A Critical Analysis of Travel Demand Estimation for New One-Way Carsharing Systems

Reza Vosooghi, Jakob Puchinger, Marija Jankovic, Göknur Sirin

A Critical Analysis of Travel Demand Estimation for New One-Way Carsharing Systems

Reza Vosooghi[1,2], Jakob Puchinger[1,2], Marija Jankovic[1], and Göknur Sirin[3]
[1]*Laboratoire Génie Industriel, CentraleSupeléc, Université Paris-Saclay, Chatenay-Malabry, France*
[2]*Institut de Recherche Technologique SystemX, Palaiseau, France*
[3]*Direction de la Recherche / Nouvelles Mobilité (DEA-IRM), Technocentre Renault, Guyancourt, France*

***Abstract*—Technologic advancements have contributed to the spread of sharing economy concepts, a developing phenomenon that favors the shift from private mobility to service-use (shared mobility). One-way carsharing is a most recent and popular kind of shared mobility, that is growing and developing rapidly in various forms. These systems are considered to have a transformative impact on future urban transportation. Despite all of the benefits that have been reported from the use of new one-way carsharing (e.g. Autonomous Mobility-on-Demand systems), their impacts on the mobility are not certain yet. This comes from the fact that in such services supply and demand influence each other in a significant way in short-, mid-, and long-term. Also service characteristics at the level of each vehicle strongly affect the demand. In this paper methods, paradigms, toolkits and platforms used in the literature for the demand estimation of the new one-way carsharing systems, as well as their potential drawbacks are discussed. A review of the literature reveals that despite the considerable number of studies related to balancing vehicle stocks across stations in one-way systems, the investigation about demand estimation of such services for which the complex relationship between supply and demand is considered, remain very limited. The majority of current platforms and toolkits used for demand estimation of new one-way carsharing systems are based on activity-based multi-agent simulations. In these simulations several main components are not yet taken into account, which could dramatically change the results. Data detail, accessibility and reliability, high computational time, calibration and validation still remain major challenges for travel demand estimation for one-way carsharing systems.**

Keywords*—Carsharing, Shared Autonomous Vehicle, Shared Mobility, Free-floating, Station-based, Travel demand estimation, Agent-base simulation, Autonomous Mobility-on-Demand, Shared-use vehicle systems

I. INTRODUCTION

In the last years the growth of service-oriented transport alternatives is shifting the private mobility from ownership to service access/use. Carsharing is one of the first concepts for such alternatives, introduced for the first time in Switzerland in the middle of 20th century and gained worldwide popularity in the 1990s [1]. Developing the strategy for enabling users to gain short-term access to any other conventional private modes (such as bicycle) results gradually in the increase of popularity of "shared-use vehicle systems". Nowadays car producers are also directly involved in vehicle-sharing operations with the scope of finding new channels to market the produced cars and to gain the financial benefits of new car rental service systems [2].

Technologies including social networking, location-based services, the Internet, electric vehicles, keyless vehicle access, in-vehicle and mobile global positioning system (GPS) receivers have played a major role in the growth of carsharing over time [3]. Due to the development of technologies related to automated vehicle, it is expected that next generation of carsharing systems will be based upon these vehicles [4], [5]. Shared autonomous vehicles (SAVs) have the potential to take over a significant amount of traffic handled nowadays by conventionally driven vehicles, especially taking in consideration that these new services could potentially be integrated with public transportation by solving the "last mile problem"[6]. In addition SAVs can anticipate future demand and relocate in advance to better match vehicle supply and travel demand [7].

New carsharing systems are considered to have a transformative impact on many cities by enhancing transportation accessibility, increasing multimodality, changing vehicle ownership rate, and providing new ways to access services [3]. To predict this impact before placing any services in operation, it is necessary to estimate the eventual travel demand. This is usually done by travel models. Travel models produce quantitative information about travel demand and transportation system performance that can be used to evaluate alternatives and make informed decisions.

The aim of this paper is to give a holistic view into the existing methods of travel demand estimation for one-way carsharing systems. We outline also the identification of appropriate platforms (travel models) to model innovative carsharing services when they are applied for a multimodal integrated transportation system. To the authors' best knowledge this paper presents for the first time a through comparison of all methods, platforms and toolkits used to estimate the demand of new one-way carsharing systems and discusses their potential drawbacks. Another important contribution of this study is the illustration of why and how activity-based multi-agent simulations are often used to demand estimation of such new systems and which limitations they have.

