Transportation Research Part B 120 (2019) 193–204

Contents lists available at ScienceDirect

Transportation Research Part B

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

Review

Literature review of the vehicle relocation problem in one-way car sharing networks

Stefan Illgen*, Michael Höck

Technical University Bergakademie Freiberg, Department of Business Administration Schlossplatz 1, Freiberg 09596, Germany

ARTICLE INFO

Article history:
Received 19 January 2018
Revised 19 December 2018
Accepted 20 December 2018
Available online 23 December 2018

Keywords:
Car sharing
Vehicle relocation problem
Fleet rebalancing
Simulation
Optimization

ABSTRACT

In this paper, we perform a systematic review of selected publications that offer method-based solutions to the vehicle relocation issues in car sharing networks. Asymmetric networks allowing one-way trips are the most promising form of car-sharing systems. However, the resulting vehicle imbalance across the station grid requires relocations. Typical approaches to solving the vehicle relocation problem include mixed-integer programming for strategic or operation-oriented design problems, as well as simulation models for management tasks. We survey how researchers define the decision problems related to the vehicle relocation issue, and consider their division into multistage approaches. This article offers a starting point for researchers interested in modeling one-way vehicle sharing.

1. Introduction

Initially developed in Switzerland in 1948, car sharing (CS) experienced considerable growth around the world during the 1990s. With the availability of mobile internet services and supported by other factors, such as reasonable usage fees due to competition from other logistical options, CS companies face everincreasing demands as they strive to extend their areas of operation (Lindloff et al., 2014; Shaheen and Cohen, 2013). However, the flexibility and improved lifestyle spontaneity that distinguishes CS from conventional car rental poses a challenge for many CS companies. In order to compete with or complement other modes of transportation, such as local public transport and individual car ownership, CS operators must improve their overall effectiveness, while maintaining a high level of efficiency. Against this background, a key operational issue persists in the so-called Vehicle Relocation Problem (VReP) and its resolution. Fig. 1 offers an overview on CS modes and their relevance (marked in gray) for this review paper.

2. The vehicle relocation problem

One of the most important characteristics of vehicle sharing networks is the symmetry of their configuration. Symmetric systems only allow two-way trips, which require that customers return vehicles to the pick-up location. Asymmetric systems, on the other hand, forgo that restriction by accepting one-way trips, thus allowing customers to drop vehicles off at any station or within an operation zone. If operated efficiently, one-way CS can be advantageous for both customers and enterprises when compared with two-way CS (Martin and Shaheen, 2016; Shaheen et al., 2015). However, asymmetric CS

* Corresponding author.
E-mail addresses: stefan.illgen@bwl.tu-freiberg.de (S. Illgen), michael.hoeck@bwl.tu-freiberg.de (M. Höck).

https://doi.org/10.1016/j.trb.2018.12.006

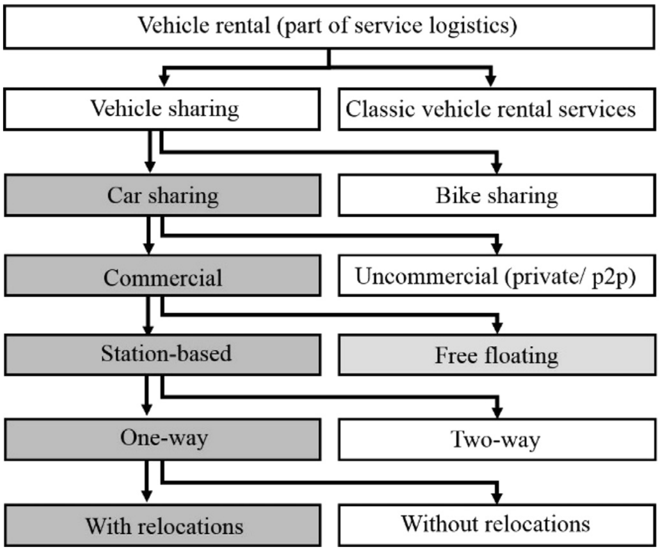

Fig. 1. CS classification and scope.

networks tend to suffer from vehicle imbalance across their station grid. Demand variability can lead to unpredictable agglomerations and shortages, resulting in poor service levels and low customer satisfaction. In contrast to CS, the one-way mode is already the norm for inner-city bike-sharing systems, where high numbers of available bikes and mass relocations (performed with the help of trucks) guarantee good service levels. Unfortunately, such strategies are less suitable for CS, as it is too costly to raise the number of vehicles far above the level of actual demand or to relocate multiple vehicles at one time by truck. In addition, it should be noted that increasing the number of available vehicles assists in delaying, but not preventing, vehicle shortages at stations with high demand. Nevertheless, it affords providers more flexibility in redistributing free vehicles across the network. It is evident that adopting strategies from bike-sharing into CS would not be effective, so this survey focuses on car-related relocation strategies.

The main premises behind and characteristics of CS typically include the following: short-term usage; self-service during booking and take-over processes; and spontaneous occupation and drop off (Luca and Di Pace, 2015). The high levels of flexibility demanded by customers render conventional reservation policies with long downtimes between occupations useless. Cars should re-enter the available pool immediately after the previous customer checks out. Ancillary process times – e.g. for cleaning and refueling – should also be reduced to a minimum: for example, by passing on the responsibility to customers. The challenge for providers and operators is to react to actual demand situations and initiate vehicle relocations between the stations before shortages occur and customer satisfaction levels drop (Jorge and Correia, 2013). The VReP includes control parameters and key performance indicators necessary to allow an analytical solution process in order to optimize relocations. This includes vehicle stock levels, safety stocks, parking space number and availability and actual or expected demands so that the optimal point in time, source and target station for an individual relocation or general relocation strategy can be determined. The VReP is thereby related to daily activity within a CS provider, but can also influence strategic planning decisions as the number of vehicles and the distances between stations can contribute to or hinder effective relocation. Thus, much of the VReP research available in the literature covers different problem settings, aims and solution methods. In this article, we seek to provide an overview, and to compare and categorize different investigations in order to highlight the most promising approaches and identify potential research gaps. Fig. 2 offers typical key points related to the modeling of the VReP. Researchers need to find the appropriate model to solve any given problem based on available data.

The interested reader is also redirected toward the exhaustive literature review of Gavalas et al. (2015), which covers multiple topics surrounding vehicle sharing systems in general, as well as toward the literature review section included in the paper of Jorge and Correia (2013), which focuses on the modeling of vehicle sharing systems.

