MULTIPLE-DAY AGENT-BASED MODELING APPROACH OF STATION-BASED AND FREE-FLOATING CARSHARING

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Paper prepared for presentation at the
94th Annual Meeting of the Transportation Research Board
5721 words (including references)
4 figures, 1 table (5 * 250 words = 1,250 words)
Total: 7357 words (including abstract, text, cover page, and figures)
Submission date: 05.11.2014 (revised version)

ABSTRACT

The number of carsharing users and cars is growing all over the world and although there is a comparatively small share in modal shift, carsharing is getting more and more important as additional transport mode especially in metropolitan regions. The consequence is a growing usage of carsharing and therewith a changing travel behavior. This implies a need for a further development of planning tools so that this "new mode" can be considered in the planning process. This paper illustrates the integration of carsharing in an agent-based travel demand model that simulates the travel behavior of the population in the Greater Stuttgart area within one week. Since it is the first time that carsharing usage is simulated for more than one day, the described model allows analyzing the intensity and variability of carsharing usage from a longitudinal perspective. The model results show the variation of carsharing usage between the days of the week.

INTRODUCTION

The importance of carsharing as a mode of transport is increasing. Especially in metropolitan areas carsharing is a growing market and more or less part of urban mobility. In Germany, the number of carsharing users and the number of cars offered in sharing systems has increased throughout the last years and forecasts show an ongoing trend. Within the last year, for example, station-based carsharing had an increase in customers by 50,000 (+18.7%), free-floating carsharing even had an increase in customers by 254,000 (+138.8%) (*1*). Hence, the use of the "new mode" carsharing has more than ever become a component of many people's daily travel.

Commercial carsharing can be classified into two systems: station-based and free-floating carsharing. Station-based carsharing is the traditional carsharing system in Germany. The cars are located at stations where the customers can rent a car. After the ride, the car has to be returned to the same station. Customers have to make the reservation for the booking in advance. Station-based carsharing providers usually offer different types of cars, like compact cars, station wagons and vans. Free-floating systems operate without stations. The cars are spread within a defined area. Customers check the availability and location of cars online with a computer or a smartphone. In contrast to station-based systems, customers are able to rent a car without making a reservation. At the end of a ride, customers can park the car where ever they want within a certain area. Free-floating carsharing providers typically offer just one type of car.

The ongoing success of free-floating carsharing during the last years is also largely driven by car manufactures. In addition, they invest in upcoming mobility-service companies such as moovel (Car-2-Go by Daimler) or Drive-Now (BMW) to offer flexible mode choices options to the trip makers and promote their carsharing services. These mobility-service companies provide multi- and intermodal information about trips with all modes to improve customers' mobility planning.

Growing usage of carsharing cars (*1*) and thus changing travel behavior (*2*), especially in large cities, implies a need for further development of planning tools so that this "new mode" can be considered in the planning process. In this paper, we describe how we integrate carsharing in the agent-based travel demand model mobiTopp (*3*) which simulates travel behavior within one week. To our knowledge, this is the first time carsharing usage is simulated with a transport planning tool for more than one day and therefore can be analyzed from a longitudinal perspective.

This paper is structured as follows: First, we briefly introduce the related work. Second, we describe the agent-based model mobiTopp. Third, we discuss the implementation of the customer model, the modifications of the mode choice model and the calibration processes. Finally, we show the results and end with a short conclusion.

LITERATURE ANALYSIS

Since we model carsharing customers and their usage of carsharing services in a microscopic travel demand model, our literature analysis focusses on two topics – estimating the number of carsharing customers and the travel demand of carsharing customers.