This paper is structured as follows. Initially different types of carsharing systems are classified. Then all travel demand estimation methods for one-way services are described, as well as existing literature on this subject is reviewed. After that application of these methods is analyzed and criticized. Finally, the conclusion as a base for future work is provided.

II. Carsharing Classification

Carsharing is generally defined as short-term vehicle access among a group of members who share a vehicle fleet that is maintained, managed, and insured by a third-party organization [8]. With respect to the operating model carsharing systems can be classified in two general types: (1) round-trip, in which users must return the car to its departing point, and (2) one-way, in which users may drop off the car to a different location from where they started [9]. In the last decade round-trip carsharing systems were more common, but over the last years with the important development on electric vehicles, smart phones and information technologies there has been a significant growth of one-way systems [10], [11].

One-way carsharing systems could fall in three general types: (1) station-based, (2) free-floating, and (3) shared autonomous vehicles (SAVs). One-way station-based carsharing provide short term car rentals enabling users to take a car from the initial station and return it to any other station. The advantages of such services include the reliability and predictability of car locations and parking, as well as the ability to reserve cars in advance. However, this comes for the price of less freedom of movement and spontaneity for members. Free-floating carsharing - where cars may be picked up by members wherever they are available and parked anywhere on the street, within the service area -has appeared afterwards. This type of carsharing is more financially attractive for short trips and allows greater flexibility [12].

One-way carsharing present new and important operational challenges, such as vehicle rebalancing and parking management [8], [13]. It’s expected that with autonomous vehicle technology there will be no more such challenges in the future. This is the reason why self-driving capability has the potential for more vehicles sharing, including robotaxis, and more sharing of private vehicles [4]. It should be mentioned that concerning park space problem for free-floating services as the vehicle can be parked anywhere on the street, there won’t be any problem related to the limitation of park space in the contrary to station-based services. But comparing to SAVs there will be more limitation for finding park space in congested areas.

Table I illustrates all types of carsharing systems. A complete classification of carsharing and more overall “shared-use vehicle systems” is described in [14]. One-way carsharing services are the ones in the focus of this paper. Various economic models of station-based and free-floating carsharing are under development nowadays and considerable efforts are being made for the planning of future SAVs. Thus, the estimates of travel demand for these new innovative systems turn more and more important.

TABLE I. Classification of Carsharing Systems

	Carsharing types			
	Round-trip	***One-way***		
		Station-based	***Free-floating***	***SAVs***
Pick-up	Specified points	Any rental station	Anywhere available	Anywhere
Drop-off	Same point	Any station	Anywhere authorized	Anywhere
Park space problem	No	Yes	No/Yes	No
Rebalancing problem	No	Yes	Yes	No

III. Demand Estimation

A. Approaches

To estimate travel demand of one-way carsharing systems several approaches might be applied depending on data availability, expected accuracy and study scale. In general, these approaches fall into three categories or better say evolutionary levels: (1) survey and analysis, (2) discrete choice modeling, and (3) agent-based simulation.

Less precise methods are based on survey and analysis. These methods are designed to produce rough estimations of potential demand and range from demand elasticity analysis (e.g. pivot-point) to modal diversion estimation [15]. These approaches have been developed when one can have already existing data, thus hindering the prediction when it comes to new innovative systems. It is nevertheless important to take this approach into account because by coupling with regression or logit models it may be used for service membership prediction [16].

The second group of methods are discrete choice models. They have been employed widely in travel demand analysis with the most common application being in the choice of travel mode, aim and destination [15]. Within this approach stated-preference (SP) surveys are also required. One of the most important parameters used in discrete choice models is travel time (indoor, waiting, etc.). The time (commonly converted to equivalent cost) is usually calculated by separate traffic simulators.

More sophisticated and common solutions for estimating the travel demand of one-way carsharing systems are agent-based transport simulations. Their roots lay on activity-based travel demand models and are commonly characterized by a similar feature[17]. An agent-based simulation is developed in which travel demand emerges from the interactions of four types of agents in the transportation system: node, arc, traveler and vehicle. This approach is mostly used for demand estimation of one-way carsharing, ridesharing SAVs, and Autonomous Mobility-on-Demand (AMoD) systems.

B. Challenges

In general, three major challenges facing travel demand estimation of innovative one-way carsharing systems have been found in the literature: (1) data detail, accessibility and reliability, (2) high computational time, and (3) calibration and validation.