3. Literature review

3.1. Scope and survey methodology

The following review is based on literature research carried out through databases and search engines, primarily initiated through EBSCOhost (Business Source Complete), Elsevier and ResearchGate but includes findings from papers reference sections as well. The time span of publications covered ranges between 2010 and 2018, with older exceptions pertaining to papers of particular relevance. All papers that include the VReP in CS networks lie within the scope of the review, and

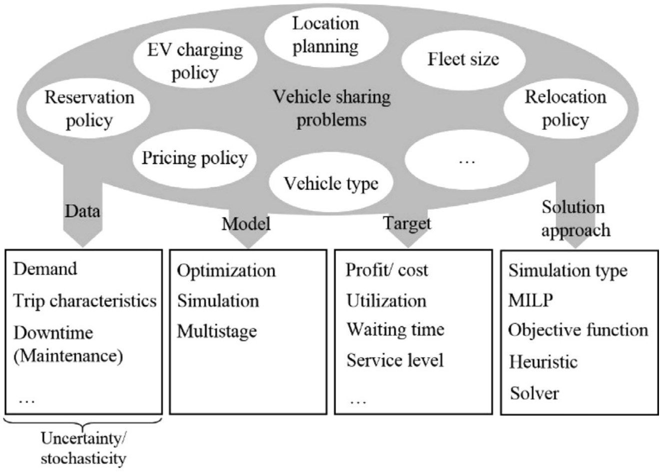

Fig. 2. Vehicle sharing modeling framework.

this applies mostly for one-way and station-based CS. Symmetric organization could also require that relocation strategies facilitate changing demand: however, these are long-term strategic decisions. With respect to the station-based or free-floating modes of organization, our investigation focuses on station-based interurban CS systems. Free-floating systems lack the ability to operate within multimodal transportation setups, as there is no transition between the vehicles and public traffic nodes like train stations or airports. For everyday usage, it is important for end-users to be able to find vehicles at such designated hubs, where passengers could change their mode of transportation. However, free-floating or nonstation related systems are excluded from the study, though the following two points should be taken into consideration. Firstly, free-floating operation areas are usually partitioned into smaller zones that serve as virtual stations, such that the VReP can be applied perfectly for relocations that occur between those zones instead of from station to station (Weikl and Bogenberger, 2015). Secondly, free-floating CS exhibits a number of drawbacks that prevent small and medium-sized enterprises from operating their fleets this way. Free-floating systems can be found in larger cities, and are usually run by major enterprises. The idea of improving the service offered by switching from a symmetric toward an asymmetric system does not apply here. Studies on private and informal CS, conventional car rentals and bike sharing are excluded from the review unless their findings are also related to one-way station-based CS. This applies for the bicycle-type vehicles in Cepolina and Farina (2012), which is also valid for motor vehicles. Another example is the space reservation in bike-sharing networks, where the authors emphasize its applicability for CS (Kaspi et al., 2014; Kaspi et al., 2016). An overview of papers that include models with one-way trips and categories that are of high relevance to research aimed at modeling the VReP is provided in Table 1. Firstly, it is shown whether a model covers one-way trips, relocations, and whether it serves an operational or strategic aim (in most cases, 'operational' means that performing relocations is part of the research question). However, in many optimization models relocations are only considered once a day in order to reset the initial vehicle balance, so called static relocations. We then highlight the utilization of MIP, simulation or multistage approaches. In short, MIP offers optimal solutions but is limited to manageable problem sizes and smaller numbers of considered variables due to computational restrictions, while simulation offers more flexibility to include stochastically distributed demand and larger problem sizes. Both may be effectively combined in multistage approaches. Finally, two more categories cover the consideration of electric vehicles and the application of a generic or real world case study.

3.2. Interdependencies related to the VReP and common solution approaches

Although the VReP represents a clear operational issue, it should not be considered as a fully isolated problem within that dimension. There is an overlap between long-term and short-term decision-making problems, whereby the VReP is a function of the one-way design, fleet size, and demand situation of a CS network. Hence, this review covers publications targeting strategic, tactical and, of course, operational dimensions as long as they determine the VReP. However, assigning research questions from Fig. 2 to one of the three levels is rather difficult, as decisions affect each other (see Fig. 3). The articles found in the literature are not, in general, strictly limited to a strategic or operational viewpoint. However, the tactical dimension is not studied in isolation. Most researchers present their findings as decision-support systems for overlapping design and operational problems.

The first strategic decision defines the mode assumed by the network (one-way, two-way, free-floating), and is characterized by other long-term issues, e.g. number of stations, station locations and fleet size (Alfian et al., 2014; Correia and Antunes, 2012; Correia et al., 2014; Fassi et al., 2012). Some authors also examine stations of limited size due to the constraints of parking space availability (Nair and Miller-Hooks, 2014; Kaspi et al., 2014; Kaspi et al., 2016). Potential tactical dimensions may also include the restoration of daily starting distributions of vehicles at the stations (Nair and Miller-Hooks,

Table 1
Literature review.

	One-way trips	Relo-cations	Scope	EV	Type	Approach	Multistage	Stochastic demand	Case study
Ait-Ouahmed et al. (2017)	•	•	Operational	•	Opt	MIP			Nice / generic
Alfian et al. (2014)	•	•	Strategic		Sim	Discrete event, deterministic			Seoul
Balac et al. (2019)	•	•	Operational		Sim	Agent based			Zurich
Barth et al. (1999)	•	•	Operational		Sim	Queing-based, discrete event		•	Coachella Valley
Barth et al. (2004)	•	•	Operational	•	Sim	Queing-based, discrete event		•	Generic / UCR IntelliShare
Boyacı et al. (2015)	•	•	Strategic/ Operational	•	Opt	Multi-objective MIP			Nice
Brandstätter et al. (2017)	•		Strategic	•	Opt	Two-staged stochastic ILP		•	Generic/ Vienna
Brendel et al. (2017)	•	•	Operational	•	Sim	Discrete event, deterministic			Generic
Brendel et al. (2018)	•	•	Operational	•	Sim	Discrete event, deterministic			Generic
Bruglieri et al. (2014)	•	•	Operational	•	Opt	MIP			Milan
Cepolina et al. (2012)	•	•	Strategic/ Operational	•	Opt (Sim)	MIP			Genoa
Clemente et al. (2013)	•	•	Strategic	•	Sim	Queing-based, stochastic, discrete event		•	Generic
Correia et al. (2012)	•	•	Strategic/ Operational		Opt	MIP			Lisbon
Correia et al (2014)	•		Strategic		Opt	MIP			Lisbon
Fassi et al. (2012)			Strategic		Sim	Queing-based, stochastic, discrete event		•	Québec
Fink et al. (2006)			Strategic		Sim/ Opt	stochastic, discrete event	•		Germany
Gambella et al. (2018)	•	•	Operational	•	Opt	MIP / rolling horizon			Singapore / generic
He et al. (2017)	•	•	Strategic	•	Opt	MIP Second-order cone program			San Diego
Illgen et al. (2018)	•		Strategic/ Operational		Sim	Discrete event, stochastic		•	Generic
Jorge et al. (2014)	•	•	Operational		Opt/ Sim	Dedicated CS control software	•		Lisbon
Kaspi et al. (2014)	•		Operational		Sim	Continuous time Markov chain/ discrete event		•	Tel-Aviv
Kaspi et al. (2016)	•		Operational		Opt/ Sim	MIP/discrete event		•	Tel-Aviv/ Washington D.C.
Kek et al. (2009)	•	•	Strategic / Operational		Sim/ Opt	Optimization-trend-simulation time stepping/ MIP	•		Singapore
Li et al. (2016)	•		Strategic	•	Opt	Continuum approximation		•	Chicago
Li et al. (2017)	•	•	Strategic / Operational		Sim	Discrete event			Generic
Li et al. (2018)	•		Strategic		Opt	MIP, Activity-travel path disutility			Generic
Nair et al. (2010)	•	•	Operational		Opt	Stochastic MIP		•	Singapore
Nair et al. (2014)	•		Strategic		Opt	MIP			Generic
Nourinejad et al. (2014)	•	•	Operational		Opt/ Sim	Binary integer programming/ discrete event	•	•	Toronto
Nourinejad et al. (2015)	•	•	Operational		Opt	MIP, LP Monte Carlo simulation			Toronto
Santos et al. (2015)	•	•	Operational		Opt	MIP / rolling horizon			Generic
Wang et al. (2010)	•	•	Operational		Sim	microscopic traffic simulation	•		Singapore
Waserhole et al. (2013)	•		Operational		Sim	Queuing based Markovian process			Generic
Weikl et al. (2015)	•	•	Operational	•	Opt	MIP	•		Munich
Xu et al. (2018)	•	•	Strategic / Operational	•	Opt	MIP / dynamic pricing			Singapore