Research on carsharing customers is often related to studies on the potential growth of carsharing. The main statement is that the number of carsharing systems, as well as their demand, is growing over the world. After the first commercial introduction in the late 1980s in Switzerland, station-based carsharing services arose in Germany (*4*) and in North America (*5*) at the beginning of the 1990s followed by Japan and Singapore (*6*) at the beginning of the millennium. With the start of the first free floating operation system in Ulm, Germany, in 2008, an innovative and more flexible form spread into the market to make carsharing more flexible and attractive. Germany has recorded yearly growth rates of carsharing members of more than ten percent. In 2014, 750,000 people are carsharing customers of more than one hundred operators in Germany (*7*). Several studies on the estimation of carsharing potential focus on the yearly car-mileage of users. Petersen (*8*) and Prettenthaler and Steininger (*9*) determine a break-even-point of yearly car-mileage, where people switch from owning a car to sharing a car. Schuster et al. (*10*) developed an economic model, which describes costs as central to the decision of owning or sharing a car, and applied it to the City of Baltimore, USA. Nobis (*4*) estimated a potential for carsharing customers of about 6 % of licensed drivers living in cities with more than 20,000 inhabitants in Germany, considering both socio-demographic criteria and current travel behavior. Ciari and Weis (*11*) were probably the first to take a microscopic approach to modelling the choice of becoming a customer of a carsharing provider considering personal socio-demographic attributes and the accessibility to shared cars by using a binary logit model.

In spite of increasing membership and usability rates, the state of research in modeling carsharing is still at the beginning. Probably Rodier and Shaheen (*12*) were the first attempting to estimate the demand of carsharing. However, the representation of carsharing in the mode choice of their four-step demand model was very basic: Stations were distributed at transit stations and employment centers only, and the usability was restricted on direct links between these stations which resulted in a high level of vehicle availability but a low level of flexibility. Since every agent could use carsharing, a customer model has not been implemented. The mode choice of travelers was mainly based on travel time and costs.

In recent literature, the MATSIM community deals with representing carsharing in a microscopic agent-based model. Ciari et al. (*13*) already discuss several reasons why agent based simulation is a good tool to simulate carsharing: An agent-based model is not only suitable for modeling rational choices, it is also suitable for a description of the environmental framework at a high resolution. Ciari, Schuessler and Axhausen (*14*) describe how the existing microscopic travel demand model MATSim was adapted to represent carsharing. They employ a station-based carsharing system with a first simple approach (no membership is needed, availability of an unlimited number of cars at the stations, costs are not considered), using the existing MIV utility function for carsharing, and applying it to the simulation area of Greater Zurich. The results show that the approach basically works, but further extensions are needed to get reliable results. Ciari, Bock and Ballmer (*15*) developed the approach further in various points: station-based systems as well as free-floating systems are represented, the capacities of the system are taken into account, carsharing vehicles are physically simulated and specific components like time and cost for access and egress, rental time, etc. of carsharing travel are defined. With this model, which is applied to the Berlin area, it is possible to analyze comprehensive information on travel demand in geographical as well as in behavioral matters in the course of one day.

In distinction to the approaches mentioned above our simulation represents car sharing usage during one week. Due to this, we are able to analyze intensity and variability of carsharing usage from a longitudinal perspective.

THE AGENT-BASED SIMULATION MOBITOPP

MobiTopp (*3*), (*16*) is a travel demand model based on the principle of agent-based simulation (*17*). In the simulation model, each person of the planning area is represented as a separate entity, a so-called agent. Each agent has an activity schedule, consisting of activities of different types (e.g. home, work, education, leisure, shopping), to be executed during the simulation period of one week. During the simulation, each agent makes decisions where to execute each activity and which mode to use to get to the chosen destination. Each agent is modeled in the context of its household, cars are owned by households not by the individual agents, meaning that actual car availability for an agent in a multi-person household may depend on the behavior of the other household members. The temporal resolution of the simulation is one minute; the spatial resolution is based on zones.

The process flow of mobiTopp consists of two phases: a setup phase and a simulation phase. In the setup phase, facts that do not change over a longer period are modeled, e.g. population, car ownership or season ticket ownership for public transport. During the simulation phase, destination choice and mode choice are modeled for all agents in a chronological manner.