The most important challenge is data. As various types of these systems are not yet in operation issue-specific SP surveys are needed. Such surveys are costly and might not necessarily result in reliable and complete models. Also in order to assign travelers to the right alternative, travel needs to be modeled at the individual level with explicit modeling of the modal choice, which requires individual socio-demographic data. Likewise, in order to create a model sensitive to short-distance trips (trips in which new carsharing services are more interesting for travelers) extremely fine-grained spatial information at the parcel level is needed. All these data are not necessarily accessible and available.

A second challenge is computation time. In theory there are two major components of transportation models: travel demand (represented classically by the trip matrix) and traffic assignment (estimates the traffic flows on a network). Traffic assignments can be either static -as in most four step trip-based models (FSM) - or dynamic, as recently applied especially in activity-based models. The assignment outputs -mainly traffic volumes and travel times- in their turn are used as inputs to the travel demand models. The big challenges for coupling these two components of modeling is that the models typically compute probabilities for a large number of alternatives at the individual level, which demands an explicit choice set. To account for such alternative sets in assignment or simulation procedures for real size networks and huge number of individuals would result in very long computation times.

Finally, there is be a big challenge regarding to calibration and validation of models. For innovative one-way carsharing forms (e.g. SAVs) there are no real data on hand, so it is difficult to validate if the model runs correctly or not.

C. Application in Literature

Significant literature can be found on the topic of carsharing, especially describing how to explore the demand of real round-trip services. Jorge and Correia [18] have reviewed all the studies where car-sharing has been modelled after 2000 and they concluded that despite the considerable number of studies related to demand modeling for round-trip systems, there is a clear predominance of studies about balancing vehicle stocks across stations in one-way systems, mainly through relocation operations performed by the company or the users. However, there are some studies concerning travel demand estimation of one-way carsharing.

Catalano et al. [19] estimated the potential demand for one-way car-sharing and car-pooling in Palermo, Italy. They used a SP survey for calibrating a multinomial logit model and applied it to a future scenario characterized by some transport policy actions. Kouwenhoven et al. [20] used SP and discrete choice modeling (IMPACT4) to estimate the potential demand for the Autolib' service (one-way station-based carsharing) in Paris. In this study service membership was modeled separately. Several other works have been done, proposing the use of spatial and temporal disaggregate models. Ciari et al. [21] used for the first time an agent-based approach to model one-way carsharing. Their research used the open source multi-agent simulation tool MATSim [22] and was based on their previous research aimed to simulate classic two-ways carsharing. In this research demand is considered as independent from the supply and vice-versa. Ciari et al. [23] used the same platform later to consider station-based and free-floating carsharing in both their demand and supply side case-study in Berlin. Balac et al. [24] used also MATSim to investigate the effects of supply on the demand of the existing round-trip service in Zurich and compared the results with those of one-way station-based systems. They concluded that there is still untapped potential for round-trip carsharing.

The more complex supply—demand relationship has been studied by Martínez et al. [25] by using a different agent-based simulation tool applied to Lisbon. They propose a new agent-based model that simulates a one-way carsharing system as part of the transport supply in a city, accurately describing the demand mode choice and the operation of the system. In their simulation travel times were obtained from AIMSUN [26] for each arc of the network, varying with the time of the day. Also an optimization model was developed to estimate the location and relative dimension of the stations, based on the mobility patterns of Lisbon. Heilig et al. [27] used a travel demand model (trip-based) based on the principle of agent-based simulation, to model both round-trip and one-way (free-floating) carsharing systems. In their work for the first time carsharing usage was simulated for more than one day.

The demand for SAVs also have been recently explored by using activity-based multi-agent simulation tools. Fagnant et al. [7] used MATSim to estimate the demands for a fleet of SAVs (with a low level of market penetration: 1.3% of regional trips) serving travelers in Austin, Texas. Hörl et al. [28] explored the demand for autonomous taxis with the same tool by simulation of different scenarios. Azevedo et al. [29] used an integrated agent-based traffic simulator built on disaggregated behavior models in both demand and supply (SimMobility [30]) to study the potential impacts of introducing of an AMoD service in a car-restricted zone of Singapore. In their work individual preferences to use autonomous vehicle were kept unchanged and only cost of the service was assumed as 40% less than the regular taxi service in Singapore.