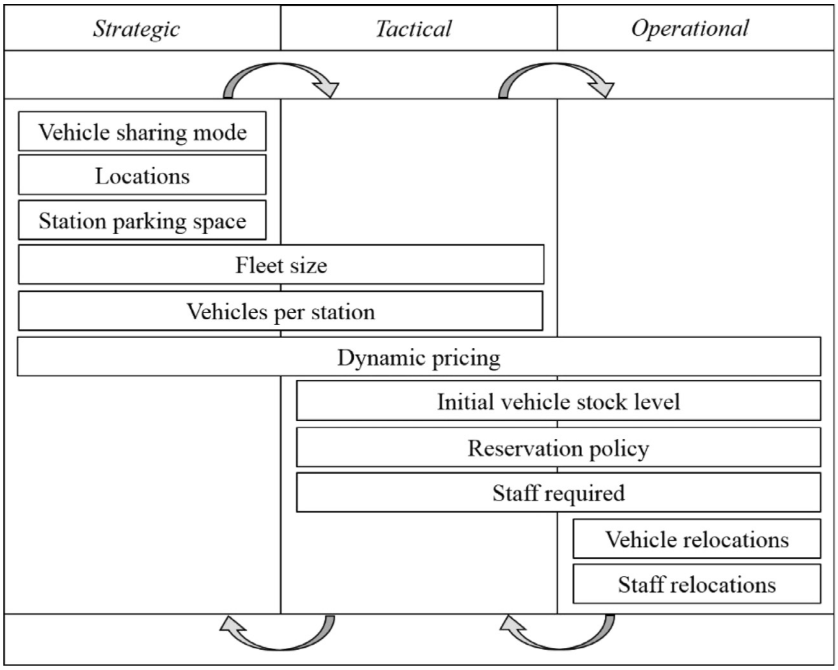

Fig. 3. Dependent decision problems associated with the VReP.

2010; Correia and Antunes, 2012) and reservation policies, such as the minimum time span a reservation needs to be placed in advance of the desired vehicle pick-up (Nourinejad and Roorda, 2014). Dynamic pricing policies are found to affect all dimensions, as long-term profitability must be achieved. However, pricing can be altered depending on actual demand (Waserhole et al., 2013; Chow and Yu, 2015). Finally, research questions pertaining to the operational dimension include relocation policies and the mode of execution of relocations (Boyacı et al., 2015; Jorge et al., 2014; Nair and Miller-Hooks, 2010; Nourinejad and Roorda, 2014; Wang et al., 2010; Weikl and Bogenberger, 2015) as well as vehicle space reservations (Nair and Miller-Hooks, 2014; Kaspi et al., 2014; Kaspi et al., 2016). Because redistributing imbalanced stocks of vehicles also results in imbalance in staff availability at the stations, so-called staff relocations also need to be performed (Bruglieri et al., 2014; Nourinejad et al., 2015; Lee and Park, 2014). The number of staff required and their activities (Kek et al., 2009) can be assigned to the strategic, tactical and operational level as a function of workforce flexibility and legal restrictions.

3.3. Optimization models

Many approaches to solving the VReP revolve around optimization models that maximize profit for providers and customers or minimize costs, and are modeled by means of mixed integer (linear) programming (MIP). For a full overview of all of the publications included in this review, please refer to Table 1: Literature Review. To begin with, vehicle-sharing models originate from classical routing models, and are based on findings from studies of well-known car rental systems (You and Hsieh, 2014). An example represents the article from Correia and Antunes (2012), which optimizes vehicle depot locations and describes how demanded customer trips are merged with available vehicles. The initial vehicle stock level for each station is reset at the end of the day. Under a few simplifying assumptions, such as – no relocations during the daily operations, it is shown – by means of a case study from the city of Lisbon – that one-way CS can be profitable. The model includes up to 75 locations for stations and 1776 trips. Exact solutions are obtained from a brunch-and-cut algorithm programmed in the software Xpress for the easier experiments in the study. More demanding settings are limited by the authors with the help of a time-out rule. The nonoptimal results are exploited as they point into a clear direction – e.g. already show an improvement over other previous settings (Correia and Antunes, 2012). The model was later extended by the authors to take account of the main assumptions – its nonvariable and linear trips: Correia et. al. (2014) increased adaptability by only allowing customer trips to commence at stations with vehicles in stock. One of the key assumptions of the previous model (fixed and deterministic demand) as well as the solution methodology remain unchanged. The paper thus focuses primarily on flexible customer behavior and information sharing. It allows operators and customers to adjust their behavior according to current and predicted vehicle availability. Although the new MIP model results in higher profits, it also relies on multiple assumptions, such as the complete absence of dynamic relocations. Real-world application is limited (Correia et al., 2014). Finally, another extension of the article above can be found in the short paper of Correia et al. (2014). Here the authors examine the influence of relocation strategies on profit. Two different relocation strategies and related subvariants are created on top of the MIP model which is calculated continuously based on the results from a simulation model. The utilized software "PTV Visum" is a dedicated control software for vehicle sharing applications mainly responsible for demand and trip generation. The particular solution approach is not presented in detail but was taken from Correia and Antunes (2012) according to the authors. The newly developed relocation strategies differ with respect to their evaluation and points in time where customer trips avoid relocations in the same direction (Jorge et al., 2014). In contrast to the less convincing model of fixed demand, Nair and Miller-Hooks (2010) introduce stochastic demands in their MIP formulation – the so-called Vehicle Sharing Problem for fleet management. Relocations are performed in this model to prepare initial inventories that allow the satisfaction of all previously known reservations. Overall, the authors assume fixed time points for vehicle redistribution and calculate the optimal relocation operations four times per day. vehicle sharing system. The two strategies presented for resetting vehicle inventories follow different solution procedures. The first is based on a divide-and-conquer p-efficient points – enumeration algorithm while the alternative is a cone generation method. Ultimately, the calculations are carried out in such a manner that a trade-off is found between service levels and redistribution costs. The Singapore case originates from Kek et al. (2009) and includes a data set of 14 stations, 94 vehicles and 45,570 trips in total. However, the split into time windows reduces the number of trips to zero to eight per station (Nair and Miller-Hooks, 2010). Later, the authors also extend their model through an equilibrium approach, considering the two incongruent aims of the provider's revenue and the customer's advantages. Exact optimal solutions are generated for a varying number of stations and station sizes, but under fixed demand with the help of a not closer specified solver in CPLEX. The network size limit for computational reasons is 40 nodes (Nair and Miller-Hooks, 2014). The same tradeoff is modeled in one of the most sophisticated and complex MIP models, which is presented by Boyacı et al. (2015). The multiobjective MIP calculates the trade-off between customers' advantage and operators' profit. The model considers strategic location of additional stations and operational vehicle relocations in one unified optimization. Unfortunately, it suffers from the computational limits pertaining to the formulation of large problems. The instance of a relatively large problem – i.e. the case study of Nice, France with 70 stations (nodes) – required the transformation of the initial model toward the final aggregate model that handles an average of 155.2 trips per scenario. The introduction of formulations generating upper and lower bounds allows the problem to be solved exactly through a branch and bound algorithm in CPLEX (Boyacı et al., 2015). Another example of near-optimal problem solving by means of heuristics can be found in Cepolina and Farina (2012). The fleet size for the problem size of 9 stations and 925 trips is optimized through a random search algorithm based on simulated annealing. Adjustments to the cooling component allow for best possible solutions within practical computing times. Some of the input data are generated with the help of a separate micro simulation that generates the demand so this model can be seen as a light form of a multistage approach as in chapter 3.5 (Cepolina and Farina, 2012). MIP formulations are also a common solution approach for the short-term staff relocation problem as an extension of the VReP. Nourinejad et al. (2015) develop an optimization model for vehicle and staff relocations. The optimization model is based on two integrated multitraveling salesman problems. An individual heuristic solution method is proposed that decomposes the combined traveling salesman problems into two separate problems. The first step solves the vehicle relocation problem without the desired staff rebalancing and a second step uses the relocation plan so far to solve the actual staff rebalancing problem. Iterative repetitions of this heuristic lead to a final result. Their findings are similar with respect to the relations between fleet size and relocation times when expanded into staff size and staff relocation time. However, fleet size is still more sensitive to customer demand satisfaction (Nourinejad et al., 2015). The included case study is the same as in Nourinejad and Roorda (2014). The practical research question of Bruglieri et al. (2014) offers recommendations for the handling of staff relocations. Staff redistributions between the stations are facilitated by foldable bikes, which can be carried in a car's trunk while the worker performs the actual vehicle relocation. The combined pickup and delivery problem is solved exactly with the help of the simplex algorithm provided in CPLEX. In this case the problem size is limited e.g. by a reduced number of relocation requests from the network so that a maximum allowed computation time does not limit the experiments. Authors compare the obtained results with the results from a heuristic that sets upper bounds for the number of relocations in a preliminary stage based on expected outcomes depending on other model parameters. The problem size consists of 9 stations and is solved (Bruglieri et al., 2014). All of the above-mentioned relocation models are based on a cost-minimization approach. Despite the cost for one relocation exceeding the profit for one additional possible trip, vehicle relocations may be part of the optimal solution. Due to other factors – e.g. higher service levels or possible fleet size reductions – the overall profit may still increase. As a result, all of the optimization models are highly dependent on the particular problem settings and the manner in which the cost of an increased service level is calculated. This can be carried out based on penalty costs for refusing a trip due to lack of inventory (Kek et al., 2009). Most papers rely on case studies with either real-world data or synthetic data to validate their models. However, any implications must then be recalculated to determine their profitability for any other application scenario. The approach of maintaining a supply and demand equilibrium by Li et al. (2018) does not include relocations as such and is therefore out of scope in regard of this review. However, it is mentioned as it offers a good starting point for modeling of unusual free floating CS. Instead of simple one-way trips the authors consider realistic multimodal activity-based user trips with multiple stops in a row (Li et al., 2018).

