Multimodal Transportation 1 (2022) 100028

Contents lists available at ScienceDirect

Multimodal Transportation

journal homepage: www.elsevier.com/locate/multra

Modeling and optimization for carsharing services: A literature review

Ting Wu, Min Xu*

Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, PR China

ARTICLE INFO

Keywords:
Carsharing
Decision-making
Optimization model
Algorithm
Literature review

ABSTRACT

This study conducts a holistic and in-depth review of the modeling and optimization problems arising from the carsharing service operations. The aims of this review are twofold. First, this review attempts to assist carsharing operators in (i) operating carsharing systems in a better way, and (ii) gaining a forward-looking understanding of the operation of the upcoming autonomous carsharing services. Second, this study seeks to provide the transportation and management science researchers with an overview of the literature on the optimization problems for the carsharing service operations and offer directions for future research. We classify the literature into three categories, i.e., strategic, tactical, and operational, according to the level of the decisions involved in the optimization problems. For each category, the optimization models and solution methods proposed in existing studies are surveyed. Finally, we conclude the literature review and discuss several possible future research directions for the carsharing service operation management.

1. Introduction

The sustainable principles in urban mobility have prompted the emergence of many alternative transportation modes. A prominent one of them is carsharing, which allows users to access private cars without paying ownership costs (Yang et al., 2021; Zhang et al., 2019). By October 2014, more than 104,000 carsharing vehicles were accessible for about 4,800,000 registered users or members in over 1531 cities of 33 countries (Huang et al., 2018). Early carsharing operators provided round-trip services that require users to return vehicles where they are picked up (Boyacı et al., 2015; Golalikhani et al., 2021a; Nourinejad and Roorda, 2014). To attract more users by offering more flexible services, many carsharing operators, e.g., Car2Go in Germany (Car2Go, 2021) and Smove in Singapore (Smove, 2021), have allowed users to pick up and drop off vehicles at different stations by providing one-way services. According to whether a vehicle is picked up and dropped off at designated stations or non-designated stations (i.e., operation areas that allow parking), one-way carsharing services (CSSs) can be further divided into station-based services and free-floating services (Balac et al., 2017; Li et al., 2018; Weikl and Bogenberger, 2013, 2015; Xu et al., 2018).

Over the past few years, owing to the breakthroughs in battery technology and the incentive programs offered by the government, some carsharing operators have adopted electric vehicles (EVs) in their services, e.g., EVCARD in China (EVCARD, 2021) and AutoBleue in France (AutoBleue, 2021), and the traditional carsharing with gasoline vehicle (GV) fleet is undergoing electrification. In an electric carsharing system, the users pick up and drop off vehicles at charging stations. They can only pick up vehicles with the battery level that can cover their mileage, and they are usually required to connect the vehicles to chargers before they leave to ensure the vehicles are recharged. In addition, the emerging autonomous driving technology in the new era is greatly revolutionizing the future of transportation and the potential application of autonomous vehicles (AV) in CSSs has also received attention. In an autonomous

* Corresponding author.
E-mail address: min.m.xu@polyu.edu.hk (M. Xu).

https://doi.org/10.1016/j.multra.2022.100028
Received 22 November 2021; Received in revised form 9 March 2022; Accepted 17 April 2022

Table 1
The list of decisions involved in the reviewed studies.

Levels	Decisions
Strategic	Locations, amounts, and capacities of stations
Tactical	Fleet size & deployment and staff size & deployment
Operational	Vehicle relocation and trip price

carsharing system, the users no longer need to pick up and drop off vehicles at stations. Instead, AVs can drive to the user locations and take the users directly to their destination. Vehicle electrification and autonomous driving further intensify the diversification of carsharing systems.

In order to seize the market in the highly competitive environment, the carsharing operator, a for-profit business organizer, naturally needs to provide high-quality services while pursuing profit maximization. In fact, various optimization problems arising from the existing carsharing service operations, which generally seek to realize profit maximization, cost minimization, or service level maximization (i.e., the number of satisfied users) by optimizing service-related decisions, have been the subject of research and they are considered significant in advancing the development of the carsharing market. For example, how to deploy charging stations for the electric carsharing systems (Brandstätter et al., 2017; Brandstätter et al., 2020; Deza et al., 2020), how to determine the fleet size to be operated in a carsharing system (Fan, 2014; Monteiro et al., 2021; Xu et al., 2018), and how to make relocation strategies to cope with the vehicle imbalance problem in the one-way carsharing system (Lu et al., 2021; Nourinejad and Roorda, 2015). In addition, a number of studies have focused on the optimization problems of the autonomous CSSs over the past few years (Iacobucci et al., 2019; Levin, 2017; Li et al., 2021; Ma et al., 2017). This, to a certain degree, caters to the needs of operators to make adequate forward-looking preparations for the smooth application of AVs to the CSSs in the visibly near future. An overview of the research on the optimization problems arising from carsharing service operations is instructive for the operators to (i) achieve a win-win situation by providing high-quality services while realizing profit maximization, and (ii) gain a forward-looking understanding about the operation of the upcoming autonomous CSSs.

A few relevant works have attempted to review the literature on CSSs. For instance, Illgen and Höck (2019) performed a systematic review on the method-based solutions to the vehicle relocation problem in the one-way carsharing networks. Jorge and Correia (2013) conducted a literature review on demand modeling and the ways to balance the vehicle stocks in the one-way carsharing systems. Both of the two studies only focused on a particular operation problem in the CSSs. Narayanan et al. (2020) comprehensively consolidated studies in the shared autonomous vehicle services, i.e., the shared mobility services (including CSSs) with AVs. However, their main focus was on the foreseen impacts of the shared autonomous vehicle services without factoring in the service optimization problems. Ferrero et al. (2018) introduced a taxonomy that can categorize the existing literature and by applying it, they analyzed the different aspects of CSSs and derived some general trends and research perspectives. Gavalas et al. (2016) presented an extensive literature survey on models and algorithmic techniques for the design, operation, and management of vehicle (bikes or cars) sharing systems. In order to design an integrated conceptual decision-support framework for the carsharing systems, Golalikhani et al. (2021a) provided a holistic view of the current state of literature, the business practices, and the context. All of the three studies made a review on the optimization problems in the human-driven CSSs without including the upcoming autonomous CSSs. Very recently, Golalikhani et al. (2021b) proposed a detailed description of the current carsharing business practices by describing, conceptualizing, and analyzing 34 business-consumer carsharing organizations. Their main focus was to close the gap of understanding of the scientific community concerning the business practices and contexts.

