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Carsharing systems demand estimation and defined operations: a literature review

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Efforts have been made in the last few decades to provide new urban transport alternatives. One of these is carsharing, which involves a fleet of vehicles scattered around a city for the use of a group of members. At first, part of the research effort was put into setting up real life experiments with vehicle fleets and observing the performance of major private operators. In the meantime, with the growth of this alternative and the need to better plan its deployment, researchers started to create more advanced methods to study carsharing systems' planning issues. In this paper, we review those methods, identifying gaps and suggesting how to bridge them in the future. Based on that review we concluded that carsharing demand is difficult to model due to the fact that the availability of vehicles is intrinsically dependent on the number of trips and vice versa. Moreover, despite the existence of carsharing simulation models that offer very detailed mobility representations, no model is able to characterise accurately the supply side, thus hindering the cost-benefit assessment that is fundamental to justify investment in this transport alternative, in particular those that are being endorsed by the European Union. More complex, however, is the operation of the emerging one-way carsharing systems, where a vehicle may be dropped off at any station, which adds uncertainty as to the location where vehicles can be picked up. Several optimisation approaches have been proposed to mitigate this problem but they are always limited in scope and leave other aspects out for model simplification purposes. Some simulation models have also been developed to study the performance of this type of carsharing system, but they have not included ways of balancing the vehicle stocks.

Keywords: one-way carsharing, demand modelling, mathematical modelling, operations research, literature review.

1. Introduction

In recent decades there have been some changes in how the use of urban transport is viewed. At first, the increasing use of private transport in industrialised countries provided greater accessibility. In the long-term, however, it has resulted in serious negative externalities, such as pollution, and excessive consumption of energy and time due to congestion problems. This has

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happened mainly in urban areas where demand is concentrated in peak hours (Texas Transport Institute, 2010). Moreover, land prices and vehicle ownership costs such as fuel, parking and the cost of purchasing and insuring the vehicle itself are increasing. 'These last costs are sunk costs even before a mile is driven' (Mitchell et al., 2010), which means that they are unrecoverable, even if the vehicle is no longer used. In addition each vehicle use is very low. In America, for example, automobiles spend around 90% of their time parked (U.S. Department of Transportation, 2001). Public transport could be a good alternative, but it has several shortcomings. For instance, coverage does not allow a door-to-door service even in those European cities that have an outstanding public transport network. Moreover, schedules are not flexible and services lack personalisation. Providing public transport for the peak hour demand also means that vehicles are idle for the rest of the day, which decreases its efficiency.

Since all these issues matter to society they have been handed over to policymakers, who should act in the public interest. It is now generally agreed that strategies are needed that will minimise these impacts while simultaneously allowing people to participate in the same activities as before. One strategy that has been indicated to manage demand is providing a transportation alternative in the form of carsharing which is a system that is somewhere between private and public transport. The classical definition of carsharing states that it is a system that involves a small to medium fleet of vehicles, available at several stations, to be used by a relatively large group of members (Shaheen et al., 1999).

1.1 Round-trip versus one-way carsharing

Traditional carsharing system operators require users to return cars to the station where they were picked up. These are round-trip carsharing systems, which simplify the task of the operators because they can plan stocks based on the demand for each station. But it is less convenient for the users. Better suited to personal needs are one-way carsharing systems. In one-way carsharing, users can pick up a car from one station and leave it at a different one. If they need a vehicle later on, they can pick up another one. Therefore, in theory, one-way carsharing systems allow more trips to be captured than the alternative round-trip system, which can only be used by a small market share for leisure, shopping and sporadic trips (Barth and Shaheen, 2002). Firnkorn and Müller (2011) concluded exactly this through a survey that shows that market penetration of *car2go*, a German one-way carsharing company is about 0.37%, which is 25 times higher than the market penetration of round-trip carsharing in Germany. However, it is relevant to note that this figure depends on their computation process, which was based on member subscriptions and not on the number of active members.

A study based on a stated-preference survey performed in Greece (Efthymiou, 2012) (respondents were aged between 18 and 35) also concluded that the flexibility to return the vehicle to a station different from the one where it was picked up is a critical factor to joining a carsharing scheme. Although stated-preference only shows how things could be and not what would really happen if they were implemented. Costain et al. (2012) studied the behaviour of a round-trip carsharing company in Toronto, Canada, and concluded that most trips are made for grocery or other household shopping purposes, which supports the idea that reasons for making trips are limited.

Despite the apparent advantages of one-way systems they do present the operational problem of creating unbalanced vehicle stocks in the stations due to the uneven nature of the trip pattern in a city. Nevertheless, a great effort has been made to provide these flexible systems for users in recent years. One notable example is the *car2go* company (car2go, 2012), implemented first in Germany by the Daimler carmaker and recently extended to some other European and North American cities.

1.2 Motivation

The complexity of managing carsharing systems, especially one-way trips, is directly linked to the interplay effect of supply and demand. One must be able to accurately model the demand and supply of these systems to better operate carsharing and estimate its effect on mobility management and the accessibility that it provides in urban areas.

Carsharing has gained great momentum in the European Union as a measure to manage transport demand, resulting in the implementation of a very significant number of private and public carsharing initiatives. For instance the Covenant of Mayors' initiative was created to get European municipalities to work to reduce vehicle emissions by 20% by 2020, and one of the measures that repeatedly appears in the plans presented by cities is the promotion of carsharing systems. However, despite the interest shown in carsharing, there are not yet many instruments to measure the impact of carsharing systems on the sustainability of urban mobility. Moreover, it is often difficult to define their operational principles, especially in the fastest growing market of one-way carsharing systems.

This paper sets out to give a comprehensive overview of the research that has been conducted on this alternative transport system, mainly in the last few years. The focus is on the mathematical models developed so far, especially those that address demand modelling and ways of balancing vehicle stocks across stations in one-way carsharing systems. The objective is to create a milestone, identifying the existing research gaps and proposing possible paths for future development in this field. Our strategy consisted of reviewing all the research articles and scientific reports on carsharing, especially those that use mathematical modelling to understand the behaviour of these systems and devise better operational principles for managing carsharing.