3.4. Simulation models

In order to avoid computational limitations of optimization models, such as in Boyacı et al. (2015), simulation models of CS networks are applied. It is evident that the stochastic occurrence of demand or stochastic occupation times can be part of MIP formulations, but that they require sophisticated heuristic algorithms or transformation into more manageable subproblems (Nair and Miller-Hooks, 2010). If simulation models are chosen, researchers must be cognizant of the fact that optimal or near-optimal results are not generated. Instead, solutions will be realized with multiple simulation runs generating break-even points or acceptable profits. Simulation must also take account of drawbacks with respect to transparency and reproducibility. While optimization models consist of clearly formulated target functions and constraints, simulation is more dependent on the simulation framework utilized, on the assumptions made and on detailed validation and verification procedures.

A general overview of a simulation approach is offered by Fink and Reiners (2006). The authors create a broad decision support system for a nationwide car rental system, showing that overall efficiency can be increased through enhanced fleet management. Nonetheless, this study is not related to operational one-way CS problems, though it demonstrates how simulation and flow models offer useful findings when compared with MIP on a strategic level. In addition, the proposed decision support system offers insights into the organization of CS enterprises and the importance of integrated systems with fleet control and relocation tools. Moreover, a simple optimization for the classic car rental distribution problem is part of the simulation approach in the study from Fink and Reiners (2006). The also contained flow problem in the minimum cost network is solved with the help of a polynomial time algorithm (not NP-hard) which is not discussed explicitly in the study. Another noteworthy contribution to CS simulation comes from Fassi et al. (2012). The simulation model they present is also a strategic planning approach to determine network growth strategies. In this case it is limited to round trips and includes only 9 stations, but could be extended with one-way trips as well (Fassi et al., 2012). A similar discrete event simulation is conducted by Li and Petering (2017). It is realized in a specific C++ program but offers comparable results regarding basic key characteristics of CS networks especially fleet size and station size. At the strategic level a simulation model is offered by Alfian et al. (2014). A complex CS network is simulated as a function of the organization modes used, e.g. one-way or two-way trips. No actual customer trips are simulated, though customer's requirements are satisfied by 36 different combinations of organization parameters. The minimum number of relocations, occupation times and utilization rates are simulated (along with a range of other factors), resulting in an average daily profit. The case consists of 5 stations, 100 vehicles and 7 days. CS enterprises could use this framework to decide on an appropriate business model (Alfian et al., 2014). On the operational level, Barth and Todd (1999) propose a simple but robust tool, allowing for investigation of the relations between the number of relocations, the service level (e.g. customer waiting times) and the resulting costs. One-way CS was less popular when this paper was published 18 years ago, but it still holds many useful key findings for research in this field. This includes potential performance indicators to evaluate CS network effectiveness, typical daily and weekly demand patterns, and initial investigations of the trade-off between the number of relocations, the fleet size and the service level. However, problem size was rather small (6 stations) and the number of trips and estimation of up to 2261 per 24 h (Barth and Todd, 1999). Later Barth et al. (2004) used the same simulation tool (now with a more realistic number of 200 trips per day) for balancing vehicle distributions through the simulation of trip joining or trip splitting. The approach simulates the effectiveness of customers contributing to the balancing process by towing additional vehicles to their desired target location (relocation) or by taking another customer with them if an impending vehicle shortage is observed (Barth et al., 2004). Kaspi et al. (2014) apply their model comparing parking spot reservation versus nonreservation policies to a larger sized problem. The simulation model represents a network of 130 stations and 900 vehicles. The discrete event simulation features randomly occurring demand and the results help identifying critical parameters like penalty costs in contrast to the findings from an optimization approach (Kaspi et al., 2014). The extension and refinement in Kaspi et al. (2016) follows the same approach but also includes small optimization program of parking space policies in a previous model stage. The small MIP is solved with the help of the simplex algorithm in CPLEX. A simulation approach on electric vehicle carsharing is presented by Clemente et al. (2013). Besides the interesting initial model presentation and findings based on the service level as a key performance indicator it demonstrates the applicability and flexibility of a generic simulation approach. However, the problem size is rather small (2 stations) and the resulting computational effort is very low (15 seconds per simulation run). So the study highlights the general methodological approach instead of an practical solution to the problem (Clemente et al., 2013). The recent studies of Brendel et al. (2017) and Brendel et al. (2018) prove the applicability of a discrete event simulation approach for various problems. The authors create a specific discrete event simulation tool to compare different relocation configurations or management systems against each other. One step further goes the publication of Balac et al. (2019). The proposed MATSim tool simulates two CS companies operating in the same area at the same time. One offers CS service with a relocation policy while the other one doesn't. Notably the CS provider with the relocation policy in place could end up with less revenue than the more reactionary organized opponent (Balac et al., 2019).

