduling Time-dependent travel times Valid inequalities
Levin et al. (2019)	Public transport		Total travel time	Linear programming Rolling horizon heuristic	Case study from Sioux Falls network	First-come-first-served greedy algorithm
Nguyen et al. (2022)	Public transport		Revenues- VR costs- vehicle maintenance and depreciation costs- parking lot maintenance costs	Bi-level Stackelberg game Link-based method	Case study from Fort-Worth network	VR Prices Transportation mode selection Routing
Pinto et al. (2020)	Public transport		Waiting times Unserved users	Bi-level optimization Heuristic	Case study from Chicago	Explicit modeling users' demand
Wang et al. (2022b)	Bikes	Bike-sharing	Subsidies to the users	MILP Genetic algorithm	Case study from Shanghai	User-based relocation
Warrington and Ruchti (2019)	Electric scooter Bikes	Bike-sharing	Penalties for unserved users + VR costs + costs for loading/ unloading shared vehicles	Two-stage stochastic programming Separable, projective, approximation routine-based algorithm	Case study from Philadelphia	Dynamic Repositioning Routing Stochastic demand
Yu and Shen (2020)	Shared cars	Ride-sharing	Travel costs + expected penalties due to users' waiting and system overtime	Stochastic optimization	Case study from Washtenaw County	Two types of passengers

Concerning the second thread, Santos and de Almeida Correia (2019) propose a real-time decision support tool for VR in OW CS as detailed in Section 2.2.2. Hua et al. (2019) consider an OW EV sharing system operating in an urban area. They design a framework that supports, at the same time, decisions about long-term infrastructure planning (i.e., fleet distribution and charging SL) and real-time fleet operations management (EV charging and relocation). In order to also consider a time-varying uncertain demand, they develop a multistage stochastic model. Finally, they draw significant insights through numerical experiments and a realistic case study with EV sharing service in New York. Real-time requests are considered in Yang et al. (2021) where the problem of finding the optimal requests served, the relocation tasks, and the operators' routes are addressed, minimizing the generalized daily operational cost (i.e.,penalties for unserved users, VR costs, dispatcher relocation costs, and dispatcher movement costs). Both a mathematical formulation and a rolling horizon algorithm combined with a customized decomposition method are proposed. Numerical results are carried out on a real scenario taken from Lanzhou (China). Lin and Kuo (2021) address both vehicle deployment and relocation in FF ECSSs considering demand and parking space stochasticity. The problem is solved by two-stage stochastic programming. Based on historical user requests, the first stage aims at deploying EVs such that the total profit (i.e., the revenues minus the purchasing costs plus the expected profit from relocation in the second stage) is maximized. In the second stage, the relocation decisions are taken, maximizing the expected profit and implementing an operator-based relocation strategy in response to demand uncertainty. The authors develop an L-shaped method. Hellem et al. (2021) address both the operator-based relocation problem and the EVs recharging problem considering a real-time user demand. The resulting periodic planning problem is mathematically modeled through MILP with the aim of maximizing the total profit (i.e., the total revenue minus the total cost due to movements with rental cars, tolls, and wear). Such a problem is then solved by a rolling-horizon approach, assuming that the operators can move through the public transport or folding bikes. In order to efficiently address large-sized instances, an ALNS is also designed and tested on a real scenario taken from Oslo (Norway). Li et al. (2022b) design a data-driven optimization-based approach for VR, considering stochastic demands, as detailed in Section 2.2.2. For the same problem but with EVs, Lai et al. (2022) develop a rolling-horizon decision framework, considering also the users' spatial flexibility as explained more in detail in Section 2.2.2. Lu et al. (2021a) address the problem of allocating EVs to the stations in OW CSSs, for maximizing the total profit, i.e., the total revenue minus the total cost (including supply, travel, and holding costs plus penalties due to unserved users). They propose a MILP model, formulated on a multi-layer time-space network. Moreover, they apply robust optimization and chance-constrained techniques for the fleet allocation with uncertain and stochastic demands, respectively. In order to efficiently solve the problem also on large-sized instances, a network decomposition-based math-heuristic is designed. Warrington and Ruchti (2019) propose a two-stage stochastic programming based approach for managing the relocation activities in shared mobility systems, where several modes may coexist (e.g., bikes, electric scooters, cars), considering stochastic demands and minimizing the penalties for unserved users, the relocation costs, and the costs for loading/unloading the shared vehicles. The decisions of the first stage concern VR by trucks and the loading/unloading operations. Whereas, those of the second-stage concern vehicle journey plans, using the decisions taken at the first stage. The proposed approach is tested on a real case study taken from the Philadelphia bike-sharing system. Finally, in Huang et al. (2021), a long-term pricing strategy and a real-time VR are combined to each other in a two-stage stochastic programming model, considering OW CSSs. Two-stage stochastic programming is used for maximizing the difference between the revenues and the costs due to the fleet and the operations. At the first stage, decisions concerning the FS and the prices are taken, whereas at the second stage VR is solved. A gradient search algorithm and a genetic algorithm are developed to solve the resulting two-stage stochastic programming model, tested on a real CSS operating in Suzhou (China)