The essential step in the setup phase is population synthesis. Population synthesis is based on socio-demographic data of persons and households on a zonal level and on a household travel survey. For each household of the survey a weight is calculated by an iterative fitting procedure similar to the approach used by Müller and Axhausen (*18*), adjusting the survey data to the zonal statistics. The population is generated by randomly drawing the adequate number of households from the weighted survey data. For each household drawn from the survey a corresponding simulation household is created, inheriting the attributes (e.g. household size, number of cars owned) from the survey household. For each person of the survey household an agent is created, inheriting the attributes (e.g. age, sex, employment) and the activity schedule (sequence of activities with start time and duration for each day) of the survey person. In the next step, fixed locations for work and education activities are assigned, as the locations for these types of activities usually don't change during a week; the location for home activities is already determined by the zone for which the household was created. Ownership of season tickets for public transport is determined based on a binary logit model.

During the simulation phase, the travel behavior of all agents is simulated chronologically and simultaneously based on their individual activity schedules. When an agent finishes an activity, he looks for the next activity in his activity schedule. The agent chooses a location for this activity. In the case of an activity with fixed location (home, work, education), the location determined during the setup phase is used; in all other cases a destination choice model is used. Afterwards the agent makes a mode choice. When the mode is chosen, the agent starts the trip to the destination. When the destination has been reached, the agent executes the activity and the cycle of executing an activity, destination choice, mode choice, and making a trip repeats. The number of activities and hence the number of cycles is determined by the activity schedule; so are the planned start times and the durations of the activities.

Destination choice is modelled as an extended gravity model, based on the attractivity of the possible destinations, the necessary travel time and cost to reach not only the possible destination but also the next fixed destination (*3*), taking into account that the way back from a possible destination is also important in the choice of a destination.

For mode choice a multinomial logit model is used (*16*). The choice set of available modes is modeled carefully: in principle the full choice set is only available when the agent is at home, when there is a car available in the household and the agent is the holder of a driver's license. If the agent is not at home and the last mode used has been walking, public transport or car passenger, the choice set consists only of these three modes, since the agent has neither a car nor a bicycle available. If the agent is not at home and the last mode used has been car driver or cycling, the choice set comprises only the last mode. This simplification is made to guarantee that a used vehicle returns home in any case. The simplification is justified because a tour starting and ending at home which starts with a bicycle or car typically ends with the same vehicle. The possibility of sub-tours, starting and ending at another location than home and using another mode than the main tour is ignored by this simplification. The inaccuracy made by this simplification is not severe, since the share of such sub-tours observed in reality is low. Executing an activity is modeled as waiting for the duration of the activity. Making a trip is modeled as waiting for the duration of the trip and a subsequent arrival at the destination zone in case of one of the modes walking, cycling, car passenger, public transport. When the mode car driver is chosen and the agent executes a trip beginning at home, the agent uses a household's car, which then is temporarily not available for other household members. Ending a car trip at home involves returning the car to the household's car pool.

The scenario used in the following is a model of the Greater area of Stuttgart consisting of the city of Stuttgart and the five surrounding administrative districts. The Greater area of Stuttgart has a population of about 2.7 million inhabitants of which 2.5 million are modeled (only persons aged 6 and above are modeled). The Greater area of Stuttgart is divided into 1012 model zones. In addition there are 159 zones covering the surrounding area that are potential destinations in the destination choice model.

The destination choice model and the mode choice model have been jointly calibrated to match trip length distribution and modal split for several aggregation levels of data of a household travel survey conducted in the Greater Stuttgart area (*19*).

MODELING CARSHARING

Modeling carsharing is a complex task. First, there are hardly any usable data of carsharing users and usage, which is the base of every model and crucial for its quality. However, especially in the fast-growing free-floating carsharing sector, data about users and usage of carsharing is too valuable for most of the companies to make it available to someone who is not a research-partner. Second, the share of people using carsharing is still very small, so it is hard to validate and calibrate the model parts. And third, the modeling process itself is complex due to the load of indispensable additional model objects like carsharing stations, the exact positions of the free-floating cars or essential new model features such as a carsharing customer model or an extended mode choice model.