Different from the studies mentioned above, this paper conducts a more systematic and comprehensive review on particularly the optimization problems arising from the carsharing service operations by including the autonomous CSSs. The aims of this review are twofold. First, this paper attempts to assist operators in operating carsharing systems in a better way such that they can obtain high profit while offering good-quality services and obtaining a forward-looking understanding of the operations of autonomous CSSs. Second, this paper seeks to provide the transportation and management science researchers with an overview of the state-of-the-art mathematical modeling-based literature on CSS operations and to identify the gaps in the current literature that offer directions for future research. To achieve these aims, a search in Google Scholar is conducted to identify the articles related to modeling-based optimization problems arising from carsharing service operations. The search is confined to the articles published over the past decade and particularly in the last five years. Since the conference papers are difficult to trace, we exclude them although they may be good sources of knowledge about the considered topic. Specifically, we first locate the most relevant articles published in the leading journals, such as Transportation Research Part B, Transportation Research Part C, and Transportation Research Part E. Then we identify the key references cited in the most relevant articles. Finally, we find the key literature citing the articles identified in the previous two steps. As a result, more than 70 articles were identified, which were deemed to be enough to cover the main body of work to date on the considered topic. Since the decisions involved in CSSs can be classified into the long-term strategic, the mid-term tactical, and the short-term operational depending on their impact scope on a carsharing system (Boyacı and Zografos, 2019; Boyacı et al., 2017), we group the selected papers into the corresponding three categories according to the level of the targeted decisions. To be more specific, the first long-term strategic category refers to the station planning; the second mid-term tactical category includes the fleet sizing & deploying and staff sizing & deploying; the third short-term operational category involves the vehicle relocation and trip pricing (Boyacı et al., 2015; Xu et al., 2018; Zhao et al., 2018). Table 1 lists all the decisions involved in the studies we have reviewed. It should be noted that a study may integrate the decisions at all of the above-mentioned three levels (Boyacı et al., 2015; Golalikhani et al., 2021a), we classified them according to their major focus.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the long-term strategic station planning, followed by the summary of the literature on the mid-term tactical fleet sizing & deploying and staff sizing & deploying in Section 3. Section 4 summarizes the studies regarding the short-term operational vehicle relocation and trip pricing problems. Section 5 identifies research gaps and indicates the directions for future research. Finally, the conclusions are presented in Section 6.

2. Long-term strategic station planning

As the top-level decision making, proper station planning for gasoline-powered carsharing systems or charging station planning for electric carsharing systems, which generally includes the determination of locations, amounts, and capacities, is crucial to struggle a trade-off between enhancing service capability and reducing infrastructure construction cost. Table 2 summarizes the studies focusing on strategic station planning, which includes the type of service, the research objective, the formulated model, the solution method, and the evaluation approach. In the following, we analyze these studies in more detail.

2.1. Station planning for human-driven gasoline-powered CSSs

A few studies have attempted to address the decision makings on station planning in the human-driven gasoline-powered CSSs. de Almeida Correia and Antunes (2012) developed an integer linear programming model to deal with the depot (i.e., station) location problem in one-way carsharing systems under three trip selection schemes. A case study on the municipality of Lisbon, Portugal was conducted to analyze the impact of depot location and trip selection schemes on the profitability of such systems. For the joint determination of station capacity and fleet size, Hu and Liu (2016) formulated a mixed queueing network model and a non-convex profit-maximization model. In the mixed queueing network model, they considered the road congestion and embedded the booking process to capture the vehicle idle time caused by the pick-up time window. A genetic algorithm was proposed to solve the non-convex optimization problem and two algorithms that belong to the class of mean value analysis were used to solve the equilibrium distribution of queuing network with a product-form solution. Huang et al. (2018) proposed a mixed-integer nonlinear programming model to address the station location and station capacity problem. They used a logit model that determines the potential demand for CSSs to account for the competition with private cars and adopted a customized gradient algorithm to obtain near-optimal solutions in a reasonable time. In order to determine the parking planning and vehicle allocation for the one-way (including station-based and free-floating) CSSs, Lu et al. (2018) proposed a two-stage stochastic integer programming model and developed a branch-and-cut algorithm with mixed-integer, rounding-enhanced benders cuts to solve the model. Similarly, Zhang et al. (2021) introduced a two-stage risk-averse stochastic model for the determination of station location, station capacity, and fleet size. A branch-and-cut algorithm and a scenario decomposition algorithm were designed to solve the proposed model.