Concerning the second research direction, i.e., the time-varying recharge cost, Iacobucci et al. (2019) address the problem of optimizing at the same time the routing, the relocation, and the charge with vehicle-to-grid of a fleet of EAVs. Their approach optimizes transport service and charging at the same time, with two different optimization algorithms. Indeed, charging is optimized over a longer time period, minimizing both electricity costs and approximated waiting times. On the other hand, routing and relocation are both addresses at a shorter time period, minimizing waiting times by imposing the results of the long-time-period optimization as charging constraints. The approach is tested on a case study based on transport and electricity price data for Tokyo. Numerical results show that the method can significantly reduce charging costs without substantially affecting waiting times. Iacobucci et al. (2021) propose a simulation-based optimization approach in order to route, relocate, and charge a fleet of EAVs, for providing users with lowest waiting times while minimizing charging costs considering also time-varying electricity costs. Their approach is tested on real transport and electricity data exploiting a dataset of taxi trips from New York City. The solutions obtained with this method substantially reduce charging costs and carbon emissions with respect to those of an uncoordinated charging strategy, leading to advantageous synergies for fleet operators, passengers, and power grid.

Inside the third research direction, similarly to the first one, we can find two main research threads: the one where the variation of travel-time over time is estimated and the one where it is considered dynamically in real time.

Concerning the first thread, Lee et al. (2020) consider time-dependent travel times for the problem of both locating and sizing the charging stations in FF CSSs with a fleet of EAVs. Their objective is to minimize the total cost of system design while satisfying the target reliability of the customer wait time. To this purpose, a reliability-based design optimization is applied. Different waiting time constraints and probabilities of failure are considered, and the corresponding optimization results are compared to derive useful insights. Time-dependent travel times are also considered in the MILP formulation proposed by Lee et al. (2022) for integrating the use of shared AVs with public transport, as discussed in Section 3.3. Finally, time-dependent travel times are also considered in the bi-objective multi-modal CS problem addressed by Enzi et al. (2022) with the aim of minimizing the total cost and maximizing the user satisfaction, as described in detail in Section 3.3.

Concerning the second thread, Yu and Shen (2020) propose a two-phase optimization approach for combining CS services with ride-sharing ones. In particular, two types of users are assumed in the system: one type who requires renting a car and one type who instead wants to share a ride. Then, in the first phase, they decide the initial car allocation and which users of type 1 have to be satisfied. Whereas, in the second phase, they solve the problem of matching users of type 1 with those of type 2. This last decision problem is solved through stochastic optimization since random travel times are considered. The objective function to minimize represents the total travel cost plus expected penalty cost of users' waiting and system overtime. As a real-life case study, they use data from a system operating in Washtenaw County, Michigan. Charkhgard et al. (2020)

address the uncertainty related to the travel times for the problem of relocating a fleet of AVs in FF CSSs through chance-constraint programming as detailed in Section 3.1.1. Li et al. (2022a) develop a simulation-optimization method to optimize VR in OW CS with stochastic road congestion as described more in detail in Section 2.2.2.

All the contributions cited in this section are summarized in Table 9.

4. Future perspectives for the optimization of car-sharing systems

In this section, we want to investigate new research directions that are not yet (or little) considered from the optimization point of view, but that would be useful to address with the operations research tools. To this purpose, in the next three subsections, we consider the following topics: peer-to-peer (P2P) CS services, CS services in suburbs and low-density areas, and, finally, CSSs supporting goods distribution.