The paper is structured as follows. The next section gives the background to carsharing systems. This is followed by a review of the research that has produced models to characterise carsharing demand. Then the models that have been developed to study one-way carsharing systems are reviewed, but specifically focused on creating ways to solve the vehicle imbalance problem, which is one of the major issues with running these systems. After that we have a tabular summary of the studies that have been carried out so far. The paper ends with a section where we point possible ways to plug the gaps in the literature, thus identifying potential paths of future research in this field.

2. Carsharing: history and trends

The origins of shared-use vehicles can be traced back to 1948, when a cooperative known as *Sefage* set up services in Zurich, Switzerland (Shaheen et al., 1999). These first experiments were mainly motivated by economic reasons. Elsewhere, a series of 'public car' experiments were attempted, but failed. Among the failures were a carsharing initiative known as *Procotip*, which began in Montpellier, France, in 1971 and another, called *Witkar*, which was deployed in Amsterdam in 1973 (Shaheen et al., 1999). However, failure breeds experience, which, coupled with the advances in communication technology, enabled several successful programmes to be launched in the 1980s. In these programmes we may include *Mobility Carsharing* in Switzerland, and *Stattauto* in Germany.

At first it was predicted that carsharing would not work in the US because 'American cities have, with almost no exception, become motor cities – adapted to the owner-driver form of transport' (Fishman and Wabe, 1969). So carsharing programmes only appeared later in the 1980s, under the *Mobility Enterprise* programme. In contrast to early users in Europe those in the US were motivated more by convenience than by affordability, possibly because driving is very cheap in the US (Lane, 2005). The concept of shared vehicles only started to become popular in the US in the 1990s. Several pilot projects were carried out to achieve a better understanding of how to implement and operate this kind of system. These include *UCR Intellishare* at the University of California at Riverside (Barth and Todd, 2001), *ZEV.NET* at the University of California at Irvine, and *Carlink I* and *II* at the Bay Area Rapid Transit station in Dublin-Pleasanton (Shaheen et al., 2000; Shaheen and Wright, 2001). The projects provided insights on user responses to shared-use vehicles and allowed the assessment of the possibility that these systems could be operated as a business. Hence, a natural progression to the commercialisation of the concept in many countries such as the United States, Japan, and Singapore, was expected (Kek et al., 2006). Currently, the largest carsharing company in the World is *Zipcar*, which was founded in 2000. In May 2012, this company had a fleet of 9,000 vehicles and 700,000 members (Wikipedia: Zipcar, 2012).

Carsharing has been observed to have a positive impact on urban mobility, mainly because each car is used more efficiently (Litman, 2000; Schuster et al., 2005). Shared vehicles can have much higher utilisation rates than single-user private vehicles because each vehicle spends more time on the road and less time parked, thereby diluting the sunk costs. When cars are being used they are not occupying parking places, so in the medium- to long-run higher vehicle utilisation rates should also mean less land needed for parking (Mitchell et al., 2010). The use of carsharing systems has sometimes led to a fall in car ownership rates and thus to lower car use, according to Celsor and Millard-Ball (2007). Martin et al. (2010) conducted a stated-preference survey in North America and concluded also that carsharing members reduced their vehicle holdings significantly, from an average of 0.47 vehicles per household to 0.24 vehicles per household. More recently, Schure et al. (2012) based on a survey conducted in 2010 on 13 buildings in San Francisco concluded that the average vehicle ownership for households that use carsharing systems is 0.47 vehicles/household compared to 1.22 vehicles/household for those that do not. Moreover, a recent study by Sioui et al. (2010) surveyed the users of *Communauto inc.*, a Montreal carsharing company, and concluded that a person who does not own a vehicle and makes a high use of the carsharing systems (more than 1.5 times per week) never reaches the car-use level of a person who owns a vehicle: there was a 30% difference between them. This idea is reinforced by Martin and Shaheen (2011) who found through a survey in US and Canada that the average observed vehicle-kilometres travelled (VKT) by respondents before joining carsharing was 6468 km/year, while the average observed VKT after joining carsharing was 4729 km/year, which is a decrease of 27% (1749 km/year). Furthermore, results of recent survey studies seem to indicate that carsharing systems can have positive environmental effects: for instance, Martin and Shaheen (2011) noted from the VKT estimations presented above that the greenhouse gas (GHG) emissions of the major carsharing organisations in the US and Canada can be statistically significantly reduced by -0.84 t GHG/year/household. While most members increase their emissions; there are compensatingly larger reductions for other members who decrease their emissions. Moreover, Firnkorn and Müller (2011) conducted a survey of a German carsharing company and concluded that the CO_2 emissions have decreased by between 312 to 146 kg CO_2/year per average user.

In the meantime several studies have been conducted to find out who the users of these systems are. Most of the studies were done through user surveys and have repeatedly demonstrated important tendencies: for instance, it has been shown that many carsharing members are frequent public transport users and tend to live in medium to high density areas (Cervero, 2003; Shaheen and Rodier, 2005; Burkhardt and Millard-Ball, 2006). The users tend to be in their mid 30s to mid 40s, be highly educated (Brook, 2004; Lane, 2005), belong to a household of less than average size (Brook, 2004; Millard-Ball et al., 2005) and be environmentally aware people (Costain et al., 2012; Efthymiou et al., 2012). Moreover, the accessibility to the stations, in terms of the distance between home/work and the nearest station, is a critical factor to joining carsharing (Zheng et al., 2009; Costain et al., 2012; Efthymiou et al., 2012).

3. Demand modelling

One of the most productive streams of research on carsharing has been the study of the characteristics of its users. Most works report on the mean value of population characteristics using a sample of carsharing users. But other studies have used more sophisticated models to better support their conclusions.

Stillwater et al. (2008) compared the use of carsharing vehicles over a period of 16 months with the built environment and demographic factors for an urban US carsharing operator. They used regression analysis to explain the average monthly hours of carsharing use and concluded that the most significant variables were: street width, the provision of a railway service, the percentage of drive-alone commuters, the percentage of households with one vehicle, and the average age of the stations. The percentage of drive-alone commuters, street width, and heavy rail availability were negatively related to carsharing, that is, the higher these factors the lower the demand. The percentage of households with one vehicle, the average age of the stations, and light rail only availability were positively related to carsharing use, meaning that the higher these factors the higher the demand.