Table II presents a summary of the studies where travel demand of one-way carsharing systems has been estimated. For each study the demand estimation approach used, the type of carsharing and the case study are indicated. The references are in chronological order.

TABLE II. SUMMARY OF THE STUDIES ON TRAVEL DEMAND ESTIMATION FOR ONE-WAY CARSHARING SYSTEMS

Authors	Year	Case study	Demand estimation approach	Type of shared-use vehicle services
Catalano, Lo Casto and Miglior	2008	Palermo urban area	SP + random utility model	One-way station-based
Kouwenhoven, Kroes, Gazave and Tardivel	2011	Autolib	SP + discrete choice model	One-way station-based
Ciari, Dobler, and Axhausen	2012	Zurich area	Activity-based multi-agent simulation (MATSim)	One-way station-based
Ciari, Bock and Balmer	2014	Berlin	Activity-based multi-agent simulation (MATSim)	One-way station-based and free-floating
Balac, Ciari and Axhausen	2015	Zurich area	Activity-based multi-agent simulation (MATSim)	Round-trip and one-way station-based
Heilig, Mallig, Schroder, Kagerbauer, & Vortisch	2015	Greater Stuttgart area	Aent-based simulation (MobiTopp) + Traffic simulation (VISUM)	Round-trip and one-way free-floating
Fagnant, Kockelman and Bansal	2015	Austin	Activity-based multi-agent simulation (MATSim)	SAVs
Hörl, Earth and Axhausen	2016	Sioux Falls	Activity-based multi-agent simulation (MATSim)	Free-floating and SAVs
Azevedo et al.	2016	Singapore	Multi-scale integrated activity-, agent-based Simulation (SimMobility)	SAVs (non-carpooling)
Martínez, Almeida Correia, Moura and Lopes	2017	Lisbon	Agent-based modeling + Traffic simulation (AIMSUN)	One-way station-based

As mentioned before in the literature the largest attention was given to the possibility of fleets to become unbalanced and the works on travel demand estimation of this services are limited [18], [24]. However there are some studies about the influence of different factors on demand related to one-way station-based and free-floating services [31], or membership prediction [16], [32]. Also there are many works in which the preferences of travelers to use SAVs have been studied [33]–[38]. All these studies do not focus on whole travel demand model but their results could potentially be useful for model calibration.

IV. ANALYSIS

A. Travel Model

As shown in the table II most of the above mentioned studies use an activity-based approach for estimating travel demands for one-way carsharing. Activity-based travel demand estimation is the application of discrete choice analysis methods to model the decision making process that motivates daily trip tours. A trip tour is the sequence or chain of trips in time and space throughout a particular day. However, in transportation modelling trip-based models are more popular. These models are often referred to as “four step models (FSMs)” because they commonly include four primary components: (1) trip generation, (2) trip distribution, (3) mode choice, and (4) traffic assignment. FSMs have evolved over many decades and are widely used and the question is why for demand forecasting of one-way carsharing systems, activity-based models are employed? There are some reasons for that:

Firstly, FSMs do not consider the entire tour made by an individual and typically have high numbers of non-home-based trips, which do not include important information such as trip purpose, traveler income, or relation to other trips in the person’s day. These trips are considered to be captured more by one-way systems [14]. That has been approved in the literature. Heilig et al. [39] use a trip-based aggregated model for simplification and ignored sub-tours. They admitted in their revised paper that this simplification could be the reason why their modeled outputs do not match the real data. Martínez et al. [40] also used trip-based approach in their first simulation for Lisbon city but they developed afterwards an activity-based model to simulate shared mobility systems in larger area (Lisbon Metropolitan Area).

Secondly, the mode choice functionality in FSMs is based on behavioral models that usually rely on revealed preferences (RP) data, which for new services -as these new systems are not in operation yet- is not available, especially in the case of SAVs.

Thirdly, to model one-way carsharing both spatial and temporal location of vehicles are needed which aggregated FSMs cannot provide.

Fourthly, typically FSMs are not sensitive to short-distance trips. This is because in any FSMs some aggregated spatial zoning (traffic analysis zone) are used. Heilig et al. [39] pointed that in their model access and egress trips to the carsharing are not modeled explicitly due to the zone-based spatial resolution. Martínez et al. [25] used extremely fine-grained spatial zoning (homogeneous grid of 200 m x 200 m cells) for their simulation.