4.1. Peer-to-peer car-sharing services

P2P CS services provide car owners with the possibility to rent their private vehicles to other users, usually via a system provider (Olaru et al., 2021). Therefore, three roles are played in P2P CSSs (Nansubuga and Kowalkowski, 2021): the car owner makes the vehicle available to others, the car renter who is the service user, and, finally, the service provider which has not the fleet but plays the role of a service intermediary. In addition, the car renter pays a fee for using the vehicle, whereas the service provider receives a percentage of the fee received by the car owner. So far, to the best of our knowledge, only a few examples of such platforms exist, e.g., *Getaround* operating in the United States and in some European countries. Some studies are mainly focused on examining the behavior of both renters and owners (e.g., Dill et al., 2019; Barbour et al., 2020; Olaru et al., 2021). Some factors, among which autonomy loss, privacy invasion, as well as data misuse, are analyzed in Hunecke et al. (2021) and individuated as the main barriers to the diffusion of P2P services (including also the ride-sharing, i.e., car owners share the trips with others). Rotaris (2022) discuss the potential demand and supply of P2P CS services in Friuli Venezia Giulia (Italy). Among the aspects that may affect the demand and the supply of such services, they find that an important factor is the rental rate.

An application example of P2P CS services is described in Nakamura et al. (2021). In fact, they address the problem of properly managing the round trips from the university to the station, using private cars as CS services. They impose both a minimum and a maximum number of passengers per car and also that each car has to be returned to the university. All users have a driving license. The car owners make profits by renting their cars, fixing a fee lower than that of a taxi service for offering a competitive service. The proposed system can replace the traditional transportation service with buses, and it is modeled via queuing theory. It is shown that waiting times at the university are significantly reduced. In addition, they optimally determine the minimum number of passengers per car that guarantees the same mean waiting time, minimizing the total operational cost. Moreover, a pricing mechanism is proposed that provides a *win-win* solution for both passengers and owners. University of Tsukuba, Japan, is their case study.

Table 9
Main features of the papers discussed in Section 3.4

Paper	CS type	Fleet type	Time-dependent data	Known in advance estimated real-time data	Problem(s) addressed	Objective(s)	Solution method(s)	Instance type	Further feature(s)
Babicheva and Burghout (2019)	OW	AVs	Demand	Estimated	VR	Average and max passenger waiting time Unserved users	Index-based redistribution algorithm	Case study from Palaiseau	Expected user arrivals and predicted waiting times
Charkhgard et al. (2020)	FF	AVs	Travel-time	Real time	VR	Unserved users Operating costs	MILP Chance-constraint programming	Simulated data	New reformulations
Enzi et al. (2022)	NS	NS	Travel-time	Estimated	Mode of transport assignment Scheduling the routes of available cars and users	Total cost and Users preferences	Branc-and-Cut algorithm ϵ-constraint method Weighting binary search method	Case study from Vienna	Multimodality
Hellem et al. (2021)	FF	EVs	Demand	Real time	VR Charging decisions	Revenue- costs for relocation, tolls, wear	Rolling horizon optimization ALNS	Case study from Oslo	Operators use public transport or folding bikes
Hua et al. (2019)	OW	EVs	Demand	Real time	Charging SL Fleet distribution VR Charging decisions	Total expected cost	Multi-stage optimization	Data from NY	
Huang et al. (2021)	OW	ICEVs	Demand	Real time	VR and FS and Pricing	Revenues- fleet costs- expected operational costs	Stochastic programming Gradient search algorithm Genetic algorithm	Case study from Suzhou Industrial Park	
Iacobucci et al. (2019)	OW	EAVs	Recharge cost	Known in advance	VR Charging decisions	Waiting times Electricity costs	MILP	Case study from Tokyo	Vehicle-to-grid discharge
Iacobucci et al. (2021)	OW	EAVs	Recharge cost	Known in advance	EAV routing, charging and relocation	Waiting times Charging costs	Simulation-based optimization	Data from NY	
Lai et al. (2022)	OW	EVs	Demand	Real-time	VR	Revenues- fare discounts to users- staff movement costs- charging costs	Iterated local search	Data from network of GoFun	Car and staff relocation User flexibility EV charging
Lee et al. (2020)	FF	EAVs	Travel-time	Estimated	SL Station capacity	Fleet costs Electricity costs Charging station operating costs	Reliability-based design optimization	Simulated data	
Lee et al. (2022)	FF	AVs	Travel-time	Estimated	Integrating AVs with public transport Path-oriented scheduling	Total waiting time Total in-vehicle time Early arrival time Late arrival time	MILP	Data from Copenhagen	Valid inequalities are also proposed

Continued

Table 9
(Continued)