2.2. Station planning for human-driven electric CSSs

To cater to the needs of vehicle charging brought by the introduction of EVs with limited driving range into CSSs, some scholars have made great efforts to investigate the charging station planning for human-driven electric CSSs. For the determination of the service regions (i.e., non-designated stations) for a one-way free-floating carsharing system, He et al. (2017) established a mathematical programming model that incorporates details of both customer adoption behavior and fleet management, i.e., EV repositioning and charging, under imbalanced travel patterns. To overcome the possible ambiguity of data brought by the uncertain adoption patterns, they employed a distributionally robust optimization framework. With the demand uncertainty taken into account, both Brandstätter et al. (2017) and Çalık and Fortz (2019) dealt with a charging station location problem by a mixed-integer stochastic programming model. Cocca et al. (2019) proposed a data-driven & simulation-based optimization approach to determine the optimal placement of charging stations, and the smart vehicle return policies. A case study on Turin showed that few charging stations were enough to make the system self-sustainable. Deza et al. (2020) presented a mixed-integer linear programming model and adopted a column generation approach to find the optimal locations of charging stations for one-way electric CSSs among a large number of potential charging station locations. Taking the constraint of the limited cost of the company and the multiple influencing factors of carsharing to meet the maximum user demand into consideration, Sai et al. (2020) built up a mixed-integer nonlinear programming model and designed a genetic algorithm for the corresponding model to determine the location of charging stations. Using the number of expected trips that can be accepted as a gauge of quality, Brandstätter et al. (2020) introduced a mixed-integer linear programming model and heuristic algorithms for the determination of the optimal location and size of charging stations. Based on the survival analysis, Bi et al. (2021) constructed a bi-level optimization model that maximizes profit and service level, respectively, for the planning of station location, parking spots, charging piles. To determine the number and location of fast chargers to be deployed in one-way electric carsharing systems, Bekli et al. (2021) proposed an integer programming model based on a time-space-battery level network and introduced three heuristics to cope with the computational intractability.

Different from the above studies, which focused only on the decision making of station planning, several studies attempted to address the joint determination of station planning and fleet size and/or fleet management. Boyacı et al. (2015) developed a multi-objective mixed-integer linear programming model for the planning of one-way electric carsharing systems involving decision makings of station location, station capacity, and fleet size. To scale to the problem size, they transformed the proposed model into an aggregate one using the concept of the virtual hub. Hua et al. (2019) proposed an innovative framework for the joint determination of charging

Table 2
A summary of studies on the strategic station planning.

(1) Station planning for human-driven gasoline-powered CSSs					
Literature	Service type	Objective	Model	Solution method	Evaluation
de Almeida Correia and Antunes (2012)	Station-based	Profit maximization	Integer linear programming	Solver Xpress	Case study
Hu and Liu (2016)	Station-based	Profit maximization	Mixed queuing network model & mixed-integer linear programming	Exact mean value analysis algorithm & Approximate Schweitzer-Bard mean value analysis algorithm	Computational experiments
Huang et al. (2018)	Station-based	Profit maximization	Mixed-integer nonlinear programming	Customized gradient algorithm	Case study
Lu et al. (2018)	Station-based and free-floating	Cost minimization	Two-stage stochastic integer programming	Branch-and-cut algorithm	Computational experiments
Zhang et al. (2021)	Station-based	Cost minimization	Two-stage risk-averse stochastic programming	Branch-and-cut algorithm & Scenario decomposition algorithm	Computational experiments
(2) Charging station planning for human-driven electric CSSs					
Literature	Service type	Objective	Model	Solution Method	Evaluation
He et al. (2017)	Free-floating	Profit maximization	Mixed-integer second-order cone programming	Mixed-integer second-order cone programming approximation	Case study
Brandstätter et al. (2017)	Station-based	Profit maximization	Two-stage stochastic integer linear programming	Heuristic algorithm	Computational experiments & case study
Çalık and Fortz (2019)	Station-based	Profit maximization	Mixed-integer linear stochastic programming	Benders decomposition algorithm	Case study
Cocca et al. (2019)	Free-floating	Service level maximization	Data-driven optimization	Heuristic algorithm & simulation-based approach	Case study
Deza et al. (2020)	Station-based	Service level maximization	Mixed-integer linear programming	Column generation approach	Case study
Sai et al. (2020)	Station-based	Service level maximization	Integer nonlinear programming	Genetic algorithm	Case study
Brandstätter et al. (2020)	Station-based	Profit maximization	Integer linear programming	Path-based heuristic & flow-based heuristic	Computational experiments & case study
Bi et al. (2021)	Station-based	Service level maximization & Profit maximization	Mixed-integer nonlinear programming	Bi-level heuristic algorithm	Case study
Bekli et al. (2021)	Station-based	Profit maximization	Integer linear programming	Heuristic algorithm	Computational experiments & case study
Boyacı et al. (2015)	Station-based	Profit maximization	Multi-objective mixed-integer linear programming	Aggregate modeling method	Case study
Hua et al. (2019)	Station-based	Cost minimization	Multi-stage nonlinear integer stochastic programming	Accelerated solution algorithm	Computational experiments & case study
Huang et al. (2020a)	Station-based	Profit maximization	Mixed-integer nonlinear programming	Golden section line search method & shadow price algorithm	Case study
(3) Charging station planning for autonomous electric CSSs					
Literature	Service type	Objective	Model	Solution Method	Evaluation
Kang et al. (2017)	Station-based	Profit maximization	Mixed-integer linear programming	Genetic algorithm & sequential quadratic programming	Case study
Lee et al. (2020)	Station-based	Cost minimization	Reliability-based design optimization model	Reliability-based design optimization	Computational experiments
Ma et al. (2021b)	Station-based	Cost minimization	Mixed-integer nonlinear programming	Genetic algorithm	Computational experiments
Zhao et al. (2021)	Station-based	Cost minimization	Dynamic, stochastic, and nonlinear programming	Customized heuristic algorithm	Case study

station location, fleet distribution, and real-time fleet operations considering demand uncertainty. A multi-stage stochastic model was built up to overcome the challenge brought by the demand uncertainty and an accelerated solution algorithm, which is based on lagrangian relaxation and the stochastic dual dynamic programming method, was designed to obtain the operation policy while checking the optimality gap to the optimum. Huang et al. (2020a) developed a mixed-integer nonlinear programming model and a hybrid solution method of golden section line search approach and shadow price algorithm to optimize the station capacity and fleet size of one-way electric CSSs.