In the same year a study by Catalano et al. (2008) was published reporting on a stated-preference survey in Palermo, Italy, with the objective of forecasting the modal split of the urban transport demand in that city. The respondents could choose from different transportation alternatives, which were private car, public transport, carsharing, and carpooling. A random utility model was estimated using the survey data. The authors concluded that in a future scenario characterised by active policies to limit private transport use the carsharing market could increase up to 10%.

Zheng et al. (2009) studied the potential carsharing market at the University of Wisconsin-Madison performing a stated-preference survey about transportation habits and carsharing preferences, namely travel habits (primary mode of travel and trip purpose), attitudes on transportation and the environment, and familiarity with carsharing, in the university community. With the data obtained from the survey, logistic regression models were developed to predict the willingness to join a carsharing program. This study led to the conclusion that the status in the university (student, staff, etc.) and people's attitudes have a great impact on the acceptance of carsharing: students are more willing to use carsharing than other faculty members; the same happens with people who are concerned about the environment and the cost of owning and driving a vehicle.

More recently Lorimier and El-Geneidy (2011) studied the factors affecting vehicle usage and availability in the carsharing stations from *Communauto inc.*, a Montreal carsharing company. With this data, they developed a linear regression model to explain vehicle usage, and a logistic regression model to explain vehicle availability (binary response variable). The authors concluded from the results provided by the two models that the size of a carsharing station has a large impact on both variables. Larger stations offered more vehicle options and had a larger catchment basin than smaller stations. Moreover, the seasonal impact on both availability and usage was clear: fewer vehicles were available in the summer, which required an increase in both the number of stations and the number of vehicles in each station. Vehicle age was also considered as a key factor. It increased availability and decreased usage, since members tend to prefer newer vehicles. Having child seats was another factor that corresponded to higher availability and lower usage, probably because of the demographic characteristics of carsharing users in the study region (Lorimier and El-Geneidy, 2011).

A study by Morency et al. (2011) analysed the carsharing transaction dataset of the same company, *Communauto inc.*, with a view to establishing a typology of carsharing users. This transaction dataset included all trips of all the clients, even those that were cancelled, modified, or not concluded. The main focus of the authors was frequency of use and distribution of distance travelled. With respect to the weekly distance travelled, a cluster-based classification process resulted in two distinctive behaviours with respect to the distance travelled and trip frequency: either urban distances throughout the week, or long distances on just one day of the week.

Motivated by the increasing use of carsharing systems in Europe and the need to understand their effect on urban mobility, Ciari et al. (2011) have developed an activity-based micro-simulation model to estimate travel demand for carsharing, considering that users have different transportation modes available, such as public transport, car, bicycle, walking and carsharing. The authors opted for this disaggregated model because of the specificity of carsharing with respect to the users' characteristics, which makes it difficult to estimate travel demand using an aggregated model, such as the classical four steps method. The authors followed the round-trip carsharing systems' organisation, and so the main features of the modelled system were: carsharing is available to everybody with a driving licence (membership was not modelled); agents can pick up, park and drop off cars only at predefined locations (stations); agents have to drop off the car at the same station where it is picked up (round-trip); it was assumed that agents walk to the pick-up point and from the drop-off point; and an unlimited number of cars are available at the stations (no reservation, every agent trying to use the service will find a car) (Ciari et al., 2011). Hence the model did not focused on the carsharing operations themselves but on what the demand would be if a high level of this service was provided for the clients. The model was applied to part of Zurich city centre, Switzerland. The aggregate results matched what is happening in reality, given the specifications and the level of detail that was considered. However, the authors stated that the model should be improved to represent the characteristics and the way real carsharing services work, i.e. by imposing constraints on vehicle stocks.

Recently, Morency et al. (2012) took a two-stage approach to study the behaviour of carsharing users. In the first stage, the probability of each member being active in a given month was studied using a binary probit model. In the second stage, the probability of an active member using the service multiple times per month (monthly frequency of use) was determined by a random utility-based model. These models were estimated using data from 40 months of *Communauto inc*. operations. The authors concluded that the activity of members in the previous 4 months influences their behaviour in the current month, that is, the number of times that users avail themselves of the service in the previous 4 months is directly proportional to the amount of times they use it in the current month. Moreover, some attributes of the users, such as gender and age, have an impact on their behaviour: males and people aged between 35 and 44 are more inclined to favour carsharing.

In general, almost all the studies presented, except the one performed by Ciari et al. (2011), are context specific, and local and regional characteristics make standardisation more complex. Nevertheless, they do reveal user preferences and provide new models that can be used by other carsharing operators to guide their system's growth. The study by Ciari et al. (2011) is innovative in using simulation to predict demand. However it does not include a representation of the supply side. Furthermore, all the studies are related to the round-trip carsharing. As far as we know, demand estimation has not so far been addressed in the literature for one-way carsharing systems, and it is increasingly important to study it since these systems might be able to capture a higher share of the demand and they are certainly a tendency in recent years.

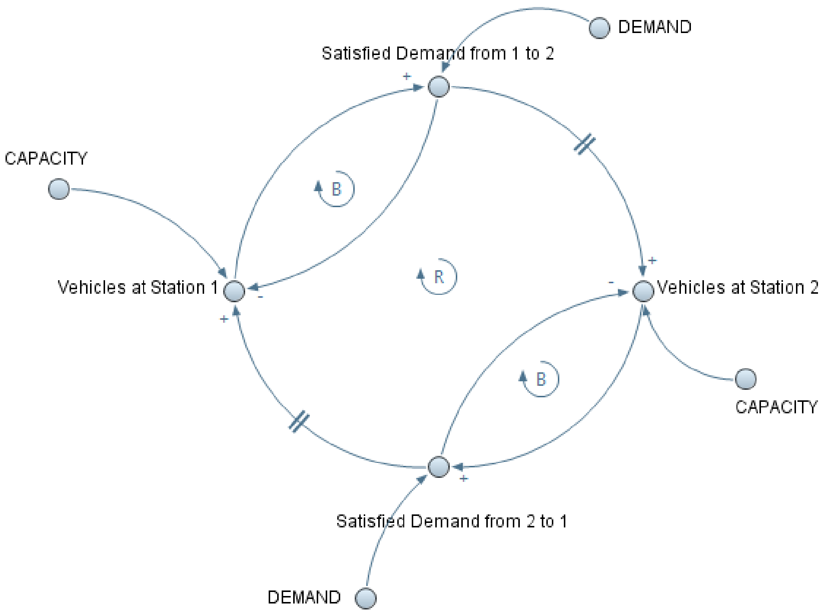
4. Modelling one-way carsharing systems

Recent research has been examining one-way carsharing systems. The key issue in them is the dynamically disproportionate distribution of vehicles across the stations, so researchers are currently developing methods to analyse and mitigate the effects of this problem.