3.5. Multistage approaches

More recent papers utilize multiple methodologies in combination (see Fig. 4), thus reducing the disadvantages of isolated tools while increasing the significance of the results.

One multistage approach is the MIP model proposed by Nourinejad and Roorda (2014). The MIP model is recalculated whenever a new customer enters the CS network. Thus, the authors consider their model as a discrete event simulation. At each event the relocation operations are optimized by solving binary integer programming formulations with CPLEX. Typical network characteristics, such as fleet size and relocation time are measured and can be reduced. The approach was applied to a case study of 200 vehicle requests per day and 209 stations (Nourinejad and Roorda, 2014). The major difference between their approach and other MIP models is that such models are calculated once for the complete preknown

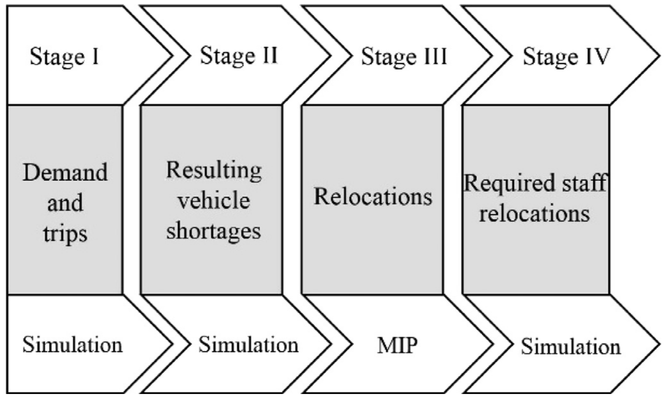

Fig. 4. Example for the distribution of tasks within a generic multistage approach.

demand, and consequently offer fewer dynamic changes. Another good example is the multistage simulation approach by Wang et al. (2010). Microscopic traffic simulation, forecasting and inventory replenishing tactics are solved sequentially and build upon each other's results. Some authors use MIP for optimization of strategic figures like fleet size and simulation for demand and trip generation or relocation decisions (Jorge et al., 2014). Weikl and Bodenberger (2015) successfully demonstrate the operation of a multistage CS relocation management tool in a free-floating (one-way trip) CS network. Based on forecasted demand, vehicles are relocated between zones and, later, within those zones. The stages begin with a strategic definition of the zones and calculation of the expected demand. If there is a mismatch between supply and demand, MIP is applied separately for macroscopic and microscopic zones to search for relocations that maximize profit. Finally, additional service trips are generated and included. Dividing the model into separate stages facilitates the necessary computational effort for exact solutions from the applied branch and cut algorithm (CPLEX). It is not, however, fully dynamic, and only preknown demand is used for calculation of the necessary vehicles. Backflow of incoming customers into zones, for instance, is not considered in actual vehicle stock levels. The problem size for the optimization step are 15 zones where 390 vehicles are distributed. The additional rule-based steps cover a total number of 478 zones (Weikl and Bogenberger, 2015). A similar approach that splits an operation area into zones can be found in Li et al. (2016). Another multistage approach by Kek et al. (2009) offers MIP for cost minimization in a first step and improves the results by applying an additional relocation simulation approach. The time stepping simulation part is used for efficiency evaluation after a trend filter generates feasible operational solutions from the optimization results. The system optimizes a problem set consisting of 1236 trips through the simplex algorithm provided in CPLEX (Kek et al., 2009). The same MIP model is also used by Santos and Correia (2015). The research question is made accessible by using a rolling time horizon method and dividing the desired planning period into smaller sub periods to be optimized separately. The utilized Xpress software uses a build-in combination of the branch and bound and cutting-plane method (Santos and Correia, 2015).

4. Further aspects of modeling CS networks

4.1. Dynamic pricing

In contrast to the classic car rental-style reservation method, an important policy that balances vehicle stocks in one-way CS networks is dynamic pricing. This promising idea significantly affects the modeling of CS networks, and deserves mention in this review accordingly. Dynamic pricing modifies usage fees based on actual vehicle availability. Stations overstocked with vehicles offer trips for lower prices, while stations with vehicle shortages require higher prices. Waserhole et al. (2013) utilize a simulation approach to dynamic pricing that influences demand so that vehicle imbalances are more effectively avoided. Needless to say this approach is highly dependent on any assumed demand elasticity and legal obligations (Waserhole et al., 2013). Chow and Yu (2015) provide a so-called bidding-based vehicle sharing model in the same context (Chow and Yu, 2015). However, once a one-way CS network faces similar demands across all stations, vehicle imbalances compensate themselves through statistical effects. Manipulating demand through dynamic pricing so that it equals out is a research field of its own, and goes beyond the scope of this review. However, we wish to stress that dynamic pricing could support and relieve other relocation strategies, and should be considered in relocation models due to increasing application in a range of service areas as well as for mobility products (Ma et al., 2017; Latinopoulos et al., 2017; Xu et al., 2018). The effects of dynamic pricing offer the potential to complement and support rebalancing through vehicle relocation approaches and are therefore an important part of future research. However, it represents a unique field of research that lacks practical studies on the extend CS demand can be influenced.

4.2. Modeling CS networks with electric vehicles

The role of electric vehicles in VReP problems must also be considered, as electric mobility is placed at the forefront of many recent publications that deal with transportation. Under certain conditions, vehicle sharing is a perfect application for electric vehicles (Xu et al., 2017) and offers obvious potential to reduce traffic-induced greenhouse emissions (Jung and Koo, 2018). Many models do not consider electric mobility specifically. It is evident that the issues surrounding the limited ranges and operating times of electric vehicles have almost been eliminated due to advances in battery capacities and the long recharge times available at night when CS experiences lower levels of utilization (see chapter 4.3). However, even if explicitly related to electric vehicles, models experience only minor consequences – such as different cost components in the goal function (Boyacı et al., 2015; Weikl and Bogenberger, 2015). He et al. (2017) as well as Li et al. (2016) investigate the influence of longer vehicle downtimes on required fleet size due to battery charging. The optimization model from (He et al., 2017) also utilizes the simplex algorithm from CPLEX in combination with a lower bound of the desired target value calculated based on the worst case profit. He et al. (2017) and Li et al. (2016) present a unique model and generate near optimum solutions through an individual continuum approximation approach. The CS network area is divided into smaller neighborhoods that are solved separately based on demand and inventory parameters before a final aggregation of the solutions takes place (Li et al., 2016). Yet another operational oriented approach is the more recent optimization model of Gambella et al. (2018). Relocations depending on the readiness of the electric vehicles are in the focus of this study. The MIP model is solved with CPLEX through a rolling time horizon heuristic similar to Santos and Correia (2015). In order to provide feasible solver times, dedicated relocations are taken off the model but assumed to take place during vehicle idle times (Gambella et al., 2018). Strategic location planning for electric chargers is presented in Brandstätter et al. (2017). Their stochastic integer linear programming model is solved through an individual shortest path heuristic algorithm programmed in CPLEX. The heuristic iteratively adds vehicle routes from the previous shortest path algorithm to the solution aiming to maximize the total profit of the CS network. The problem size is reduced by forming separate grids and results in a maximum of 50 stations and 100 trips.