2.3. Station planning for autonomous electric CSSs

With the advent of autonomous driving technology, it becomes possible for users to enjoy the autonomous CSSs in the foreseeable future. According to what we have reviewed, only a few studies have been dedicated to the charging station planning for autonomous electric CSSs. Kang et al. (2017) presented an integrated decision framework, which includes the decision makings of the charging station location and fleet size, for the design of autonomous electric carsharing systems. A case study for an autonomous fleet operation in Ann Arbor was conducted to compare autonomous electric CSSs and autonomous gasoline-powered CSSs in terms of profitability and feasibility for a variety of market scenarios. Lee et al. (2020) designed an autonomous electric carsharing system including charging station location and charging station capacity with the system uncertainty considered. A reliability-based design optimization approach was proposed to minimize the total cost of system design while satisfying the target reliability of the customer waiting time. Ma et al. (2021b) formulated a mixed-integer nonlinear programming model to optimize the charging station location and vehicle routing for a location routing problem arising from the autonomous electric CSSs. Zhao et al. (2021) established a simulation-based optimization model to seek a near-optimum design of charging station location and vehicle deployment for autonomous electric carsharing systems.

In comparison to the human-driven CSSs, the vehicles in an autonomous carsharing system can relocate themselves to the users' locations without any human operations (Zhao et al., 2021). This provides users with more convenience and enables operators to save labor and decision-making effort of staff movement. Nevertheless, the advanced autonomous driving technology would inevitably increase capital investment. In addition, the more flexible operation mode of autonomous CSSs, which allows remote parking and en-route pick-up and drop-off, would induce more decision-making problems. Particularly, for electric autonomous CSSs, it additionally involves the decision making of which station to charge for a vehicle before the vehicle drives to a location for picking up a user. In Section 3 and Section 4, the studies on tactical and operational decision-making problems arising from autonomous CSSs will be reviewed in detail.

We can see from the summary in Table 2 that most of the studies focused on the human-driven station-based CSSs and it is quite common for these studies to set the objective as maximizing profit or minimizing cost. Based on the specific context of the station planning problem, the solution method can vary a lot from study to study.

3. Mid-term tactical fleet sizing & deploying and staff sizing & deploying

The determination of the number of vehicles put into use and their deployment among stations, i.e., fleet sizing & deploying, is an important tactical decision-making problem for the CSSs. In particular, for the one-way CSSs, the carsharing operators may choose to hire staff to implement the vehicle relocation operations in order to deal with the vehicle imbalance issue across different stations, which we will introduce in detail in Subsection 4.1, and staff sizing & deploying is another tactical decision-making problem in the CSSs. Table 3 summarizes the related studies, in which we additionally, in comparison to Table 2, report modeling technique and the involved specific tactical-level decisions for each study.

Some studies have tried to tackle the tactical decision-making problems based on the time-space network (Boyacı et al., 2015; Huang et al., 2020a; Lu et al., 2018; Zhang et al., 2021). Specifically, Fan (2014) developed a multi-stage stochastic linear programming model to optimize the tactical allocation (i.e., deployment) of vehicles for one-way station-based carsharing systems with the demand uncertainty taken into account. Zhou et al. (2017) proposed a data-driven metamodel simulation-based optimization approach to determine the profit-optimal deployment of vehicle fleet across a large-scale network of round-trip carsharing stations. Xu et al. (2018) formulated a mixed-integer nonlinear and nonconvex programming model to solve an electric vehicle fleet sizing and trip pricing problem for one-way CSSs. An effective global optimization method with several outer-approximation schemes was employed to find the global optimal or ϵ-optimal solution to the considered problem. Zhao et al. (2018) established an integrated framework to optimize the allocation plan of EVs and staff with the operational EV relocation and staff rebalancing decisions considered. To solve the considered problem efficiently, they proposed a Lagrangian relaxation-based solution approach to decompose the primal problem into several sets of computationally efficient subproblems and design a three-phase implementation algorithm based on dynamic programming according to the values of Lagrangian multipliers. Monteiro et al. (2021) proposed a mixed-integer linear programming model to optimize the fleet size of a carsharing system for the one-way and round-trip modes while simulating the clients' interaction. Huang et al. (2021) developed a two-stage stochastic programming model for the demand-supply imbalance problem of one-way CSSs under demand uncertainty, with the fleet size and deployment determined at the first stage.

In addition to the time-space network approach, some other modeling techniques were also adopted in the existing studies. These modeling techniques include connection-based multi-commodity formulation (Ma et al., 2017; Xu et al., 2021), mixed queuing network approach (Hu and Liu, 2016), set partitioning formulation (Xu and Meng, 2019), and multi-state super-network approach (Li and Liao, 2020). Focusing on the human-driven autonomous carsharing systems, Ma et al. (2017) proposed a linear connection-based programming model to efficiently obtain the optimal solution to the fleet sizing problem. With the battery degradation considered,

Table 3
A summary of studies on the tactical-level decision-making problems.