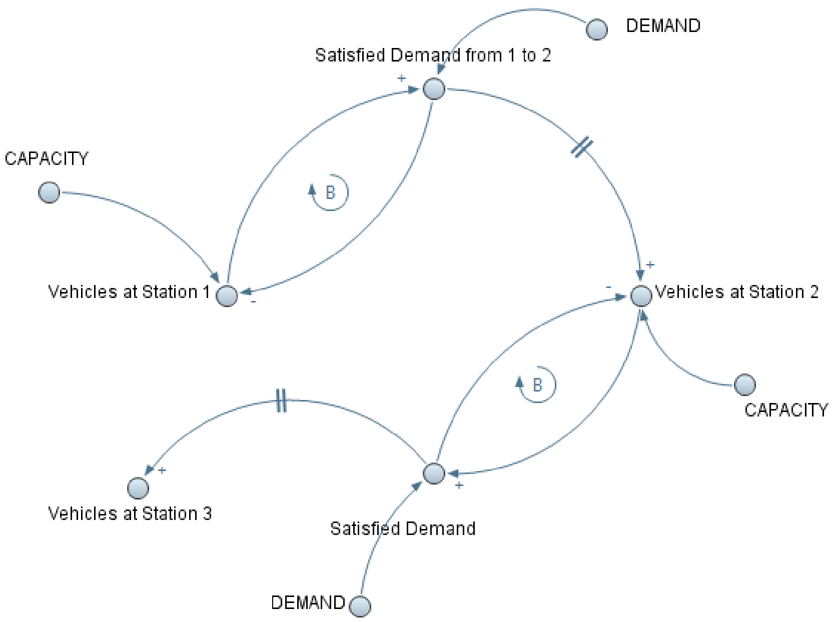
Comprehensive approaches have aimed at modelling the one-way system as a whole, while other specific techniques have been proposed for balancing the systems.

4.1 A comprehensive approach to the vehicle imbalance problem

The problems of one-way carsharing systems are mainly the effect that demand has on the supply characteristics and the effect of supply on demand. To depict this important aspect of one-way carsharing systems we have created the following simplified causal loop diagram (Figure 1).



(a) Two station system



(b) More than two stations

Figure 1 – Feedback in one-way carsharing systems

In Figure 1-a) we can see that when the number of vehicles in station 1 is higher more demand is satisfied and transferred to station 2 with a delay corresponding to the travel time between the stations. If the trips that request a vehicle at station 2 have station 1 as destination a reinforcing loop is formed, where the most important behaviour parameters are the demand pattern that controls the vehicle flows, the delay that controls when vehicles will be available at a station, and the capacity of each station.

But hardly any system has just 2 stations and a balanced number of trips between them, thus in Figure 1-b) we can see that the loop may be cut open by trips from station 2 to other stations, which will stop feeding station 1 with vehicles, thereby limiting the demand satisfied in station 1.

Papanikolaou (2011) addressed this problem in a recent paper, reporting a system dynamics model to describe the complexity behaviour of one-way carsharing systems under non-homogeneous demand patterns. This aggregated simulation model consisted of three stock-flow sub-models: stations, users, and vehicles, and about 120 equations. Papanikolaou's objective was to develop a study tool to understand how these systems evolve over time and to explore organisational solutions to mitigate the feedback loop effect.

After running the model using a synthetic case study area, Papanikolaou concluded that the framework could model delays and capture the essential dynamic behaviour of the system, but the model still needs to be validated with data from real systems. Furthermore, the aggregate nature of system dynamics models does not take into account the strong spatial and temporal characteristics of complex urban networks. Another limitation inherent to all continuous forecasting models for system dynamics 'is the simplification of behaviour due to the mixing that occurs when aggregating resources in the stocks, that tends to drift the results as simulation time advances sometimes overestimates performance' (Papanikolaou, 2011). The testing of different relocation techniques and the study of random events such as vehicle breakdowns or different reservation schedules are highly compromised by this approach. Besides, it is harder to integrate the effect of other transport modes in this type of model. The authors are planning to compare this aggregate model to a micro agent-based model where the emergence of the system behaviour comes from the decisions of the individual travellers.

4.2 The performance of one-way systems

Some authors have been trying to study the performance of these systems by considering different scenarios and using micro models.

Li (2011) developed a discrete-event simulation model to study the performance of one-way carsharing systems under different configurations and customer behaviours. They used different performance measures such as average vehicle utilisation, reservation acceptance rate, full parking time, and profit. Configurations include fleet size, number of stations, number of parking spaces, and the distribution of vehicles and parking spaces across stations, while customer behaviours included the time when a customer reserves a vehicle, whether or not they will cancel the reservation, when they will pick up/return the vehicle, what the requirement for parking at pickup/return location is, etc. A reservation is accepted if there is a vehicle available in the origin station for the time the user needs to make the trip and a parking space available in the destination station at the end of the trip. Round trip carsharing was also simulated to compare the behaviour of the two systems. The author concluded that concentricity, that is high population density in big cities where origin and destination stations are concentrated at few locations, helps one-way carsharing to perform better, while round trip carsharing performs better for a more dispersed population. Moreover, increasing the number of parking spaces for a one-way system can help improve the reservation acceptance rate and vehicle utilisation. The allocation of parking spaces among stations should correspond to the customer demand distribution among stations, so as to achieve the best performance.

More recently, Barrios (2012) developed an agent-based simulation model to measure and predict the level of service offered to users of car2go, a one-way carsharing system, in Austin, Texas, and San Diego, California. In this simulation model, cars are initially evenly distributed throughout a schematic square city. Users come into the system at a given demand density and have random origins and destinations, searching for the nearest car. If a user is 'created' in a place where there are no cars within walking distance, they cannot travel. Then the simulation model was used to simulate the two cities. Simulation results were compared with the reality of these systems in the two urban areas in terms of accessibility, that is, the proportion of the operating area with an available car within walking distance (0.33 miles). The author concluded that the model reasonably estimates the level of service of a one-way carsharing system. Hence it can be used to make planning level decisions.