The simulated scenario models the current situation in the Greater Stuttgart area, where three major carsharing companies exist. Two of them, Stadtmobil Stuttgart and Flinkster, offer a station-based system. Stadtmobil Stuttgart is the leading provider of station-based carsharing services in the Greater Stuttgart area with about 11.000 customers in the private and commercial sector and over 450 cars. Flinkster is a subsidiary of the German railway company Deutsche Bahn AG and runs its business nationwide. With around 70 cars in the Greater Stuttgart area they also play an important role in the carsharing business. Flinkster operates mainly in the center of Stuttgart (urban area), whereas Stadtmobil also operates in rural areas. The third provider, Car2Go, offers a free-floating system. Car2Go is a joint-venture of the Daimler AG and the car rental company Europcar. With around 27.000 customers and around 500 cars, Car2Go is the only provider of free-floating carsharing in the Greater Stuttgart area. Car2Go operates in the inner city of Stuttgart as well as in the inner cities of Esslingen and Böblingen. All 500 cars of Car2Go are electric cars (Smart eDrive) and thus have a range of 100 – 130 km.

In order to model carsharing for this area, it is crucial to model both station-based and free-floating carsharing systems to cover all aspects and effects of carsharing within the model. However, these two systems differ in their usage rules. In the station-based system, the user has to rent and return the car at the same place, whereas in the free-floating system the user can rent and return a car anywhere within a defined area. Both rules have to be considered. In addition, we modeled each provider in order to be able to evaluate them separately.

We model carsharing cars explicitly with attributes like current position and current availability. The current stock of available cars at the corresponding carsharing station and in the corresponding zone changes when the usage of a carsharing car starts or ends. Furthermore, variables like the current user, the mileage driven and the current fuel/power level are stored during and after the simulation.

Carsharing Customer Model

In order to integrate carsharing into mobiTopp, it is crucial to assign memberships of carsharing providers to the agents. Customers have to be at least 18 years old and they need to have a driver’s license. We use a binary logit approach with several socio-demographic input variables to determine the carsharing customers. Due to the different socio-demographics of their customers, we calibrated an independent car sharing customer model for each carsharing provider.

The data used to estimate and calibrate the models are from different sources. Due to the lack of household travel survey data on carsharing membership for the Greater Stuttgart area, we used survey data from a 2012 household travel survey (HTS) in the Greater Karlsruhe area for our estimation of the carsharing customer model. One has to note that Karlsruhe has an exceptional position regarding carsharing. Though there is only one station-based carsharing provider, the number of carsharing cars and customers per 1,000 inhabitants is highly above the nationwide average. There are also differences in the socio-demographics between Stuttgart and Karlsruhe. Hence, we weighted the Karlsruhe data by age, sex, household size and numbers of cars owned by the household. The sample size of the Karlsruhe HTS amounts 7,840 respondents with 216 carsharing customers.

The carsharing customer model contains seven influencing categorical variables that are coded as 25 binary variables, and one with ratio level (see Table 1). The ratio variable “fz_fl” is the number of carsharing cars of the carsharing providers per square kilometer. For the estimation of the parameters of the costumer model we used the logistic regression procedure in the software SAS. The estimation was based on the weighted data from the Karlsruhe HTS.

Calibration of the Customer Model

We calibrated the parameters for the three carsharing providers in the Stuttgart area, so that the model results match the real data. For the calibration of the Stadtmobil customer model, we used detailed customer data provided by Stadtmobil Stuttgart. This data contains detailed information about age, sex and the residence of all customers. For the Car2Go customer model we used socio-demographic data of customers of Multicity (free-floating provider) and for the Flinkster customer model we used socio-demographic data of customers of Flinkster. Both data are from the Berlin area and were provided by the Innovation Centre for Mobility and Societal Change (InnoZ) collected in the project “BeMobility 2.0”. This data contains information about age, sex and profession of 160 customers of Multicity and 213 customers of Flinkster. The estimated and calibrated parameters for the Stadtmobil customer model are shown in Table 1. As mentioned before, the variables are the same for all customer models.