Literature	Service type	Fleet type	Modeling technique	Tactical-level decisions	Objective	Model	Solution method	Evaluation
Fan (2014)	Station-based	Human-driven & gasoline-powered	Time-space network approach	Fleet sizing & deploying	Profit maximization	Multi-stage stochastic linear programming	Scenario-tree-based approach	Computational experiments
Boyacı et al. (2015)	Station-based	Human-driven & electric	Time-space network approach	Fleet sizing & deploying; Staff sizing & deploying	Profit maximization	Multi-objective mixed-integer linear programming	Aggregate modeling method	Case study
Zhou et al. (2017)	Round-trip	Human-driven & gasoline-powered	Time-space network approach	Fleet deploying	Profit maximization	Metamodel	Data-driven metamodel simulation-based optimization approach	Computational experiments & Case study
Lu et al. (2018)	Station-based and free-floating	Human-driven & gasoline-powered	Time-space network approach	Fleet deploying	Cost minimization	Two-stage stochastic integer programming	Branch-and-cut algorithm	Computational experiments
Xu et al. (2018)	Station-based	Human-driven & electric	Time-space network approach	Fleet sizing & deploying; Staff sizing	Profit maximization	Mixed-integer nonlinear programming	Outer-approximation method	Case study
Zhao et al. (2018)	Station-based	Human-driven & electric	Time-space network approach	Fleet deploying; Staff deploying	Cost minimization	Mixed-integer linear programming	Lagrangian relaxation-based solution approach	Computational experiments & Case study
Huang et al. (2020a)	Station-based	Human-driven & electric	Time-space network approach	Fleet sizing & deploying	Profit maximization	Mixed-integer nonlinear programming	Golden section line search method & shadow price algorithm	Case study
Monteiro et al. (2021)	Round-trip and one-way	Human-driven & gasoline-powered	Time-space network approach	Fleet sizing & deploying	Service level maximization	Mixed-integer linear programming	Simulation-based optimization	Computational experiments
Zhang et al. (2021)	Station-based	Human-driven & gasoline-powered	Time-space network approach	Fleet sizing & deploying	Cost minimization	Two-stage risk-averse stochastic programming	Branch-and-cut algorithm & Scenario decomposition algorithm	Computational experiments
Huang et al. (2021)	Station-based	Human-driven & gasoline-powered	Time-space network approach	Fleet sizing & deploying	Profit maximization	A two-stage stochastic programming	Dedicated gradient search algorithm	Case study
Ma et al. (2017)	Free-floating	Autonomous & gasoline-powered	Connection-based formulation	Fleet sizing	Cost minimization	Linear programming	A linear programming approach	Case study
Xu et al. (2021)	Station-based	Human-driven & electric	Connection-based formulation	Fleet sizing	Profit maximization	Mixed-integer nonlinear programming	Piecewise linear approximation & outer-approximation	Case study
Hu and Liu (2016)	Station-based	Human-driven & gasoline-powered	Mixed queuing network approach	Fleet sizing & deploying	Profit maximization	Mixed queuing network model & mixed-integer linear programming	Exact mean value analysis algorithm & Approximate Schweitzer-Bard mean value analysis algorithm	Computational experiments
Xu and Meng (2019)	Station-based	Human-driven & electric	Set partitioning formulation	Fleet sizing	Profit maximization	Set partitioning model	Branch and price	Computational experiments & Case study
Li and Liao (2020)	Free-floating	Autonomous & gasoline-powered	Multi-state super-network representation	Fleet sizing & deploying	Profit maximization	Integer, time-dependent nonlinear programming with equilibrium constraints	Lagrangian relaxation-based heuristic	Computational experiments

Xu et al. (2021) developed a connection-based mixed-integer nonlinear programming model with concave and convex terms in the objective function to address the tactical electric vehicle fleet sizing problem faced by the carsharing service providers. Piecewise linear approximation approach and outer-approximation method were employed to linearize the proposed model. As we have reviewed in Subsection 2.1, Hu and Liu (2016) formulated one-way station-based carsharing systems as a mixed queueing network model and built up a profit-maximization model for the joint design of fleet size and station capacity. Xu and Meng (2019) formulated a set partitioning model to determine the electric vehicle fleet size for one-way CSSs by maximizing the profit of carsharing operators while taking into account the vehicle relocation operations and nonlinear electric vehicle charging profile. By taking into account the interplays among vehicle relocations, supply-demand dynamics, and travelers' multi-modal multiactivity schedules, Li and Liao (2020) proposed a bi-level system optimal model for the deployment of autonomous vehicles in the free-floating CSSs. A heuristic algorithm based on Lagrangian relaxation was developed to solve the considered problem.

From Table 3 we can conclude that researchers are more interested in the fleet sizing & deploying problems in the one-way CSSs and the time-space network approach is mostly adopted.

4. Short-term operational vehicle relocation and trip pricing

At the operational level, vehicle relocation and trip pricing are the two most frequently encountered decision-making problems in CSSs. In the following, we will first review the studies on the vehicle relocation problem, and then the trip pricing problem.

4.1. Vehicle relocation

In comparison to round-trip carsharing service, one-way carsharing service provides users with more flexibility since it allows users to pick up and drop off vehicles at different stations. However, this flexibility would inevitably induce the vehicle imbalance issue among stations, i.e., the number of vehicles/parking spots available at a specific station cannot well match users' demand over a particular period. To solve this issue, vehicle relocation operations among stations are imperative for the carsharing operators (Boyacı et al., 2015; Nourinejad and Roorda, 2015; Xu and Meng, 2019). According to the relocation strategies concerned, two approaches are identified in the literature, i.e., the operator-based approach and the user-based approach (Gambella et al., 2018). As we have mentioned in Section 3, to deal with the vehicle imbalance problem, the carsharing operators may choose to hire staff to implement the vehicle relocation operations by driving vehicles from saturated stations to the ones that suffer from vehicle shortage, which belongs to the operator-based approach. The user-based approach mainly incentivizes users to change their trips such that the carsharing systems can restore a balanced distribution of vehicles in the network. Tables 4 and 5 summarize the studies on the operator-based vehicle relocation problem and the user-based vehicle relocation problem, respectively.

4.1.1. Operator-based vehicle relocation

The operator-based vehicle relocation problem has been investigated extensively by scholars. The early studies focused on human-driven gasoline-powered CSSs. By incorporating a discrete choice model that depicts users' mode choice, Jian et al. (2018) proposed a mixed-integer nonlinear programming model linking the supply and the demand to solve the vehicle relocation problem for station-based CSSs. Zakaria et al. (2018) presented a multi-objective integer linear programming model for solving the one-way carsharing relocation problem. In order to allow substantially longer reservation times while keeping the system profitable and achieving high service quality, Molnar and de Almeida Correia (2019) proposed a relocation-based reservation enforcement method combining vehicle locking and relocation movements. By this method, a variable quality of service model was developed and an iterated local search metaheuristic based on simulation was used to solve the model. Lu et al. (2021) constructed a mathematical programming model that minimizes the sum of relocation distance and travel distance of vehicles for the vehicle relocation problem with operation teams. To solve the model efficiently, an adaptive large neighbourhood search algorithm was developed.