These methods could be very useful, since they present advanced simulation tools to evaluate the performance of one-way carsharing systems prior to their implementation, which can help carsharing companies to plan the service. However, they do not include any relocation feature which, as shown in the next section, should be an important leverage for the profitability of one-way carsharing.

4.3 Solving the vehicle imbalance through relocation operations

One of the ways that has been suggested to balance vehicle stocks is the operator-based approach that corresponds to the periodic relocation of vehicles among stations by staff members.

In 1999, Barth and Todd (1999) developed a queuing based discrete event simulation model that included relocations and a number of input parameters that allowed different scenarios to be evaluated, such as the vehicle-to-trip ratio and payment scheme. Some of the events were customer arrival at a station, vehicle departure from a station, vehicle arrival at a station, relocation start and relocation end. Three ways of deciding when relocations should be performed were presented: 'Static relocation' based on immediate needs in a station; 'Historical predictive relocation', which uses knowledge of expected future demand, looking 20 minutes into the future, and 'Exact predictive relocation' that can be used if perfect knowledge of future demand is available, which is impossible in the real world. The model was applied to a community in Southern California and some measures of effectiveness were calculated, showing that the system is most sensitive to vehicle-to-trip ratio, relocation method used, and charging scheme employed. The authors also concluded that this system can be very competitive with other transportation modes, particularly taxis.

Later, the operator-based approach was tested in the Honda ICVS system, which started in March 2002. This system allowed one-way trips, with no reservation required and no return time needing to be specified (Kek et al., 2006). Periodic communication with the backend computer system meant that information from these vehicles prompted the system manager to relocate vehicles between stations when needed. In May 2005 the experimental phase ended and the programme started running as a commercial enterprise (Barth et al., 2006). The system was cancelled in 2008 (The Business Times, 2011) because the operator could not keep up the initial service quality as membership grew. All users expected cars to be available but this did not happen, so dissatisfaction and complaints from members increased (The Straits Times, 2008). It still not known if the operator based approach alleviated the company's losses, but its ending is an indication that this system was not profitable.

Kek et al. (2006) developed a discrete event simulation model to help multiple-station carsharing vehicle operators implement an efficient relocation system that could minimise the allocation of resources to vehicles, staff, and parking places, while maintaining certain levels of service. Based on the available resources (vehicles and staff members) and the relocation policy adopted, the model decided which relocation operations the system should implement at each time step. The two possible relocation policies were the shortest time, i.e. moving vehicles to or from a neighbouring station in the shortest possible time (including staff movement, if necessary), and inventory balancing, i.e. supplying a station which has a shortage of vehicles with a vehicle from another station which has too many.

The proposed model was tested and validated using real data from the commercial one-way carsharing company mentioned above. The results showed that if the company adopted an inventory-balancing relocation technique, the system could afford a 10% reduction in car park spaces and 25% reduction in staff strength, generating cost savings of approximately 12.8% without lowering the level of service for users. However, this approach required an impractical number of simulation runs to test all the combinations of different parameters. Thus in 2009, Kek et al. introduced an optimisation module to the previous simulation tool to overcome this limitation.

The optimiser used the current demand and station configuration with the objective of minimising the overall cost of the relocation operations. The obtained optimised parameters were the number of people needed to perform the relocations (staff strength), the necessary relocations, and the resulting station status (number of vehicles at the stations at each time step). In phase two these optimised parameters were filtered through a series of heuristics to obtain a set of recommended parameters. On entering the set of operating parameters into the vehicle relocation simulator developed by Kek et al. (2006), phase three evaluated the effectiveness of each combination using three performance indicators: zero-vehicle time (no vehicles are available); full-station time (no parking places available), and number of relocations.

This decision support system was once again tested using operational data provided by Honda ICVS. The performance surpassed the results of the previous simulations conducted by Kek et al. (2006). This new three-phase decision support system indicated a 50% reduction in staff costs and an improvement of the performance indicators. However, there is no documented effect on the real application of the model to Honda's system and, as mentioned, the system was cancelled.

Although mathematical programming is an interesting approach to achieving good system configurations for running these systems, it needs a great many variables and constraints in the mathematical programming formulation. Several simplifications were required to reduce the problem size, such as increasing the size of the discrete time steps of the optimisation period, and this entailed further limitations to representing accurately what happens in reality.

In 2010, Wang et al. proposed a method to forecast and relocate vehicles in carsharing systems that consisted of three main components: microscopic traffic simulation, forecasting model, and inventory replenishing. The model used to forecast customer demand was an aggregated model at the station level, that is, it forecast the total number of vehicles rented out and returned over time at each station and not the trips for each origin-destination pair. The forecast demand was then fed into the inventory replenishing model to prepare relocations.

With respect to the inventory replenishing model, the stations with more vehicles available than necessary (including safety stock) were defined as overstocked stations thus candidate suppliers, while stations with fewer vehicles available than necessary were defined as understocked stations thus candidate demanders. Once the relocation decision was made (stations and number of vehicles involved, and when to relocate), the understocked stations were replenished from the nearest overstocked stations in terms of the lowest trip cost at that moment of relocation, which was determined by the microscopic traffic simulation model.

The performance of the proposed approach was tested using as case study four possible station locations in Singapore with 12 vehicles each. Experimental results showed that the system improved its efficiency. So the authors concluded that this approach had the potential to improve a carsharing service. The case study was novel in that it improved the realism of travel times and evolved from the computation of a mathematical static optimum pattern of relocation operations planned for the whole day to a policy proposal for real time operation in face of the predicted demand. Even so, it is important to note that it is very small scale in terms of the number of stations, which is smaller than most existing carsharing systems.