It can be concluded that electric mobility has become the focus of attention in vehicle sharing. Even if not considered directly, models may be applied to electric vehicle CS due to the reasons given above. We expect future publications to create models that are generally applicable for electric mobility. Furthermore, comparing the effect of utilizing conventional or electric vehicles on a given CS network offers an interesting field of research. Zero-emission vehicles (especially if charged with sustainably generated energy), the possibility to include CS into multimodal transportation networks, and intelligent energy transportation offer huge benefits for future mobility (Fuentes et al., 2017; Farid, 2017). Due to simplifying assumptions found in most current electric vehicle sharing papers there is always the need to restore 100% state of charge before vehicles are allowed to take trips again. Alternatively, a mandatory recharge break blocks every vehicle for the time span proportional to the previous trip length (Ait-Ouahmed et al., 2017). After all, realistic and individual recharging poses a noticeable research gap in electric vehicle sharing and first steps to address this issue are made by Brendel et al. (2018), Gambella et al. (2018) and Illgen and Höck (2018).

4.3. Key performance indicators and demand estimation

The findings in all of the papers reviewed were evaluated using the different key performance indicators applied by the researchers. An overview of the metrics typically utilized is of great relevance for the survey, as it provides further insight into the modeling of one-way CS.

In general, simulation models offer more possibilities to gather performance data, while in optimization models, the final values of variables work as counters, and additional time factors like average trip times are multiplied afterward to obtain performance indicators. The individual selection of performance figures also depends on the methodology and available case study data.

Firstly, the descriptions of the vehicle sharing networks are usually consistent and include, for instance, the number of stations, the number of vehicles, trips performed per day and available staff. Unfortunately, mere numbers make it difficult for the interested reader to classify the network. Instead, utilizing more comparable ratios that are fully independent from the actual case study can be helpful. The so-called ‘vehicle-to-trip ratio’ (Barth and Todd, 1999) or ‘vehicle-to-trip station ratio’ (Kek et al., 2009) offer better insights into equipment availability and workloads than mere numbers.

The ‘number of relocations’ e.g. in Barth et al. (2004), Jorge et al. (2014), Kek et al. (2009), Nourinejad et al. (2015) is important in examining the functionality of the model in general, as well as the impact of any changes to the model. The related measure ‘number of trips’ e.g. in Jorge et al. (2014) and Nair and Miller-Hooks (2014) counts all completed trips by customers – which could provide the basis for calculating the fraction of satisfied demand or the beta service level (Alfian et al., 2014; Fink and Reiners, 2006; Nair and Miller-Hooks, 2010). Additionally, the numbers of trips and relocations is used to calculate the actual vehicle utilization (Alfian et al., 2014).

In some publications, times are summed, such as with e.g. the ‘zero vehicle time’ (Barth and Todd, 1999; Kek et al., 2009) or ‘full port time’ (Kek et al., 2009). Again, the trip times are difficult to compare between different models, but assist in improving models – e.g. by minimizing zero vehicle time, which gives customers the possibility to occupy a vehicle spontaneously. Costs are used as a performance indicator in all publications based on MIP, with minimized cost or maximized profit target functions. Whatever measures are used, an exhaustive sensitivity analysis (Li et al., 2016) assists the reader in

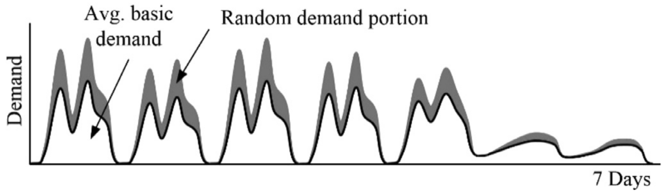

Fig. 5. Example of a weekly demand pattern.

understanding real-world implications. The usage of a set of unified performance measures (e.g. service level) could increase the level of comparability regarding the results of different studies. On a final note, we wish to highlight the topic of demand estimation. In most papers, current demand was provided by CS enterprises or derived from online reservation systems. The data obtained provided a demand matrix to be accessed by the MIP formulations, or the authors transformed the demand numbers into a demand-over-time chart (see Fig. 5) ready for simulation frameworks. The resulting typical demand pattern can be found in Barth and Todd (1999), He et al. (2017), Heilig et al. (2018), Li et al. (2016), Schmöller et al. (2015) and Schreier et al. (2015).

Alternatively, demand modeling approaches based on real world observations are presented in Ciari et al. (2012), Dias et al. (2017), Heilig et al. (2018) and Zhou et al. (2017). In general, two major issues became apparent. Firstly, the relation between trips performed and actual demand can vary due to the limited availability of vehicles during high-demand phases. Therefore, it often cannot be stated with certainty whether a demand that occurred was fully satisfied. Secondly, demand may vary due to price changes or changes in the mobility service offered. Demand elasticity can only be estimated if past data are used (Waserhole et al., 2013). This applies in particular when numbers from current two-way CS networks are used to calculate one-way systems. A poll carried out during a case study in London found that demand for one-way CS could be three to four times larger than for two-way CS (Le Vine et al., 2014). Instead of applying fixed and predictable demand from reservations, random demand fits better with the spontaneity of one-way CS. Unfortunately, it was only considered in a small number of models. The influence of unexpected demand situations should not be neglected, as it may place a high degree of stress on profit-optimized models. Lastly, the trip length represents another important part of demand. The reviewed papers rely on different methods dealing with trips. The static relocation models (see Table 1) assume that all trips are finished at a point of time where relocations are initiated. The actual time of vehicle occupation is not relevant in this case. Any further calculations are usually based on an average trip time taken from the dataset (Boyacı et al., 2015; Brandstätter et al., 2017; Cepolina and Farina, 2012; Correia and Antunes, 2012; He et al., 2017; Kek et al., 2009; Santos and Correia, 2015; Weikl and Bogenberger, 2015). Alternatively the shortest path between two stations in the grid is calculated by the model and transformed into travelling time (Bruglieri et al., 2014; Li et al., 2016; Nair and Miller-Hooks, 2014; Nourinejad et al., 2015). Simulation tools seem to offer the best opportunities to include stochasticity of trip times (Clemente et al., 2013). Depending on the CS organization mode and availability of stations, customers may check-out (one-way systems) while doing their business or keep the vehicle (two way systems). Also the utilized payment model (time and/or distance related) influences customers behavior. The aim of researchers developing future dynamic models should be to include actual observed trip times as proposed in Ciari et al. (2012), Fink and Reiners (2006) and Xu et al. (2017).