Table 1 Influencing values, variables and estimated as well as calibrated parameters of the customer model for Stadtmobil based on data provided by Stadtmobil Stuttgart

Variable	Characteristic	Estimated parameter	Standard deviation	Parameter after calibration	Level of measurement
	Intercept	-3.2062	0.9707	-6.5162	
Sex	**female**	-0.8767	0.1902	-0.5607	nominal
Season ticket ownership	**yes**	0.1395	0.1879	0.1095	nominal
Occupation	**full-time employed**	0.1263	0.4906	0.0763	nominal
	part-time employed	0.8843	0.4821	0.8843	nominal
	unemployed	-1.8083	1.1397	-1.8083	nominal
	school student	1.4458	0.7828	1.4458	nominal
	university student	-0.3485	0.6127	0.5085	nominal
	trainee	-0.5818	0.9982	-0.5818	nominal
	non-working	0.8886	0.6879	-0.2886	nominal
	retired	-0.4708	0.6666	-0.1008	nominal
No of cars in the household	**0**	2.1474	0.6009	2.1474	nominal
	1	-0.27	0.5751	-0.27	nominal
	2	-1.1234	0.5823	-1.1234	nominal
	3	-0.0864	0.6072	-0.0864	nominal
	4+	0	0	0	nominal
No of carsharing cars per km²	**fz_fl**	0.3391	0.0614	1.2591	ratio
Household size	**1**	-0.7138	0.3455	-1.5638	nominal
	2	0.00315	0.3325	-0.40315	nominal
	3	0.1005	0.3235	0.1005	nominal
	4	0.3201	0.3133	0.4201	nominal
	5	0	0	0	nominal
Age	**18-24**	0.00665	0.712	-0.69665	nominal
	25-34	0.4547	0.5728	1.3747	nominal
	35-49	0.9732	0.5556	0.9332	nominal
	50-64	0.2065	0.5264	0.9065	nominal
	65+	0	0	0	nominal

Extended Mode choice Model

In a final step the existing mode choice model was extended in order to simulate carsharing by adding the two modes free-floating carsharing and station-based carsharing to the mode choice set. Furthermore, we defined the following six principles to minimize the extensions for the existing mode choice model but still ensure the reliability of the model.

1. The carsharing modes are only available if a car of the carsharing provider is available in the origin zone.
2. As the mode carsharing is typically dominated by the mode car driver due to the lower access and egress times and lower costs, the mode carsharing is only available if the mode car driver is not available for the current trip.
3. The parameters for the carsharing modes are based on the parameters of the mode “car driver” as these modes only differ in access and egress times as well as in the cost for the trip.
4. We assume that the density of carsharing stations and the available cars correlates with the possibility to find a parking lot. Thus, we use the variable “parking pressure” of the existing model in order to compute the individual access and egress times for every zone.
5. Cars of station-based carsharing providers always have to be returned to the station where they have been picked up. To ensure this constraint in the model, the mode “station-based carsharing” can only be initially chosen when the agent is at home and it can’t be changed until the person returns back home.
6. Cars of a free-floating carsharing provider have to be picked up and returned in the operational area. Therefore, switching to another mode is not allowed when the agent is outside the operational area.

According to these principles, the mode carsharing is only available in the choice set in general, if the agent a) is customer of a carsharing provider, b) has no car available for the trip, c) a carsharing car is available in the origin zone and d) isn’t restricted to another mode. Another restriction is the above-mentioned necessity to be at home to use station-based carsharing.

The access and egress trips to the carsharing car are not modeled explicitly due to the zone-based spatial resolution, but they are considered in the access and egress times, which were added to the travel times for the mode “car driver” to get new travel times for the carsharing modes. For access and egress times, we distinguished between station-based and free-floating carsharing by considering the different characteristics of the access and egress process.