Cucu et al. (2010) have studied a forecasting model of one-way carsharing demand in greater detail. The main principle was to understand and exploit customers' preferences so as to anticipate their needs and relocate the vehicles accordingly. To solve the problems of car unavailability at peak periods and medium- and long-term management, and to test new station locations, the authors considered customer preferences related to: the time of departure; the day of the week; the weather conditions, and the traffic conditions associated with their addresses. With this, the maximum vehicle needs for a given period of the day were computed for all stations to distinguish priorities in terms of balancing order, other maintenance operations and to test the implementation of new stations. This method was applied to a small city and the authors concluded that anticipating demand would improve the vehicle availability by balancing vehicle stocks.

Nair and Miller-Hooks (2011) continued exploring optimisation methods and proposed a stochastic mixed-integer programming (MIP) model with the objective of generating least-cost vehicle redistribution plans such that a proportion of all near-term demand scenarios is satisfied, recognising the strong effect of uncertainty on carsharing planning. The model was set up for a fixed short-term planning horizon for which demand is known probabilistically. Relocation operations were performed throughout the day and assumed to be completed before the beginning of the planning period considered. For relocations the operator takes into consideration both vehicles and free parking spaces, that is, if both resources are adequate to satisfy a p-proportion of all possible demand scenarios, no corrective actions are triggered; if not enough vehicles are available this can be remedied by relocating from adjacent stations; and if not enough parking spaces are available, vehicles can be relocated to free up parking spaces in other stations. The model was also applied to Honda ICVS. Using computational experiments and simulation, authors showed that when these relocation strategies are used, the system operates at a reliability level that could not be achieved otherwise.

Very recently, Smith et al. (2012) studied how to minimise the number of rebalancing vehicles travelling within a network and the number of rebalancing drivers needed to rebalance vehicle stocks in one-way carsharing systems, considering that the number of waiting customers remains bounded. The authors state that the "two objectives are aligned" (Smith et al., 2012), so the optimal rebalancing strategy can be found by solving two different linear programs in a fluid model of the system. In this system, users arrive at one of the stations (origin) and are transported to another station (destination) by driving themselves or by being driven by an employed driver (similar to a taxi) if the system needs to move a driver to the destination station of the particular user. This happens because drivers can also become unbalanced among stations and then they have to be moved to other stations without driving a rebalancing vehicle. The results suggested that in Euclidean network topologies, the number of drivers needed is between 1/4 and 1/3 of the number of vehicles.

4.5 Using the users for system balancing

The user-based approach is a system-balancing technique that uses the clients to relocate the vehicles through various incentive mechanisms. This is very intuitive and previous studies have addressed this possibility by modelling its operation.

Uesugi et al. (2007) have proposed grouping or ungrouping parties of people to balance the system. They developed a method for optimising vehicle assignment to people according to the distribution of parked vehicles, trying to avoid vehicle imbalance. The authors proposed three ways to assign the number of in/out vehicles between pick-up/drop-off stations, depending on the number of vehicles in the stations. In a normal assignment a group of people ride in one vehicle and so they subtract one vehicle from the pick-up station and add it to the return station. In the divided assignment, m people from the group ride in m vehicles and so the user subtracts m vehicles from the pick-up station and adds m vehicles to the return station. In the combined assignment k groups with the same drop-off station carpool in one vehicle with the combined group, and so the users subtract only one vehicle from the pick-up station and add only one vehicle to the return station. The assignment is limited to the capacity of the vehicles.

In theory, a station that has excess vehicles could decrease their number by assigning a divided ride. Equally, in a station which has few vehicles it would be possible to keep the number of vehicles by assigning a combined trip. The effectiveness of this method was tested through computer simulation. The authors claimed the results showed that it was effective in minimising the imbalance problem of one-way carsharing systems. But they also stated that incentives would have to be considered to make users behave according to the proposed model.

It should also be noted that the Intellishare research team at the University of California at Riverside had already proposed and tried these two user-based relocation methods in 2004. They called them trip splitting and trip joining, and they managed to reduce the number of relocations required (Barth et al., 2004). This method was very similar to the previous one, with the advantage of having a price incentive mechanism to encourage users to sign up to trip splitting and trip joining. When users wanted to travel from a station with a shortage of vehicles to one with an excess they were encouraged to share a ride in a single vehicle (trip joining), thereby minimising the number of cars moved. Conversely, when they wanted to travel from a station with too many vehicles to one with a shortage they were encouraged to drive separate vehicles (trip splitting), thereby balancing the number of vehicles in the stations.

If these user-based relocation techniques were successful when applied to commercial one-way carsharing companies it would be possible to shift the burden of relocating vehicles to the users. But this strategy has its pitfalls. It may not be a viable option in cities where most travellers value privacy and convenience over minor transport cost savings. Moreover, trip-joining policies make carsharing similar to carpooling, which has severe sociological barriers associated with riding with strangers, mainly for safety and security reasons (Chan and Shaheen, 2011; Correia and Viegas, 2011). With respect to trip splitting, users may not be willing to be divided and this method can only work in a market where a significant number of trips are made by groups of people rather than by a single driver.

Mitchell et al. (2010) proposed another intuitive principle of dynamic pricing combined with intelligent vehicles that would enable drivers to respond appropriately to pricing. Their idea involved a pricing scheme that could be applied to several urban mobility systems, including carsharing, to make them more efficient for users and companies alike.

This method would take advantage of trip-origin-and-destination choice elasticity combined with price incentives for each specific trip. They considered that people would have the flexibility to walk a block or two to find a vehicle if one is not available right outside their door. Similarly, it might not be a problem for people to park a bit further away from their destination. And if slightly less convenient origins and destinations result in lower-priced trips this could be an incentive to use them, even if more convenient pick-up and return points are available (Mitchell et al., 2010).

Febbraro et al. (2012) proposed a similar method but only taking into consideration the trip destinations. In their system there were no stations, the city was divided into zones and the users could park the vehicle at any parking space inside these zones. A discrete event simulation model was developed to implement this method in which the vehicles are relocated by the users that can opt to end their trips in proposed zones that have a shortage of vehicles or in their desired zones. The zones were determined through a linear integer programming model aiming at minimising the rejected reservations. If the user is happy to leave the vehicle in the proposed zone they will have a fare discount. The events used in the simulation were: vehicle bookings, booking modifications, booking cancellations, vehicle pick-ups, and vehicle drop-offs. Reservations were made throughout the day using a Poisson distribution and each had a given probability of being modified or cancelled by users. In this model, users were required to establish the departure time, declare their trip origin and destination, and the time at which they will deliver the vehicle. When a vehicle is booked it is guaranteed that it will be available at the beginning of the trip. The authors tested the model for the Restricted Traffic Zone of Turin (Italy), using fifteen scenarios that differ according the probability of accepting the relocation proposed by the system and with different numbers of vehicles available in the system. They concluded that significantly fewer vehicles would be needed for the system to run efficiently using this approach.