Paper	CS type	Fleet type	Time-dependent data	Known in advance estimated real-time data	Problem(s) addressed	Objective(s)	Solution method(s)	Instance type	Further feature(s)
Li et al. (2021)	OW	AVs	Demand	Estimated	FS Parking lot design Daily operation management	Total operational cost Monetary value of the trip travel times Penalties of schedule delay early Penalties of schedule delay late	MILP Diving heuristic	Data from Ziliaskopoulos network X-shape network Nguyen–Dupuis network Sioux-Falls network	
Li et al. (2022a)	OW	EVs	Travel time	Real-time	VR	Budget allocation	Simulation-based optimization	Case study from Chengdu	
Li et al. (2022b)	OW	ICEVs	Demand	Real-time	VR	Revenues-holding and moving/transferring costs	Stochastic programming	Data from NY taxicab trip record dataset	
Lin and Kuo (2021)	FF	EVs	Demand Parking space	Real time	Fleet distribution VR	Revenues- purchasing costs, Expected profit	L-shaped method	Simulated data	
Lu et al. (2021a)	OW	EVs	Demand	Estimated and Real time	FS SL	Revenues- supply costs- travel costs- holding costs- penalties	MILP, Robust optimization Chance-constraint technique Network decomposition Math-heuristic	Case study from Sun Moon Lake Nat. Park	
Santos and de Almeida Correia (2019)	OW	ICEVs	Demand	Real-time	Costs to move vehicles for VR Costs for staff movements Profit losses for unserved users Penalties for unserved maintenance requests	Simulation-based optimization	Case study from Lisbon	Operator-based Penalties for requests unserved Carpooling among operators	
Wang et al. (2019)	OW	EVs	Demand	Estimated	VR	Inventories- thresholds after relocation	ILP and simulation	Data from EVCARD	
Warrington and Ruchti (2019)	OW	NS	Demand	Real time	VR and integration with a bike-sharing system	Penalties for unserved users + relocation costs + costs for loading/unloading shared vehicles	Two-stage stochastic programming Separable, projective approximat. algorithm	Case study from Philadelphia	
Yang et al. (2021)	OW	ICEVs	Demand	Real time	VR	Penalties for unserved users, VR costs, Dispatcher VR costs, Dispatcher movement costs	ILP Hybrid solution algorithm	Case study from Lanzhou	Operator-based VR
Yu and Shen (2020)	OW	NS	Travel-time	Real time	Car allocation and matching between user types	Travel costs + expected penalties due to users'waiting and system overtime	Stochastic optimization	Case study from Washtenaw County	Two types of passengers

One of the most significant potentialities of P2P CS is to provide an on-demand service also in suburbs (Section 4.2 is specifically devoted to this context). Therefore, although outside the time horizon of our survey, we want to mention the paper of Hampshire and Gaites (2011) that analyzes the potentialities of P2P CSSs especially in low-density neighborhoods. The P2P CS service reduces the initial costs, due to fleet purchase, thus becoming more economically compatible with the low-density neighborhoods. This way, it guarantees a higher accessibility of the cars compared to the traditional CS services.

However, to the best of our knowledge, the literature lacks contributions dealing with decision problems related to both the planning and the management of these systems, from an operations research perspective. Several research directions may be worthy of investigation, e.g., how to optimally compose trips of different travelers who use the same car made available by an owner in a P2P CSS. In particular, assuming that travelers ask for using the car at different places and times, we need to combine their different trips.

4.2. Car-sharing in suburbs and low-density areas

So far, the CSSs have spread worldwide mainly in the large cities (above 400,000 people), where they are provided by large profit oriented firms, able to offer efficient and flexible services, using the most advanced technologies. Indeed, the success of CS in large cities is due to the low level of car ownership (since the population is already well served by a capillary public transport with frequent rides and often faster than cars, considering the underground). Vice versa, in medium- or small-sized towns and in less densely populated areas (e.g., rural areas), the CS is usually absent since the scarce transport demand is not attractive for the profit-oriented CS providers. Nevertheless, as observed by Rotaris and Danielis (2018) also in this context, CS could be very useful and have a more socially oriented mission. Indeed, since here the public transport service is low (due to the weak demand), CSSs can improve the accessibility of low-income people who do not have the means to buy, park, or maintain a private car or a second/third car in the case of larger families. In this case, the CS should be provided, involving municipalities and public transport providers to offer a service, most likely at attractive prices. In a very similar context, a CSS (Mouv'nGo) has been really implemented in the outskirts of Le Mans (France), involving six small rural townships, as described by Leroy et al. (2023). Mouv'nGo is a round-trip station-based electric CS created inside a social program to provide people with low income a mobility service at an affordable cost. One of the problems arisen, in the first year of the service, has been the lack of regular users. Indeed, most of their members used the service, on average, less than once per month, mainly because the same members already own cars and then only used the service for occasional trips instead like a daily mobility solution. Since the business models of CSSs provided for low-density areas are very different from those of large cities and the need for optimization is also higher to allow their challenging spread, this particular kind of CS would deserve in the future more attention by operational research practitioners.