The introduction of EVs in CSSs creates additional managerial problems due to the limited driving range per battery charge (Brandstätter et al., 2016), and a large number of researchers have worked hard to deal with the vehicle relocation problem in the one-way electric CSSs by taking the battery-related restrictions into account. Bruglieri et al. (2014) established a mixed-integer linear programming model to solve the vehicle relocation problem in the electric CSSs. Boyacı et al. (2017) developed an integrated multi-objective mixed-integer linear programming model and a discrete event simulation framework for the optimization of vehicle relocation and personnel rebalancing in a carsharing system with reservations. A clustering procedure was adopted to deal with the dimensionality of the considered problem without compromising on the solution quality. Bruglieri et al. (2018) proposed a three-objective mixed-integer linear programming model for the vehicle relocation problem to struggle a trade-off among the users' satisfaction, the staff's workload balance, and the carsharing provider's pursuit of profit. Gambella et al. (2018) introduced an exact relocation model to manage the daily relocation operations of an electric carsharing system. This model was also extended for the overnight relocations. Boyacı and Zografos (2019) presented an integrated modeling and computational framework, which consists of preprocessing, optimization, and simulation modules, for analyzing the effect of spatial and/or temporal flexibility and reservation processing type on the performance of one-way electric carsharing systems. To tackle the electric vehicle relocation problem in one-way carsharing systems, Bruglieri et al. (2019) specially developed an adaptive large neighbourhood search and a tabu search metaheuristic. In order to circumvent battery constraints and to improve vehicle utilization rates in one-way electric carsharing systems, Zhang et al. (2019) proposed a novel space-time-battery network flow model to determine the optimal assignment and relay decisions. Folkestad et al. (2020) developed a mathematical model to optimize the charging and repositioning of a fleet of electric vehicles for CSSs. By considering a time-of-use charging pricing mechanism, Lai et al. (2020) established a framework to minimize

Table 4
A summary of studies on the operator-based vehicle relocation problem.

Literature	Fleet type	Objective	Model	Solution method	Evaluation
Jian et al. (2018)	Human-driven & gasoline-powered	Profit maximization	Mixed-integer nonlinear programming	Model linearization	Case study
Zakaria et al. (2018)	Human-driven & gasoline-powered	Service level maximization; Staff size minimization; Relocation time minimization	Multi-objective integer linear programming	Genetic algorithms	Computational experiments
Molnar and de Almeida Correia (2019)	Human-driven & gasoline-powered	Operators' preference maximization	Variable quality of service model	Iterated local search metaheuristic	Computational experiments & case study
Lu et al. (2021)	Human-driven & gasoline-powered	Distance minimization	Mixed-integer linear programming	Adaptive large neighbourhood search algorithm	Computational experiments & case study
Bruglieri et al. (2014)	Human-driven & electric	Service level maximization	Mixed-integer linear programming	Heuristic algorithm	Computational experiments
Boyacı et al. (2017)	Human-driven & electric	Service level maximization; Cost minimization	Multi-objective mixed-integer linear programming	Clustering algorithm	Case study
Bruglieri et al. (2018)	Human-driven & electric	Staff size minimization; Relocation needs satisfaction maximization; Route duration minimization	Multi-objective mixed-integer linear programming	Randomized search heuristics	Computational experiments
Gambella et al. (2018)	Human-driven & electric	Profit maximization & battery level maximization	Mixed-integer linear programming	Heuristic algorithms	Computational experiments
Boyacı and Zografos (2019)	Human-driven & electric	Cost minimization	Integer programming	Discrete-event simulation approach	Case study
Bruglieri et al. (2019)	Human-driven & electric	Profit maximization	Mixed-integer linear programming	Adaptive large neighbourhood search & tabu search metaheuristic	Computational experiments
Zhang et al. (2019)	Human-driven & electric	Profit maximization	Integer programming	Diving heuristic	Case study
Folkestad et al. (2020)	Human-driven & electric	Cost minimization	Integer programming	Genetic algorithm	Computational experiments
Lai et al. (2020)	Human-driven & electric	Sum of cost and time minimization	Mixed-integer linear programming	Solver CPLEX	Case study
Lu et al. (2020)	Human-driven & electric	Profit maximization	Stochastic sequential decision programming	Event-based strategy improvement approach	Computational experiments
Pantelidis et al. (2021)	Human-driven & electric	Cost minimization	Mixed-integer linear programming	Heuristic algorithm	Computational experiments & case study
Fan (2013)	Human-driven & gasoline-powered	Cost minimization	Multi-stage stochastic mixed-integer linear programming	Simplex method/Interior point methods/Decomposition methods	Computational experiments
Wang et al. (2019)	Human-driven & electric	Relocation needs satisfaction maximization	Integer linear programming	Ruin-probability-based predictive approach & zoning scheme	Case study
Huo et al. (2020)	Human-driven & electric	Profit maximization	Mixed-integer nonlinear programming	Data-driving approach	Case study
Yang et al. (2021)	Human-driven & gasoline-powered	Cost minimization	Integer linear programming	Decomposition algorithm	Computational experiments & case study
Huang et al. (2021)	Human-driven & gasoline-powered	Profit maximization	A two-stage stochastic programming	Gradient search algorithm	Case study
Iacobucci et al. (2019)	Autonomous & electric	Cost minimization	Mixed-integer linear programming	Model-predictive control optimization algorithms	Case study
Ma et al. (2021a)	Autonomous & electric	Weighted sum of distance, time, and energy minimization	Mixed-integer linear programming	Adaptive large neighbourhood search	Computational experiments
Hyland and Mahmassani (2018)	Autonomous & gasoline-powered	Distance minimization	Integer linear programming	Agent-based simulation approach	Computational experiments
Li et al. (2021)	Autonomous & electric	Cost minimization	Integer linear programming	Minimum drift plus penalty approach	Case study

Table 5
A summary of studies on the user-based vehicle relocation problem.