Finally, activity-based models are more sensitive to pricing policies. Therefore, for one-way carsharing systems it would be of more use in order to study the financial and economic aspects of the services.

B. Agent-based Simulation

In activity-based approaches, every individual is a decision maker who confronts a huge choice set of various activity patterns in the time-space domain. Each combination of activities and their locations, starting and ending points, and durations forms a unique activity pattern. Individuals select the patterns that maximize their utilities by somehow solving a large-scale combinatorial optimization problem conditional on others' decisions. Thus such disaggregate models require faster solution algorithms. One solution is agent-based simulation. It typically refers to a computational method and simulation for studying the actions and interactions of a set of autonomous entities. It is also called a multi-agent system or agent-based system [17]. Agent-based transport simulations usually derive travel demand from activity-based modeling approaches but employ microscopic and completely time-dynamic traffic simulation of each agent's individual demand based on system constraints given by the transport network and its attributes [41].

C. Activity-based Multi-agent Simulation: Overall Framework

Within most of the reviewed literature, demand estimation frameworks of one-way carsharing systems are structured as follows: (1) a "synthetic population" (synthetic individuals) is created from demographic data, (2) activity plans and activity locations are generated (selected) for each synthetic individual, also mode and route choice decisions are done for each individual, (3) the traffic simulation (particularly micro simulation) and plan execution are done to find performance measures, (4) activity planning, route and mode decisions are revised for each individual, and (5) iteration process is repeated until average performance measures for all agents stabilize.

For the first step of this framework some generators have been used in different studies. In fact, each activity-based model does require the development of a synthetic population that represents a region's travelers and their detailed attributes. Population generator or synthesizer generate detailed household or traveler characteristics in a way that is consistent with known aggregate population or travel characteristics. The generation of synthetic population in the most cases rely on PUMS (Public Use Microdata Sample) availability and details. To draw synthetic population from samples some methods (e.g. IPF, IPU, CO) have been employed. Activity chains are also extracted from micro census and travel surveys. The most important challenge in this steps is data detail and availability. The more data is inserted to the generator, the more synthetic individuals and its activity plan is accurate.

In the second step for every traveler in the synthetic population, a fully descriptive daily activity plan, including locations of daily activities such as work or education needs to be derived (the activities' location, its durations, start and end time, and the trips connecting two activities, including mode and route). The main process is related to a discrete choice approach that is based on the assumption of random utility maximization. In fact, almost all agent-based transport simulations do not involve discrete choice models as they are used in conventional transport demand models, but these simulations are more based on finding stochastically the maximized utility for various choices sets. In agent-based simulation every agent has the ability to learn and adapt its behaviors based on experience, which requires some form of memory. Discrete choice capability provides agents to select one plan from their memory. For this aim, in the first stage an initial set of individual choices or plans has to be determined. Then during the plan execution these set of choices would be examined.

The third step is focused on plan execution and traffic simulation. It can be done with other tools integrated to the model either by agent-based tools oneself. In the latter case it's observed that the traffic theory integrated to the model have been simplified to reduce computational time and complexity (e.g. in the case of MATSim). For instance, it couldn't be concluded if this simplification results in the important changes on outputs or not. In some agent-based tools a plugin is created to import especially the network to the model (e.g. from Open Street Map). But in almost all cases this imported network has been modified and cleaned manually. The performance measures are estimated in the end of each plan execution. In SimMobility time-variable measures (e.g. waiting time, travel time) and costs are used for this aim. The performance measure in the case of MATSim is commonly a score (the sum of activity and travel utility scores).

In the fourth step, an activity plan for each individual and respected mode and route choice (set of individual choices) are revised, regenerated and modified in the closed loop. MATSim applies genetic algorithm (GA) to revise activity plans.

Finally the model(s) will iterate many times until a systematic relaxation reached [42]. Computational time is one of the challenges that can be observed during the simulation. Usually this term depends on the number of agents and network's size. Some others challenges could be met during demand estimation process of new services dependent on service type (e.g. validation and calibration in the case of SAVs).

D. Platforms

Among the well-known activity-based multi-agent platforms, MATSim, SimMobility, and MobiTopp [43] are used to model new carsharing systems.

MATSim (Multi-Agent Transport Simulation) is the open source platform implemented in Java that is designed to run millions of agents in a metropolitan area. MATSims' framework consists of several modules which can be combined or used stand-alone. Network simulation in this platform is queue-based. MATSim is currently considered to be the most widely applied model for new innovative services [7], [28], [44], [45].