Another challenging problem is to involve in CS also the people who live in the suburbs of large cities. Indeed, several CS providers either forbid to move the cars on the outskirts of cities where the service is centered or apply fares that become prohibitive when their cars are parked on the outskirts. An interesting optimization problem to be solved is to perform a matching between the requests of users interested in moving the cars from the city to the outskirts with those of the users that are interested in the opposite move after the former, in order to rebalance, in an automatic way, the cars distribution and avoid that the cars remain trapped in the outskirts where in general the demand is low.

4.3. Car-sharing systems supporting goods distribution

Among new challenging perspectives in the services offered by CSSs, one is the use of shared cars for both transporting people and distributing goods (obviously, suitable for being transported in the trunk of a car and, also, are not dangerous to the passenger's safety). Indeed, using shared electric vans for goods distribution has already been investigated by Taniguchi et al. (2000). They propose to use electric vans such that the workers of several companies can book the service in advance via the Internet. Each worker reaches the nearest place the van is located at on foot or by bikes. Then, the worker picks the van up and reaches the company depot for loading the goods to distribute. At the end of the trip, the worker returns the van to the nearest place and reaches the office either on foot or by public transport. The advantage of such an idea is that the total traffic congestion due to goods distribution can be significantly reduced particularly because the workers either use alternative transportation modes or walk. They test such a proposal in Osaka City (Japan) and observe that half of the users reaches the van and returns to the office on foot, whereas 38% of the users use the subway. Although this work does not address the solution of decision problems, it shows how integrating goods distribution activities with the use of vehicle-sharing services can significantly support the reduction of pollution and traffic congestion, while also encouraging the use of more environmentally sustainable and/or collective modes of transport. In this context, several decision problems may be addressed via operations research techniques, e.g., how to efficiently relocate such shared vehicles for balancing the supply and the demand and also how to efficiently route the workers. In a similar way, the use of public transport, as an alternative to private trucks, for goods distribution has been already investigated in the literature. In particular, Schmidt et al. (2022) describe the use of buses and/or trams in the last-mile delivery, without varying their line and/or timetable. Bus and tram stations become depots from which the freighters pick the goods up for delivering them to final customers. The decision problem, i.e., the *last-mile delivery problem with scheduled lines*, is modeled as a route-based formulation solved via branch-price-and-cut algorithms with different hierarchical objective functions to minimize. The two aforementioned works allow us introducing a new service that may be offered by CSSs. In fact, to the best of our knowledge, CS services for both goods and passengers have not been investigated yet, particularly from the operations research perspective. For example, users may become freighters themselves. Thus, when a new request arrives, the system may assign a *distribution task* to a user who may accept according to an incentive proposed. If the user accepts the task, he/she picks the goods up and either delivers the goods at destination (e.g., if it is on the way) or just delivers the vehicle at his/her destination. In this last case, another user who accepts the task continues moving the goods. This way, the goods can arrive to its destination (that may be either a depot or the final customer). This application scenario poses new challenging decision problems, e.g., how to assign distribution tasks to users such that both time windows for goods delivery and the level of service of the passengers are respected. Figure 8 shows an application example with three car-sharing users (A, B, and C)