The costs for the carsharing modes are based on real costs for the different carsharing systems. The cost for free-floating carsharing amounts to 0.29€ per minute, whereas the cost for station-based carsharing amounts to an average of 2.80€ per hour and 0.23€ per kilometer. The hourly rate of station-based carsharing is always rounded up to the next full hour. Unfortunately, the time and therefore the cost for the whole trip cannot be considered in mode choice, so that the estimation for the trip time using station-based carsharing is slightly too high.

Calibration of the Extended Mode choice Model

We calibrated the mode choice model for the carsharing modes using trip length distributions (see Figure 3), as this was the only reliable information available for both free-floating and station-based carsharing. We used detailed booking data of Stadtmobil for the calibration of station-based carsharing. This data contains information about the distance driven during a booking and its duration. In order to compare the modeled trip data with the booking data, we had to aggregate the model results to bookings. We assumed that one booking contains all consecutive trips with the same car and that the trip started immediately after the start of the booking. Unfortunately, we had no data available for Flinkster, so we assume that the mode choice behavior of Flinkster customers resembles the behavior of Stadtmobil customers.

For the calibration of free-floating carsharing, we collected data from a Car2Go application programming interface (API). The API provides information transmitted by cars available: their actual position and their fuel level. Data were retrieved in intervals of 5 minutes over one week. The reason why a car became unavailable is a booking process for most cases, but it could also be a technical error or a maintenance operation. Hence, we evaluated the data for plausibility. Using GIS software, we were able to generate synthetic booking data. Then, we calculated the trip length by using the difference of the power level before and after the ride assuming an average power consumption of 15.1 kwh/100km for the Smart eDrive (*20*). We did not aggregate the modeled trip data for free-floating carsharing, assuming that a free-floating carsharing car is basically returned after each trip.

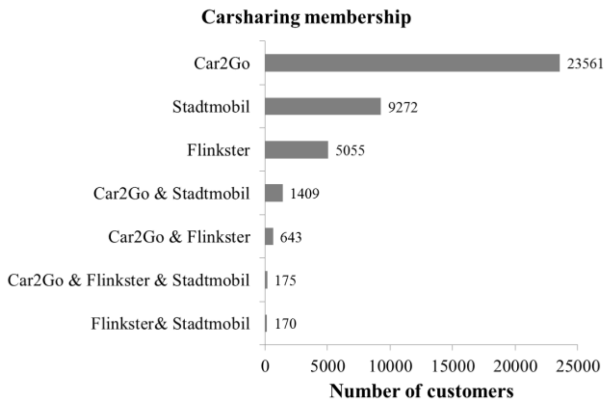
We used the parameters of the mode car driver and adjusted them for both carsharing modes. In the calibration process, we adjusted the constant parameters for station-based carsharing from 0 to -1.5 and for free-floating carsharing from 0 to -0.5. Further, we changed the parameter for the variable “short trip” from 0 to -1.0 for both carsharing modes and the parameter for the variable “distance” from 0 to 0.15 for station-based and from 0 to -0.05 for free-floating carsharing.

DISCUSSION OF MODEL RESULTS

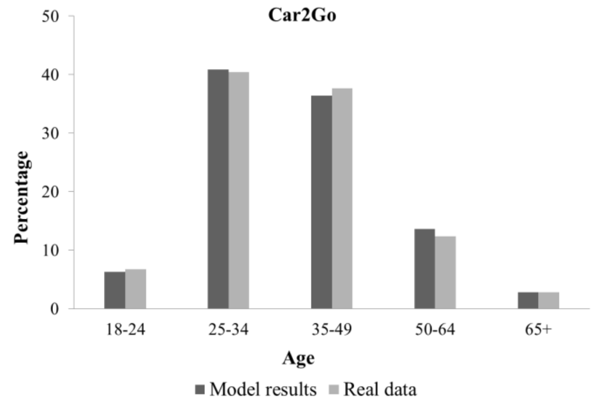
The discussion of the model results focusses mainly on longitudinal analysis. Below, we basically consider the providers Car2Go and Stadtmobil, since we have no suitable data for the provider Flinkster to validate the results.