SimMobility is the multi-modal multi-scale platform that considers land-use, transportation, and communication interactions. This platform consists of three different sub-models: (1) short-term, (2) mid-term, and (3) long-term; and is designed to run millions of agents from second-by-second to year-by-year

[46]. SimMobility particularly focuses on impacts on transportation networks, intelligent transportation services and vehicular emissions, thereby its objectives and applications are wider than MATSim.

MobiTopp is the first activity-based multi-agent platform that has been intended for an analysis period of one week when it was initially designed. This platform does not contain an internal traffic assignment procedure and relies on external tools [47].

E. Limitations

During travel demand estimation of one-way carsharing using activity-based multi-agent simulation, several main components are not yet taken into account, which could dramatically change the results:

Firstly, despite their emphasis on activities the majority of the activity-based multi-agent simulators are essentially microsimulation tour based models using a random utility choice-modelling framework. So long-term decisions of the household and its members, as well as mid-term schedules for each individual are not taken into account in the simulations (except SimMobility).

Secondly, to speed up the computation all traffic simulators used in comprehensive multi-agent platforms or those that are coupled with activity demand models have simplified microscopic rules. For instance, MATSim utilizes parallel computation of the spatial queue model in microsimulation - because the queue model needs less data and computing resources and it runs much faster- but a noticeable shortcoming of this model is that the traffic dynamics may not be realistic, and the speed of the backward wave may not be modeled correctly. However, MATSim is designed to run millions of agents in a metropolitan area and in this regard, it is computationally fast.

Thirdly, all service operational characteristics are not taken into account in these simulations. For example, initial distribution of vehicles in the network or redistribution strategy during services are the terms that have not been yet introduced to the simulations but they could result in important changes of demand.

Finally, as innovative carsharing systems (i.e. SAVs or AMoD) are expected to be used collectively, it is necessary to make these simulations sensitive to sharing strategies of rides, which is not well investigated yet.

V. CONCLUSION

In this paper methods and approaches used in the literature to estimate demands for one-way carsharing systems were presented, illustrated and analyzed. Also potential drawbacks in particular with regard to demand estimation of new innovative one-way carsharing systems were discussed. In today's literature, the investigation about demand estimation of such systems in which the complex relationship between supply and demand is considered, remain very limited. In this paper also platforms and toolkits used for the modeling process were presented and criticized. Almost all of these platforms are based on activity-based multi-agent simulation. Activity-based approach provides the feedback of travel time to a multidimensional decision domain, including not only travelers' route and mode choice decisions but also a set of activity decisions (e.g. activity location, schedule, etc.). Above mentioned simulations adopt heuristic rules in feedbacks to achieve approximate convergence and consistency. To estimate travel demand of innovative services (such as SAVs or AMoD) several components specially related to supply side are not yet taken into account. This comes from the fact that the simulation takes a huge time to run millions of agents. Therefore it is practically only possible to evaluate a limited number of pre-determined scenarios. One solution could be to reduce the number of agents (as in the case of MATSim for several cities). But to study multi-modal transportation systems, network and public transport capacities should be reduced similarly. This requires more investigations especially that the accuracy of this approach is not yet approved in the literature. The study area could be also reduced but in this case the potential demand from the agents who live out of the area or those who cross the area would be neglected. Data detail, accessibility and reliability still remain the major challenges. These data are required first to generate synthetic population and secondly to calibrate the simulation. Some local or international sources could be useful to this aim (e.g. IPUMS). To simulate innovative one-way carsharing systems such as SAVs or AMoD, as there are no real data on hand, it would be difficult to validate the simulation outputs.

Future work will involve investigations on how to integrate feasibly supply characteristics of new carsharing systems (riding and redistribution strategies of operation, fleet specification, service quality etc.) at the fine level of detail to the travel demand models.

ACKNOWLEDGMENT

This research work has been carried out in the framework of IRT SystemX, Paris-Saclay, France, and therefore granted with public funds within the scope of the French Program "Investissements d'Avenir".

REFERENCES

[1] S. Shaheen, D. Sperling, and C. Wagner, "Carsharing in Europe and North America: past, present, and future," *Transp. Q.*, vol. 52, no. 3, pp. 35–52, 1998.

[2] F. Ferrero, G. Perboli, A. Vesco, V. Caiati, and L. Gobbato, "Car-sharing services – part A taxonomy and annotated review," no. CIRRELT-2015-47, 2015.