Despite the apparent advantages of this option, the authors also recognised that not all trip origins and destinations are elastic to price: for instance, a commuting trip may be more constrained since it is a mandatory trip, usually with very rigid schedules. Other limitations are related to its practical application, since it relies on a very efficient real-time use of information and communication technology that enables people to be aware of price changes. In addition, there must be a willingness to access this information allied to a significant trip-and-station choice elasticity to price. This is yet to be fully tested in real carsharing companies operating on a one-way basis. The price instability may also be a disincentive to using carsharing, which would have a contrary effect.

4.4 Full control over where and how to supply vehicles

Other ways of balancing one-way carsharing systems through controlling the supply have been devised. Several authors have proposed trip selection for vehicle allocation in order to achieve a more favourable balance of vehicle stocks, that is, only the trips that help to balance the system should be served. Fan et al. (2008) formulated a mathematical programming model for vehicle fleet management to maximise the profits of one-way carsharing operators. In their model the carsharing operator decides which vehicle reservations should be accepted or refused and how many vehicles should be relocated or held to maximise profit. Thus, if any request was regarded as unprofitable or the system could not accommodate it, it would be declined.

A multistage stochastic linear integer model was formulated that could account for demand variations. A five-day sample network with four carsharing locations was used to test the model and some results were obtained which indicated profit improvement. Limitations of computation time and solver capability, however, meant that the model was not applied to a real network and several unreal conditions were assumed.

A more recent study has addressed the effect of the location of carsharing stations on capturing a trip pattern more favourable to a balanced distribution of the vehicles in the network, thus transferring the system imbalance to the clients by decreasing their possibility of accessing this system. Correia and Antunes (2012) developed three mathematical programming models to balance vehicle stocks through a convenient choice of the location, number and size of stations. The objective was to maximise the profit from operating a one-way carsharing system, considering all the revenues (price paid by clients) and costs involved (vehicle depreciation, vehicle maintenance and parking space maintenance).

The first scheme (model), which was similar to that tested by Fan et al. (2008), assumed that the carsharing organisation has total control over trip selection, based on a list of requests made by the clients. The second assumed that all trips requested by the clients would be accepted when they occurred between any pair of stations in the solution. And the third was a hybrid scheme in which there was no obligation to satisfy all trips between stations, but trips could only be rejected if there were no vehicles available at the pick-up station.

Each model was applied to the case study city of Lisbon, Portugal, and results showed that the scheme yielding the highest profits was the one where the carsharing operator had full control over trip selection. This was expected since it is the scheme offering the most freedom to maximise profit. The authors concluded that the imbalance situation would lead to severe financial loss in a scenario where all demand should be satisfied, even if the client is charged a very high price. They also found that financial losses could be reduced by making appropriate choices of the stations' configuration (number, location, and size), but profits could only be achieved with full control over trip selection.

The problem with these approaches is once again the limitations of computation time and solver capability, which could not accurately represent the reality of carsharing systems because some simplifications were necessary, such as 10-minute time steps. It was not possible to consider the choice of station location, trip selection schemes and vehicle relocation operations all in the same formulation, which hindered an integrated view of these systems planning. For instance the planning of station locations is intuitively dependent on the existence or non-existence of relocation operations which could mitigate the effects of an uneven trip pattern and so allow the supply to expand, as some of the previous research shows.

5. Summary

In Table 1 we present a summary of the studies where carsharing has been modelled. For each study we indicate the topic addressed, the modelling approach used and the type of carsharing. The references are in chronological order.

Table 1 Summary of the studies presented

Authors	Year	Topic addressed	Modelling Approach	Type of carsharing
Bonsall and Kirby	1979	Testing different scenarios, strategies, locations, scales and prices	Microsimulation	Round-trip
Bonsall	1982	Modelling organised carsharing systems and comparing model predictions with actual performance	Microsimulation	Round-trip
Arnaldi, Cozot, Donikian and Parent	1996	Simulation of carsharing systems	Simulation	Round-trip
Barth and Todd	1999	Operator-based relocation operations	Queuing-based discrete-event simulation	One-way
Barth and Todd	2001	User-based relocation operations	Trip joining	One-way
Barth, Todd and Xue	2004	User-based relocation operations	Simulation	One-way
Kek, Cheu and Chor	2006	Operator-based relocation operations	Discrete-event simulation	One-way
Uesugi, Mukai and Watanabe	2007	User-based relocation operations	Simulation	One-way
Stillwater, Mokhtarian and Shaheen	2008	Environmental and demographic factors that affect the usage of carsharing	Regression analysis	Round-trip
Catalano, Lo Casto and Migliore	2008	Estimation of carsharing demand for carsharing	Random utility model	Not -defined
Fan, Machemehl and Lownes	2008	Trip selection	Optimisation	One-way
Zheng et al.	2009	Carsharing market	Regression analysis	Not defined

Kek, Cheu, Meng and Fung	2009	Operator-based relocation operations	Optimisation and Discrete-event simulation	One-way
Wang, Chang and Lee	2010	Operator-based relocation operations	Microsimulation and inventory replenishing model	One-way
Cucu, Ion, Ducq and Boussier	2010	Operator-based relocation operations	Optimisation	One-way
Febbraro, Sacco and Saeednia	2010	User-based relocation operations	Discrete-event simulation and Optimization	One-way
Lorimier and El-Geneidy	2011	Factors affecting vehicle usage and availability	Regression analysis	Round-trip
Morency, Trépanier and Agard	2011	Typology of carsharing users	Cluster analysis	Round-trip
Ciari, Schuessler and Axhausen	2011	Estimation of carsharing demand	Activity-based simulation	Round-trip
Papanikolaou	2011	Describing the functioning of one-way carsharing systems	System Dynamics	One-way
Li	2011	Performance of a carsharing system	Discrete-event simulation	One-way/Round-trip
Nair and Miller-Hooks	2011	Operator-based relocation operations	Optimisation	One-way
Morency, Habib, Grasset and Islam	2012	Behaviour of carsharing users	Random utility model	Round-trip
Barrios	2012	Level of service offered to users	Agent-based simulation model	One-way
Smith, Pavone, Schwager, Frazzoli and Rus	2012	Operator-based relocation operations	Optimisation	One-way
Correia and Antunes	2012	Trip selection and station location	Optimisation	One-way

From Table 1 we can see that most of studies related to carsharing modelling were done after 2000. Moreover, despite the considerable number of studies related to demand modelling for round-trip carsharing, there is a clear predominance of studies about balancing vehicle stocks across stations in one-way carsharing, mainly through relocation operations performed by the company or the users. With respect to the modelling approaches used for studying demand, regression analysis is the most popular technique, while issues related to one-way systems tend to be studied by means of optimisation and different types of simulation.