Carsharing Customers

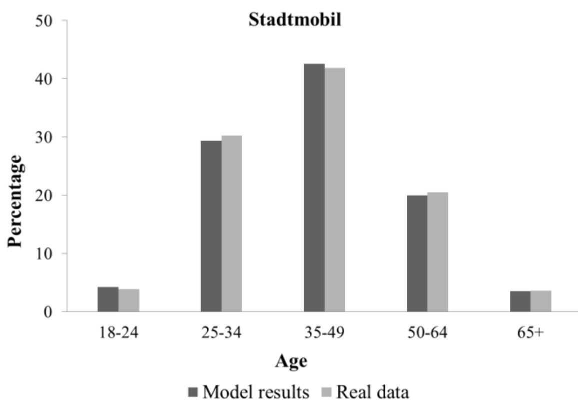
Figure 1a) shows the numbers of customers of the carsharing providers. With 25,788 customers, Car2Go is the leading provider in the Stuttgart area. Stadtmobil ranks second with a total number of customers of 10,851. Since the customer models are applied independently of each other, agents can be customers of several carsharing providers. Hence, there are 2,397 agents who are customers of more than one carsharing provider which is around 6% of all customers.



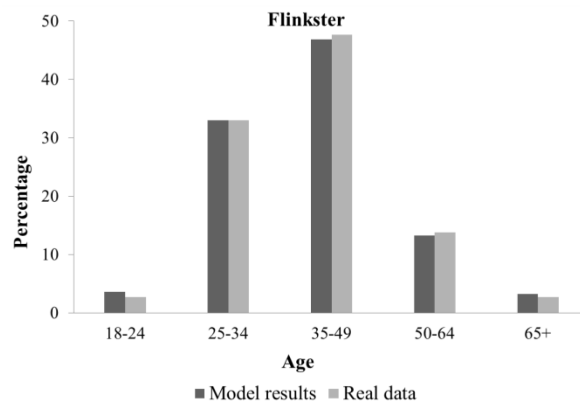
a) Number of customers per provider



b) age distribution of customers for the provider “Car2Go”



c) age distribution of customers for the provider “Stadtmobil”



d) age distribution of customers for the provider “Flinkster”

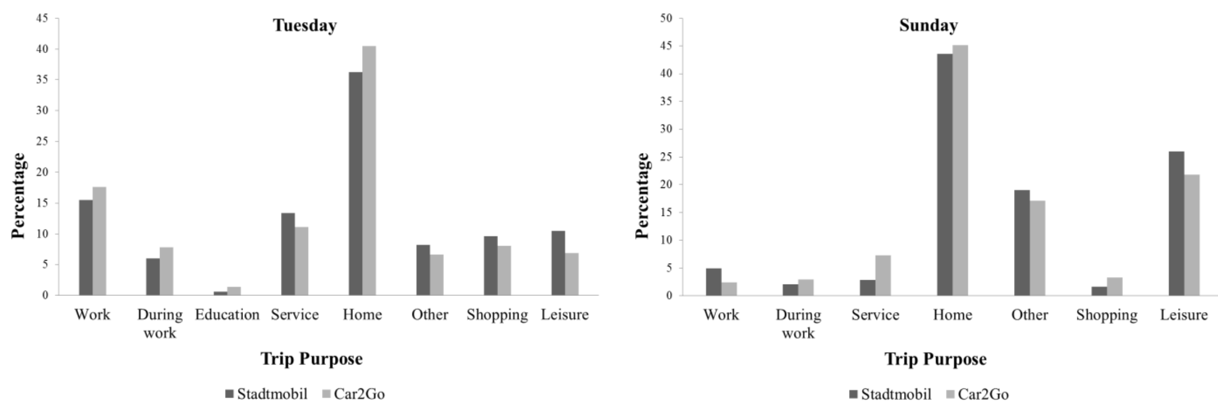
Figure 1 Distribution of carsharing customers: a) Number of customers per provider, b) age distribution of customers for the provider “Car2Go”, c) age distribution of customers for the provider “Stadtmobil”, d) age distribution of customers for the provider “Flinkster”