[3] S. Shaheen, A. Cohen, and I. Zohdy, "Shared mobility: current practices and guiding principles," Washington, D.C., 2016.

[4] T. Litman, "Autonomous vehicle implementation predictions implications for transport planning," *Transp. Res. Board Annu. Meet.*, vol. 42, no. 2014, pp.36-42, 2014.

[5] D. J. Fagnant and K. Kockelman, "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations," *Transp. Res. Part A Policy Pract.*, vol. 77, pp. 167–181, Jul. 2015.

[6] S. Shaheen and M. Galczynski, "Autonomous carsharing / taxi pathways," UC Berkeley, 2014.

[7] D. J. Fagnant, K. M. Kockelman, and P. Bansal, "Operations of shared autonomous vehicle fleet for Austin, Texas, market," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2536, pp. 98–106, Aug. 2015.

[8] S. A. Shaheen, N. D. Chan, and H. Micheaux, "One-way carsharing's evolution and operator perspectives from the Americas," *Transportation (Amst).*, vol. 42, no. 3, pp. 519–536, May 2015.

[9] S. A. Shaheen and A. P. Cohen, "Carsharing and personal vehicle services: worldwide market developments and emerging trends," *Int. J. Sustain. Transp.*, vol. 7, no. 1, pp. 5–34, Jan. 2013.

[10] S. Shaheen and A. Cohen, "Innovative mobility carsharing outlook 2013," 2013.

[11] S. Shaheen and A. Cohen, "Innovative mobility carsharing outlook worldwide carsharing growth continues," 2016.

[12] "Car share fact sheet," New York, NY 10003, 2014.

[13] G. Brandstätter *et al.*, "Overview of optimization problems in electric car-sharing system design and management," Springer International Publishing, 2016, pp. 441–471.

[14] M. Barth and S. Shaheen, "Shared-use vehicle systems: framework for classifying carsharing, station cars, and combined approaches," *Transp. Res. Rec.*, vol. 1791, no. 1, pp. 105–112, 2002.

[15] J. de D. Ortuzar and L. G. Willumsen, *Modelling Transport*. 2011.

[16] K. Kortum, "Free-floating carsharing systems: innovations in membership prediction, mode share, and vehicle allocation optimization methodologies," *Ph.D. thesis, Univ. Texas Austin, May 2012.*, 2012.

[17] H. Zheng *et al.*, "A primer for agent-based simulation and modeling in transportation applications," 2013.

[18] D. Jorge and G. Correia, "Carsharing systems demand estimation and defined operations: a literature review," *Eur. J. Transp. Infrastruct. Res.*, vol. 13, no. 3, pp. 201–220, 2013.

[19] M. Catalano and B. Lo Casto, "Car sharing demand estimation and urban transport demand modelling using stated preference techniques," *Eur. Transp. \ Trasp. Eur.*, vol. 40, no. 44, pp. 33–50, 2008.

[20] M. Kouwenhoven, E. Kroes, E. Tardivel, and C. Gazave, "Estimating potential demand for Autolib' - a new transport system for Paris," in *International Choice Modelling Conference 2011*, 2011.

[21] F. Ciari, C. Dobler, and K. W. Axhausen, "Modeling one-way shared vehicle systems: an agent-based approach," *13th Int. Conf. Travel Behav. Res.*, pp. 1–14, 2012.

[22] "MATSim | Multi-Agent Transport Simulation," [Online]. Available: http://matsim.org/. [Accessed: 30-Jun-2017].

[23] F. Ciari, B. Bock, and M. Balmer, "Modeling station-based and free-floating carsharing demand," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2416, pp. 37–47, 2014.

[24] M. Balac, F. Ciari, and K. W. Axhausen, "Carsharing demand estimation," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2536, pp. 10–18, Aug. 2015.

[25] L. M. Martínez, G. H. de A. Correia, F. Moura, and M. Mendes Lopes, "Insights into carsharing demand dynamics: outputs of an agent-based model application to Lisbon, Portugal," *Int. J. Sustain. Transp.*, vol. 11, no. 2, pp. 148–159, Feb. 2017.

[26] "Aimsun traffic modelling software | TSS-Transport Simulation Systems." [Online]. Available: https://www.aimsun.com/aimsun/. [Accessed: 29-Jun-2017].