Literature	Fleet type	Objective	Model	Solution method	Evaluation
Di Febbraro et al. (2018)	Gasoline-powered	Profit maximization	Integer linear programming	Simulation-based approach	Case study
Schiffer et al. (2021)	Gasoline-powered	Profit maximization	Integer linear programming	Polynomial algorithm	Case study
Stokkink and Geroliminis (2021)	Gasoline-powered	Profit maximization	Predictive model	Learning algorithm	Case study
Wang et al. (2021a)	Gasoline-powered	Profit maximization	Mixed-integer nonlinear programming	Approximate algorithm	Case study
Huang et al. (2020b)	Electric	Profit maximization	Mixed-integer nonlinear programming	Rolling horizon method & ϵ-optimal algorithm & iterated local search algorithm	Case study
Wang et al. (2021b)	Electric	Profit maximization	Integer linear programming	Solver Gurobi	Case study

the delivery time of customers and charging cost simultaneously while satisfying customer demands and working hour requirements. Lu et al. (2020) formulated a stochastic sequential decision programming model to investigate the charging and relocation problem for an electric carsharing system. Based on a static node-charge graph structure, Pantelidis et al. (2021) developed non-myopic idle vehicle rebalancing model, which considers queueing constraints applicable to EV charging, to jointly determine the relocation and routing decisions of vehicles under available charging capacity.

All the above studies assumed that the user demand is known a priori or can be estimated beforehand. In order to take the inherent uncertainty of user demand into account, several studies have attempted to develop vehicle relocation strategies in a dynamic fashion or by a stochastic programming approach. Fan (2013) developed a multi-stage stochastic mixed-integer linear programming model that can take the system uncertainty into account to address the dynamic vehicle allocation problem for CSSs. Wang et al. (2019) developed a new model, which consists of relocation needs computation and execution plan generation, for the relocation operations of one-way electric carsharing systems without advanced reservation information. Huo et al. (2020) constructed a data-driven optimization model considering demand uncertainty to improve the efficiency and profitability of CSSs. Yang et al. (2021) proposed an integrated model for the determination of the operations of vehicle relocation and dispatcher rebalancing. A hybrid solution method combining a rolling horizon algorithm with a customized decomposition algorithm was designed to solve the model. Huang et al. (2021) established a two-stage stochastic programming model for the demand-supply imbalance problem of one-way CSSs under demand uncertainty, with the vehicle relocation optimized at the second stage. Very recently, Xu and Wu (2022) developed column generation based algrotihm to guide dynamic vehicle relocation and charging operations for electric carsharing systems under demand uncertainty.

As the era of autonomous driving is upcoming, the potential application of AVs in the CSSs would enable the vehicles to be relocated without staff. Several studies have pioneered the investigation of vehicle relocation problem for the autonomous CSSs in either static or dynamic setting. Iacobucci et al. (2019) proposed a mixed-integer linear programming model to optimize charging schedules with vehicle-to-grid and vehicle routing & relocation at two different time scales by running two model-predictive control optimization algorithms. Ma et al. (2021a) developed a mixed-integer linear programming model for the service optimization of autonomous carsharing systems, in which the objective was expressed by the weighted sum of the total travel distance, the total travel time, and the total energy consumption. Hyland and Mahmassani (2018) presented and compared six AV-traveler assignment strategies for the operational problem associated with the on-demand autonomous CSSs. Li et al. (2021) proposed a minimum drift plus penalty scheduling policy for real-time vehicle dispatching in large-scale autonomous electric carsharing systems.

It can be observed from the summary in Table 4 that several studies proposed a multi-objective model for the operator-based relocation problem. This seems to be in line with the reality, as the carsharing operators, when providing services, may take multiple objectives into account instead of pursuing only profit.

4.1.2. User-based vehicle relocation

Regarding the user-based vehicle relocation problem, it has received much less attention compared with the operator-based vehicle relocation problem. In a user-based relocation problem setting where the users may accept to leave the car in a different location in exchange for fare discounts, Di Febbraro et al. (2018) formulated a two-stage optimization model for the determination of the alternative destinations proposed to users. Schiffer et al. (2021) introduced an integer programming model to optimize the assignment of user-based relocation strategies for the fleets in free-floating carsharing systems. Through the incentivization of customers and a predictive model for the state of the system, Stokkink and Geroliminis (2021) developed a user-based vehicle relocation approach to determine the optimal incentive as a trade-off between the cost of an incentive and the expected omitted demand loss. To mitigate the demand and supply imbalance problem and increase profits by means of combinatorial monetary incentives and surcharges, Wang et al. (2021a) proposed an optimization framework for the determination of the incentives and surcharges at different stations and times of day in one-way CSSs.

Instead of focusing on either the operator-based vehicle relocation or the user-based vehicle relocation, two studies have tried to factor in both of the two vehicle relocation strategies. With the time-varying SOC of vehicles tracked, Huang et al. (2020b) compared the efficiency of the operator-based and the user-based vehicle relocation strategies in a one-way station-based electric carsharing system. By combining operator-based and user-based relocation strategies, Wang et al. (2021b) developed an integer programming model to solve the vehicle imbalance problem in one-way electric CSSs.

Table 6
A summary of studies on the trip pricing problem.