5. Identification of research gaps and concluding remarks

CS contributes to sustainable inner city mobility, while the constantly growing numbers of customers and available CS vehicles provide an interesting field of research. The potential to improve transportation under ecological viewpoints is important for future mobility (Martin and Shaheen, 2016). After surveying multiple publications, 26 fell directly within the scope of this review. An overview is given in Table 1. Key findings can be concluded as follows: One-way CS offers more flexible and better service, and is therefore demanded more strongly by customers (Le Vine et al., 2014). Due to demand imbalances, vehicles accumulate at some nodes in the network while others run out of vehicles, thus reducing availability and customer satisfaction. Relocations eliminate this issue but increase operating costs and consume vehicle availability time in and of themselves. If managed appropriately, higher profits can be achieved using relocations (Jorge et al., 2014). Current research builds on MIP and simulation, with both offering advantages and disadvantages, while multistage approaches afford the most realistic and holistic answers. Optimization of MIP models is favored by most authors. Researchers receive optimal solutions regarding profit or costs in MIP but are limited to manageable problem sizes, less flexible with respect to stochastic or dynamically changing demand, and smaller numbers of variables due to computational restrictions. Subsequently, some approaches aim to split the problem into smaller optimization problems or to merge it with simulation. While simulation does not offer optimization at first, larger problem sizes as well as more realistic demand distributions and variables are possible. Discrete event simulation seems very promising, as it allows insights into a running, real-time CS network. Simulation proved to be effective in multistage approaches together with MIP models. A typical result is the trade-off between fleet size, relocation effort and the service level achieved (Barth and Todd, 1999; Nourinejad and Roorda, 2014). However, a larger fleet size only delays – rather than solves – vehicle inventory imbalances. The reason for larger fleet sizes in one-way CS networks is the vehicle time required for relocations and the higher flexibility necessary for operators to determine potential source stations for relocations. True multistage approaches are used in 6 out of 35 more closely reviewed articles, and 11 are based on dynamically changing stochastic demand. 27 of the proposed models have been tested in real-world case studies from around the world, proving the practical relevance of the research results. These include implications for the system that often cover strategic and tactical or operative scopes simultaneously. Furthermore, electric mobility is increasingly becoming the focus of attention in CS modeling, with consideration of recharge times and limited operation ranges. Nonetheless, findings from models not considering electric vehicles do not lose their applicability due to the recharging possibilities during low-demand periods at night. Other models could be modified to involve parameters specific to electric vehicles. Lastly, we reviewed methodological aspects regarding key performance indicators and demand estimations. Researchers are encouraged to rely on widely used measures and ratios to facilitate comparability, and demand data can be taken from multiple sources. The demand and trip characteristics of a model is mentioned by many authors as a potential drawback if assumed to be fixed and preknown. Variable and dynamically changing demand places additional stress on models and, thus, adds more realism. Finally, the case studies applied (as an approach for real-world testing) proves the robustness of the approaches. The data sets used usually consisted of a network grid with potential locations, demand points and log files of trips from the past. Some of the data for the case studies listed in Table 1 are taken from freely accessible databases (Transportation Networks for Research Core Team, 2017) and researchers are also encouraged to perform case studies with their models. However, some assumptions are required when the data is applied for different operation modes. Further research is still necessary even though many vehicle sharing enterprises are already in place. There is potential to extend current models as providers hesitate to transform two-way systems into one-way systems or extend their service into rural or less-attractive urban regions. Research gaps identified include extensions of the currently available models e.g. with regard to stochastic demands and trips, realistic staff relocation and personnel planning and up to the development of realistic multistage approaches that cover strategic and operational levels, thus offering complete business models. The relevance of e-mobility as opposed to conventionally fueled cars for CS networks also offers wide fields of research. Increased profitability through higher efficiency is required to continuously expand CS networks and make them an inherent part of sustainable future mobility.

Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

Ait-Ouahmed, A., Josselin, D., Zhou, F., 2017. Relocation optimization of electric cars in one-way car-sharing systems: modeling, exact solving and heuristics algorithms. Int. J. Geogr. Inf. Sci. 32, 367–398.
Alfian, G., Rhee, J., Yoon, B., 2014. A simulation tool for prioritizing product-service system (PSS) models in a carsharing service. Comput. Ind. Eng. 70, 59–73.
Balac, M., Becker, H., Ciari, F., Axhausen, K.W., 2019. Modeling competing free-floating carsharing operators – a case study for Zurich, Switzerland. Transp. Res. C: Emerg. Technol. 98, 101–117.
Barth, M., Todd, M., 1999. Simulation model performance analysis of a multiple station shared vehicle system. Transp. Res C: Emerg. Technol. 7, 237–259.
Barth, M., Todd, M., Xue, L., 2004. User-based vehicle relocation techniques for multiple-station shared-use vehicle systems. TRB 2004 Annual Meeting.
Boyacı, B., Zografos, K.G., Geroliminis, N., 2015. An optimization framework for the development of efficient one-way car-sharing systems. Eur. J. Oper. Res. 240, 718–733.
Brandstätter, G., Kahr, M., Leitner, M., 2017. Determining optimal locations for charging stations of electric car-sharing systems under stochastic demand. Transp. Res. B: Methodol. 104, 17–35.
Brendel, A.B., Lichtenberg, S., Brauer, B., Nastjuk, I., Kolbe, L.M., 2018. Improving electric vehicle utilization in carsharing: a framework and simulation of an e-carsharing vehicle utilization management system. Transp. Res. D: Transp. Environ. 64, 230–245.
Brendel, B.B., Lichtenberg, S., Nastjuk, I., Kolbe, L.M., 2017. Adapting carsharing vehicle relocation strategies for shared autonomous electric vehicle services. In: International Conference on Information Systems, pp. 1–20.
Bruglieri, M., Colorni, A., Luè, A., 2014. The relocation problem for the one-way electric vehicle sharing. Networks 64, 292–305.
Cepolina, E.M., Farina, A., 2012. A new shared vehicle system for urban areas. Transp. Res. C: Emerg. Technol. 21, 230–243.
Chow, Y., Yu, J.Y., 2015. Real-time bidding based vehicle sharing. In: Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, pp. 1829–1830.
Ciari, F., Schuessler, N., Axhausen, K.W., 2012. Estimation of carsharing demand using an activity-based microsimulation approach: model discussion and some results. Int. J. Sustainable Transp. 7, 70–84.
Clemente, M., Fanti, M.P., Iacobellis, G., Ukovich, W., 2013. Modeling and simulation of an electric car sharing system. In: 25th European Modeling and Simulation Symposium, pp. 587–592.
Correia, G.H.d.A., Antunes, A.P., 2012. Optimization approach to depot location and trip selection in one-way carsharing systems. Transp Res Part E: Logist. Transp. Rev. 48, 233–247.
Correia, G.H.d.A., Jorge, D.R., Antunes, D.M., 2014. The added value of accounting for users' flexibility and information on the potential of a station-based one-way car-sharing system: an application in Lisbon, Portugal. J. Intell. Transp. Syst. 18, 299–308.
Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation 44, 1307–1323.
Farid, A.M., 2017. A hybrid dynamic system model for multimodal transportation electrification. Inst. Electr. Electron. Eng.—Trans. Control Syst. Technol. 25, 940–951.
Fassi, A.E., Awasthi, A., Viviani, M., 2012. Evaluation of carsharing network's growth strategies through discrete event simulation. Expert Syst. Appl. 39, 6692–6705.
Fink, A., Reiners, T., 2006. Modeling and solving the short-term car rental logistics problem. Transp. Res. E: Logist. Transp. Rev. 42, 272–292.
Fuentes, M., Fraile-Ardanuy, J., Risco-Martín, J.L., Moya, J.M., 2017. Feasibility study of a building-integrated PV manager to power a last-mile electric vehicle sharing system. Int. J. Photoenergy 2017, 1–12.
Gambella, C., Malaguti, E., Masini, F., Vigo, D., 2018. Optimizing relocation operations in electric car-sharing. Omega 81, 234–245.
Gavalas, D., Konstantopoulos, C., Pantziou, G., 2015. Design and management of vehicle sharing systems: a survey of algorithmic approaches. In: Obaidat, M., Nicop olitidis, P. (Eds.), Smart Cities and Homes: Key Enabling Technologies. Elsevier Science Eds.