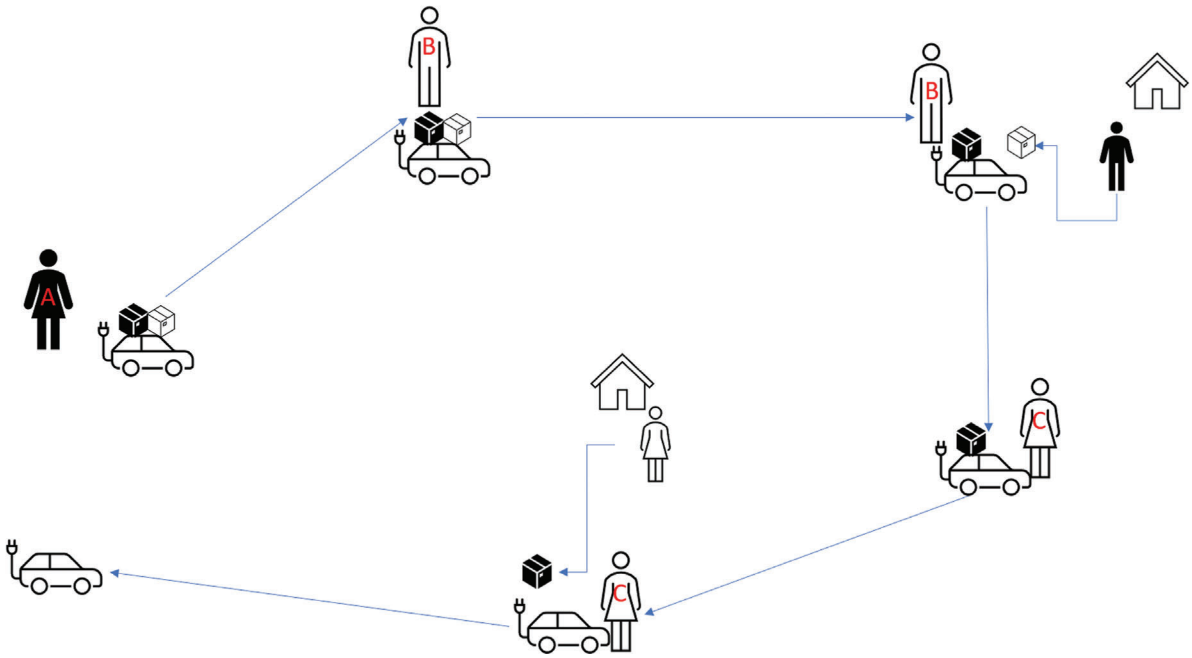

Fig. 8. An example of a new CS service for goods distribution.

and two customers (having goods requests). It is assumed that the three users accept the distribution task and also that the origin of each user is the place where he/she is located, whereas his/her destination is the place where the next user is located. Moreover, the destination of a distribution task is the place the home is located at. The users travel for reaching their destinations, whereas the customers receive one parcel each. User A picks the car up at her origin, and both the parcels are loaded into the car. Then, A reaches her destination where another user, B, is waiting for the car. However, the destination of one of the two parcels is on the way and then B stops for delivering the parcel at the customer's place. Then, B reaches his destination where another user, C, is waiting for the car. The place of the second customer is also on the way and, therefore, C stops at the customer's home before reaching her destination. If the CSS does not work on reservation, stochastic aspects, e.g., users' demand, should also be properly addressed through, for example, stochastic optimization. Two most significant advantages derive from such a new service: a reduction of pollution and traffic congestion due to goods delivery and also of the operational costs saved by the distribution companies since the number of freighters employed could be significantly reduced.

In addition, using shared autonomous shuttles (ASs) for goods distribution in the last mile logistics has been also proposed by Bucchiarone et al. (2020), as one of the possible scenarios of application of ASs. However, they do not consider the scenario where goods and passengers move together in "promiscuous" ways and do not address any specific decision problem in this context. On the other hand, it would be interesting to investigate the use of ASs/AVs for moving goods especially when they are in an idle state because the passenger demand is low in certain periods of the day and solve the corresponding decision problems.

5. Conclusions

CSSs have been extensively studied in the literature, from several points of view, among which, that one of the operations research. In fact, they represent a large source of decision problems and challenges that over the time have been investigated and for which several solution approaches have been proposed.

The aim of this research survey was threefold. First, we described the state-of-the-art of more classic decision problems occurring in CSSs with conventional vehicles and EVs. Then, we revised more innovative contributions arising in the context of CSSs with AVs or a mixed fleet, of multimodal car-sharing and of CS with time-dependent data (e.g., demand, travel time). Particular attention was devoted to how the related decision problems were mathematically formulated and solved through operations research methods. Then, we highlighted several new perspectives in the optimization of the CSSs. In particular, we detected some research topics worthy of attention from operations research practitioners i.e., P2P car-sharing system, CSSs in suburbs and low-density areas and, finally, CSSs supporting goods distribution. For each of these new research directions, we proposed and described some challenging decision problems that may inspire future work.

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