Literature	Service type	Fleet type	Objective	Model	Solution method	Evaluation
Jorge et al. (2015)	Station-based	Human-driven & gasoline-powered	Profit maximization	Mixed-integer nonlinear programming	Iterated local search metaheuristic	Case study
Xu et al. (2018)	Station-based	Human-driven & electric	Profit maximization	Mixed-integer nonlinear programming	Outer-approximation algorithm	Case study
Xie et al. (2019)	Station-based	Human-driven & electric	Profit maximization	Mixed-integer nonlinear programming	Outer polyhedral approximation	Case study
Huang et al. (2021)	Station-based	Human-driven & gasoline-powered	Profit maximization	A two-stage stochastic programming	Gradient search algorithm	Case study

As summarized in Table 5, in total, only six studies factored the user-based vehicle relocation problem for CSSs. This may indicate that there is a lot of room for future research on this problem.

Trip pricing Table 6 summarizes the studies on the trip pricing problem in the CSSs. We can see that the trip pricing problem has received little attention, in sharp contrast to the vehicle relocation problem. Specifically, Jorge et al. (2015) developed a mixed-integer nonlinear programming model for the pricing problem of the one-way carsharing systems. As we have reviewed in Section 3, Xu et al. (2018) formulated a mixed-integer nonlinear and nonconvex programming model to solve the electric vehicle fleet sizing and trip pricing problem for one-way CSSs. To determine the optimal pricing and operation strategy for a one-way electric carsharing system, Xie et al. (2019) established a bi-level model and reformulated it as a mixed-integer quadratic programming model through a global polyhedral approximation of second-order cones, primal-dual optimality condition, and product term linearization. Huang et al. (2021) proposed a two-stage stochastic programming model for the demand-supply imbalance problem of one-way CSSs under demand uncertainty, with the trip price optimized at the first stage.

5. Future research directions

Based on the reviewed papers, we identify the significant gaps that remain in the field of research and highlight several possible future research directions as follows.

From the reviewed literature, we can see that a few studies have pioneered dealing with the decision-making problems arising from the autonomous CSSs. In comparison to the traditional CSSs with human-driven vehicles, CSSs with autonomous vehicles automize users' walking to vehicles and driving for parking or refueling and thus provide users with more convenience. The convenience, however, makes it impossible to solve the decision-making problems arising from the autonomous CSSs directly by utilizing the models and methods for the decision making of human-driven CSSs. This is because the operation mode of autonomous CSSs allows remote parking and en-route pick-up and drop-off, which would induce more decision makings. Particularly, in an electric autonomous carsharing system, we need to additionally decide which station to charge for a vehicle before the vehicle drives to a location for picking up a user. Furthermore, our literature review reveals that only four studies have been dedicated to the long-term charging station planning of autonomous electric CSSs, two studies to the mid-term fleet sizing & deploying of autonomous gasoline-powered CSSs, and three studies to the short-term vehicle relocation of autonomous electric CSSs. Therefore, for the smooth and efficient operation of the autonomous CSSs in the near future, considerable efforts need to be made for the decision-making problems of autonomous CSSs

Another phenomenon existed in the reviewed literature is that almost all the studies considered carsharing systems with a single fleet type, e.g., human-driven gasoline vehicles, human-driven electric vehicles, and autonomous electric vehicles. In reality, however, a carsharing system may contain both gasoline vehicles and electric vehicles. Moreover, it is highly likely that the autonomous vehicles will be applied in the CSSs by replacing part of the human-driven vehicles. The investigation on the operations of CSSs with hybrid fleet type will be more in line with the reality. On the other hand, the optimization models formulated for the carsharing service operations in the existing literature largely ignored the user behavior. In fact, in the carsharing systems, the users, as the enjoyers of the service, usually show their subjective behavior. For example, in human-driven electric carsharing systems, users may select vehicles with certain battery levels according to their mileage and preferences. The users may also choose to advance or postpone the pick-up/drop-off time based on their own needs. Incorporating these subjective user behaviors into the model formulation would be a challenging research direction in the future.

For the vehicle relocation problem, little attention has been paid to the user-based strategy, although it is a practically effective approach to tackle the vehicle imbalance problem in one-way CSSs. Hence, in the future, more efforts should be made on the user-based vehicle relocation problem. In addition, the joint implementation of the operator-based vehicle relocation and the user-based vehicle relocation strategies may also be a potential good way to cope with the vehicle imbalance problem. For the trip pricing problem, the investigation on it in the existing literature is also insufficient, although it is an important operational decision-making problem for the CSSs. The decision making of trip pricing deserves more attention in the future. Furthermore, based on the reviewed papers, we can see that several pioneering studies have adopted the data-driven approach to solve the carsharing service operation problems by making use of the massive historical data. In the era of big data, utilizing the historical data to assist the decision making of the optimization problems arising from the CSSs would be an inevitable trend.

6. Conclusions

In this study, we conducted a comprehensive review of the state-of-the-art mathematical modeling-based literature on CSS operations. According to the level of the decisions targeted by the studies, we classified the literature into three categories: strategic, tactical, operational. Studies at the strategic level focused on the long-term planning of locations, amounts, and parking capacities of stations, whereas studies at the tactical level determined the mid-term fleet size & deployment and staff size & deployment. Apart from the studies at the strategic and tactical levels, the remaining studies mainly optimized the daily operator-based vehicle relocation, user-based vehicle relocation, and trip pricing. Comparatively speaking, the strategic station planning, the tactical fleet sizing & deploying, and the operational operator-based vehicle relocation have been investigated extensively, while the tactical staff sizing & deploying and the operational user-based vehicle relocation and trip pricing have received little attention. Overall, most of the reviewed studies considered a station-based carsharing system with human-driven vehicles and developed a mixed-integer linear or nonlinear programming model for the investigated problem. The objective of models generally maximized the system profit or the service level or minimized the related cost. The solution method for solving the model varied a lot from study to study depending on the specific model characteristics. Based on these reviewed studies, we identified research gaps and indicated several directions for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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