[27] M. Heilig, N. Mallig, J.-O. Schröder, M. Kagerbauer, and P. Vortisch, "Multiple-day agent-based modelling approach of station-based and free-floating car-sharing," *94th Annu. Meet. Transp. Res. Board, Washingt. D.C., Washington/USA, January 11-15* , 2015.

[28] S. Hörl, A. Erath, and K. W. Axhausen, "Simulation of autonomous taxis in a multimodal traffic scenario with dynamic demand," *Arbeitsberichte Verkehrs- und Raumplan.*, vol. 1184, 2016.

[29] C. L. Azevedo *et al.*, "Microsimulation of demand and supply of autonomous mobility on demand," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2564, no. 16–5455, pp. 21–30, 2016.

[30] "SimMobility – Integrated Simulation Platform | Intelligent transportation systems lab." [Online]. Available: https://its.mit.edu/software/simmobility. [Accessed: 29-Jun-2017].

[31] S. Schmöller, S. Weikl, J. Müller, and K. Bogenberger, "Empirical analysis of free-floating carsharing usage: the Munich and Berlin case," *Transp. Res. Part C Emerg. Technol.*, vol. 56, pp. 34–51, Jul. 2015.

[32] J. Zheng *et al.*, "Carsharing in a university community," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2110, no. 1, pp. 18–26, 2009.

[33] R. Krueger, T. H. Rashidi, and J. M. Rose, "Preferences for shared autonomous vehicles," *Transp. Res. Part C Emerg. Technol.*, vol. 69, pp. 343–355, Aug. 2016.

[34] P. Lavieri, V. Garikapati, C. Bhat, R. Pendyala, S. Astroza, and F. Dias, "Modeling individual preferences for ownership and sharing of autonomous vehicle technologies," *96 th Annu. Meet. Transp. Res. Board Submitt. Present. Publ.*, 2016.

[35] P. Bansal, K. M. Kockelman, and A. Singh, "Assessing public opinions of and interest in new vehicle technologies: an Austin perspective," *Transp. Res. Part C Emerg. Technol.*, vol. 67, pp. 1–14, Jun. 2016.

[36] T. D. Chen, K. M. Kockelman, and J. P. Hanna, "Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions," *Transp. Res. Part A Policy Pract.*, vol. 94, pp. 243–254, Dec. 2016.

[37] C. J. Haboucha, R. Ishaq, and Y. Shiftan, "User preferences regarding autonomous vehicles," *Transp. Res. Part C Emerg. Technol.*, vol. 78, pp. 37–49, May 2017.

[38] J. Zmud, I. N. Sener, and J. Wagner, "Consumer acceptance and travel behavior impacts of automated vehicles final report consumer acceptance and travel behavior impacts of automated vehicles," 2016.

[39] M. Heilig, N. Mallig, O. Schröder, M. Kagerbauer, and P. Vortisch, "Implementation of free-floating and station-based carsharing in an agent-based travel demand model," *Travel Behav. Soc.*, Feb. 2017.

[40] L. M. Martínez, G. H. de Almeida Correia, F. Moura, and M. M. Lopes, "Insights into carsharing demand dynamics : outputs of an agent-based model application to Lisbon , Portugal," *94th Annu. Meet. Transp. Res. Board*, vol. 272, pp. 1–18, 2015.

[41] M. Balmer, K. Axhausen, and K. Nagel, "Agent-based demand-modeling framework for large-scale microsimulations," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1985, pp. 125–134, 2006.

[42] M. Balmer, "Travel demand modeling for multi-agent transport simulations: algorithms and systems," Ph.D. thesis, Swiss Fed. Inst. Technol. Zürich, Switzerland, 2007.

[43] "MobiTopp." [Online]. Available: http://mobitopp.ifv.kit.edu/. [Accessed: 07-Jul-2017].

[44] D. J. Fagnant and K. M. Kockelman, "Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas," *Transportation (Amst).*, pp. 1–16, 2016.

[45] P. M. Boesch, F. Ciari, and K. W. Axhausen, "Autonomous vehicle fleet sizes required to serve different levels of demand," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2542, pp. 111–119, Jan. 2016.

[46] M. Adnan *et al.*, "SimMobility: a multiscale integrated agent-based simulation platform," *95th Annu. Meet. Transp. Res. Board,*. 2016.

[47] N. Mallig and P. Vortisch, "Modeling travel demand over a period of one week: the mobitopp model," unpublished.