He, L., Mak, H.-Y., Rong, Y., Shen, Z.-J.M., 2017. Service region design for urban electric vehicle sharing systems. Manufact. Serv. Oper. Manage. 19, 309–327.
Heilig, M., Mallig, N., Schröder, O., Kagerbauer, M., Vortisch, P., 2018. Implementation of free-floating and station-based carsharing in an agent-based travel demand model. Travel Behav. Soc. 12, 151–158.
Illgen, S., Höck, M., 2018. Electric vehicles in car sharing networks – challenges and simulation model analysis. Transp. Res. D: Transp. Environ. 63, 377–387.
Jorge, D., Correia, G., 2013. Carsharing systems demand estimation and defined operations: a literature review. Eur. J. Transp. Infrastruct. Res. 13 (3), 201–220.
Jorge, D., Correia, G., Barnhart, C., 2014. Comparing optimal relocation operations with simulated relocation policies in one-way carsharing systems. Inst. Electr. Electron. Eng. – Trans. Intell. Transp. Syst. 15, 1667–1675.
Jung, J., Koo, Y., 2018. Analyzing the effects of car sharing services on the reduction of greenhouse gas (GHG) emissions. Sustainability 10, 539.
Kaspi, M., Raviv, T., Tzur, M., 2014. Parking reservation policies in one-way vehicle sharing systems. Transp. Res. B: Methodol. 62, 35–50.
Kaspi, M., Raviv, T., Tzur, M., Galili, H., 2016. Regulating vehicle sharing systems through parking reservation policies: analysis and performance bounds. Eur. J. Oper. Res. 251, 969–987.
Kek, Alvina, G.H., Cheu, R.L., Meng, Q., Fung, C.H., 2009. A decision support system for vehicle relocation operations in carsharing systems. Transp. Res. E: Logist. Transp. Rev. 45, 149–158.
Latinopoulos, C., Sivakumar, A., Polak, J.W., 2017. Response of electric vehicle drivers to dynamic pricing of parking and charging services: risky choice in early reservations. Transp. Res. C: Emerg. Technol. 80, 175–189.
Le Vine, S., Lee-Gosselin, M., Sivakumar, A., Polak, J., 2014. A new approach to predict the market and impacts of round-trip and point-to-point carsharing systems: case study of London. Transp. Res. D: Transp. Environ. 32, 218–229.
Lee, J., Park, G.-L., 2014. Design of a relocation staff assignment scheme for clustered electric vehicle sharing systems. In: Hutchison, D., Kanade, T., Kittler, J., Kleinberg, J.M., Kobsa, A., Mattern, F., Mitchell, J.C., Naor, M., Nierstrasz, O., Pandu Rangan, C., Steffen, B., Terzopoulos, D., Tygar, D., Weikum, G., Murgante, B., Misra, S., Rocha, A.M.A.C., Torre, C., Rocha, J.G., Falcão, M.I., Taniar, D., Apduhan, B.O., Gervasi, O. (Eds.), The International Conference on Computational Science and Its Applications 2014. Springer International Publishing, Cham, pp. 639–651.
Li, L., Petering, M.E.H., 2017. Discrete event simulation analysis of a reservation-based, one-way car-sharing system. J. Simul. 12, 1–22.
Li, Q., Liao, F., Timmermans, H.J., Huang, H., Zhou, J., 2018. Incorporating free-floating car-sharing into an activity-based dynamic user equilibrium model: a demand-side model. Transp. Res. B: Methodol. 107, 102–123.
Li, X., Ma, J., Cui, J., Ghiasi, A., Zhou, F., 2016. Design framework of large-scale one-way electric vehicle sharing systems: a continuum approximation model. Transp. Res. B: Methodol. 88, 21–45.
Lindloff, K., Pieper, N., Bandelow, N.C., Woisetschläger, D.M., 2014. Drivers of carsharing diffusion in Germany: an actor-centred approach. Int. J. Autom. Technol. Manage. 14, 217–245.
Luca, S.de, Di Pace, R., 2015. Modelling users' behaviour in inter-urban carsharing program: a stated preference approach. Transp. Res. A: Policy Pract. 71, 59–76.
Ma, R., Ban, X., Szeto, W.Y., 2017. Emission modeling and pricing on single-destination dynamic traffic networks. Transp. Res. B: Methodol. 100, 255–283.
Martin, E., Shaheen, S., 2016. Impacts of Car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions: An Analysis of five North American Cities. Innovative Mobility Research & Transportation Sustainability Research Center.
Nair, R., Miller-Hooks, E., 2010. Fleet management for vehicle sharing operations. Transp. Sci. 45, 524–540.
Nair, R., Miller-Hooks, E., 2014. Equilibrium network design of shared-vehicle systems. Eur. J. Oper. Res. 235, 47–61.
Nourinejad, M., Roorda, M.J., 2014. A dynamic carsharing decision support system. Transp. Res. E: Logist. Transp. Rev. 66, 36–50.
Nourinejad, M., Zhu, S., Bahrami, S., Roorda, M.J., 2015. Vehicle relocation and staff rebalancing in one-way carsharing systems. Transp. Res. E: Logist. Transp. Rev. 81, 98–113.
Santos, G., Correia, G., 2015. A MIP model to optimize real time maintenance and relocation operations in one-way carsharing systems. Transp. Res. Proc. 10, 384–392.
Schmöller, S., Weikl, S., Müller, J., Bogenberger, K., 2015. Empirical analysis of free-floating carsharing usage: the Munich and Berlin case. Transp. Res. C: Emerg. Technol. 56, 34–51.
Schreier, H., Becker, U., Heller, J., 2015. Evaluation CarSharing (EVA-CS) Berlin.
Shaheen, S.A., Chan, N.D., Micheaux, H., 2015. One-way carsharing's evolution and operator perspectives from the Americas. Transportation 42, 519–536.
Shaheen, S.A., Cohen, A.P., 2013. Carsharing and personal vehicle services: worldwide market developments and emerging trends. Int. J. Sustainable Transp. 7, 5–34.
Transportation Networks for Research Core Team Transportation Networks for Research. accessed 18.12.2017.
Wang, H., Cheu, R., Lee, D.-H. (Eds.), 2010. Dynamic Relocating Vehicle Resources Using A Microscopic Traffic Simulation Model For Carsharing Services. 1. Place of Publication: Los Alamitos, CA, USA Huangshan, Anhui, China. Country of Publication: USA, Institute of Electrical and Electronics Engineers Computer Society.
Waserhole, A., Jost, V., Brauner, N., 2013. Pricing techniques for self regulation in vehicle sharing systems. Electron. Notes Discrete Math. 41, 149–156.
Weikl, S., Bogenberger, K., 2015. A practice-ready relocation model for free-floating carsharing systems with electric vehicles – mesoscopic approach and field trial results. Transp. Res. C: Emerg. Technol. 57, 206–223.
Xu, F., Liu, J., Lin, S., Yuan, J., 2017. A VIKOR-based approach for assessing the service performance of electric vehicle sharing programs: a case study in Beijing. J. Clean. Prod. 148, 254–267.
Xu, M., Meng, Q., Liu, Z., 2018. Electric vehicle fleet size and trip pricing for one-way carsharing services considering vehicle relocation and personnel assignment. Transp. Res. B 111, 60–82.
You, P.-S., Hsieh, Y.-C., 2014. A study on the vehicle size and transfer policy for car rental problems. Transp. Res. E: Logist. Transp. Rev. 64, 110–121.
Zhou, F., Zheng, Z., Whitehead, J., Perrons, R., Page, L., Washington, S., 2017. Projected prevalence of car-sharing in four Asian-Pacific countries in 2030: what the experts think. Transp. Res. C: Emerg. Technol. 84, 158–177.