6. Suggestions for bridging the gaps found

Carsharing has gained great momentum in the last two decades as an alternative to private vehicle ownership, especially for urban trips. Despite this growth, there are still many questions about its true position among the other modes of transport and the markets that it should serve. Moreover, these systems operation standards are hard to define. Modelling is increasingly being used to address these issues. Previous research has emphasised demand estimation using techniques ranging from regression analysis to more complex tools such as agent-based simulation models. In general, the statistical methods have helped to improve our understanding of the systems and they have found structural relationships between service characteristics and demand patterns. However, most of them were too context specific and therefore difficult to apply to other realities (Stillwater et al., 2008; Lorimier and El-Geneidy, 2011; Morency et al., 2011; Morency et al., 2012). Moreover, they tend to neglect the supply side and the organisational configurations needed to offer the service, which is directly connected to its economic viability. This is a key aspect for any possible candidate operator of a carsharing service.

Advanced demand studies were carried out, like the one by Ciari et al. (2011), who have set up an agent-based model to represent in detail the type of users who are likely to have carsharing as part of their mode choice set, recognising the fact that carsharing is not likely to be used for commuter trips or by certain traveller groups. However, this study did not consider the supply side, so it is not possible to understand the equilibrium between supply and demand in this system.

The articles reviewed on demand estimation have generally ignored the one-way option, which is understandable if we take into account its youth when compared to the round-trip mode. But more importantly, they tended to disregard the integration of carsharing with traditional transport modes. Hence it is our belief that a significant effort must be made to develop more general and realistic models to estimate demand, that is, models that can accurately represent the characteristics of carsharing, be valid for different contexts, and apply to one-way carsharing. One of the important questions that still remain to be answered is if carsharing has a greater effect on reducing the use of private vehicles or if, on the contrary, it reduces the number of public transport users. This is a paramount question for policymakers who may be deciding whether or not to endorse carsharing. Currently there are generous funds available for energy and emissions reduction associated with the transport sector, particularly in the European Union, and carsharing systems have been considered candidate recipients for those funds.

We have concluded that most of the literature on the modelling of carsharing systems is concerned specifically with one-way carsharing systems. Operations researchers are devoting increasing attention to its particular problems which we have seen to be mostly linked to the natural imbalance of vehicle stocks caused by the uneven pattern of trips during the course of the day. We have concluded that this is a complex problem with a feedback loop that results from the interaction of demand and supply. In classic transport systems, such as bus and underground services, the directional capacity is offered to clients irrespective of the existing demand; however, in one-way carsharing, demand can completely change the system's supply in ways that are hard to predict.

Researchers have used complex system modelling tools to address this problem, such as system dynamics to try to translate their behaviour and extract better operating principles (Papanikolaou, 2011). However, these tools bring many limitations especially in what concerns to their adherence to reality due to their aggregate nature.

Realising the need to have a micro-scale approach to the problems of one-way carsharing systems, several researchers have been developing simulation models to study their performance (Li, 2011; Barrios, 2012) and achieve higher profits, but these have not been able to handle the balancing of vehicle stocks. Other researchers have focused on individual techniques to balance those stocks. The objective has been to accomplish an optimum configuration of the systems towards some objective that has varied from the general profit maximisation of the operator and the specific minimisation of relocation costs. Researchers have mostly used simulation and mathematical programming optimisation for this.

Despite the positive results of demonstrating that there are operating principles that can be used to improve these systems' performance, there have been limitations. While simulation requires an impractical number of runs to test all the combinations of the different operational parameters (Kek et al., 2006), optimisation requires a large number of variables to integrate several decisions into the same problem in a real case study context (Correia and Antunes, 2012). Several authors tackled this by simplifying the formulations to a level where they start to be unrealistic and the efficiency improvements gained from them may be hard to transfer to real carsharing ventures.

Most of these models have worked with station-based systems, but stationless systems are currently emerging, where the vehicle may be dropped off at any parking space. If this trend develops most of the models devised for studying one-way carsharing systems will be overtaken by a reality that is not compatible with a fixed set of concentrated demand points.

Researchers should test the techniques on real case scenarios and use more advanced simulation models to address different aspects of the business, from the most strategic to the operational. We believe that it will be difficult to find optimum solutions for the operational configuration of these systems, so research should head towards developing more detailed simulation models that integrate other modes of transport and also consider operational issues. This will be at the cost of model size and limited control over the experiments, but the lack of a realistic functioning of the systems is restricting the view of the big picture on how to run carsharing schemes and find their true effect on mobility. A detailed and accurate computation of the effect of carsharing systems should make it possible to bridge a major gap in the literature: there is no measure of the balance of cost and benefits of these systems, largely because of the uncertainty about the effect that they have on users of public and private transport. A new trend of peer-to-peer systems has appeared in recent years. It has changed the cost of the systems for the operator, who now does not need to buy a whole vehicle fleet. This could greatly change the cost/benefit balance and reduce the risk of managing the systems.

Researchers must continue to closely watch the big commercial round-trip carsharing ventures such as Zipcar and Cambio Car to observe the management of their operations and the behaviour of their clients, and see how any new services provided evolve. The idea is to keep research abreast of the latest tendencies in this market, which may become more relevant in a context of financial crisis where falling household budgets could boost the use of cheaper transport alternatives. It will be especially interesting to watch the first companies that are adopting one-way trips as their core business, such as car2go.

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