Figure 1b) - d) shows the age distribution of the customers. The model results of the age distribution of Car2Go and Flinkster users are compared to the Berlin data of Multicity and Flinkster, whereas the model results of the age distribution of Stadtmobil users are compared to the customer data provided by Stadtmobil. Customers of the free-floating provider Car2Go are dominated by the age class of 25 to 34 years, whereas the dominating age class within station-based providers (Stadtmobil, Flinkster) is the class of 35 to 49 years. Hence, the more flexible free-floating concept seems to be more attractive to younger people. The share of customers younger than 25 years is very low for all providers. Nevertheless, this share is higher for Car2Go customers.

Although we used data from different sources for the providers Stadtmobil and Flinkster, the age distributions for both station-based providers are similar. However, the share of customers under 50 years is slightly higher for Flinkster customers, which could be caused by the fact that more elderly people live in rural areas and Flinkster operates in more urban areas.

Trip Purposes

Figure 2 shows the model results of different trip purposes for a regular weekday (Tuesday) and Sunday. The variation between the days of the week is as expected; in particular shopping trips, leisure trips and trips to work vary between Tuesday and Sunday. On Sunday, shopping trips and trips to work are seldom due to the fact that stores are closed and most people don't have to work. Moreover, there are no education trips on Sunday. About half of the trips are trips back home on both days. On Sunday, there are less service trips than on Tuesday.



a) Trip purposes of carsharing trips on Tuesday   b) Trip purposes of carsharing trips on Sunday

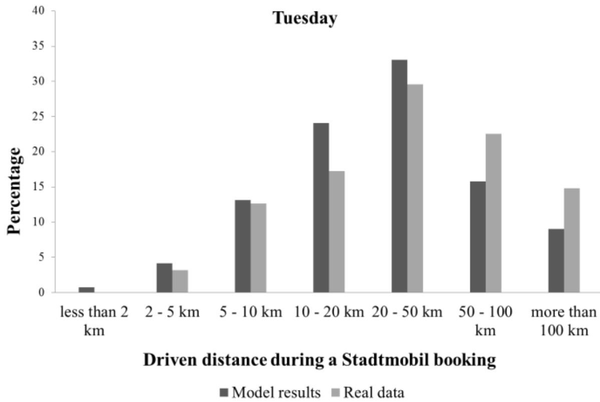
Figure 2 Trip purposes of carsharing trips on a) Tuesday and b) Sunday

Trip lengths

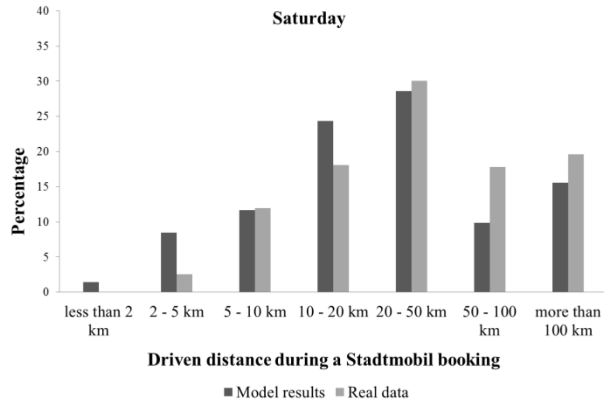
Figure 3 shows the distributions of kilometers driven during a booking regarding Stadtmobil and Car2Go for a normal weekday (Thursday) and Saturday. The model results reflect the reality regarding both providers, Stadtmobil and Car2Go.

In general, Stadtmobil is used for longer trips, whereas Car2Go is rather used for shorter trips. A reason for that could be the different pricing schemes and, of course, the fact that Car2Go uses electric vehicles which are restricted to around 100 km of range. Moreover, the type of carsharing cars offered could play a role. Stadtmobil offers different types of cars, which are more suitable and comfortable for longer distances.

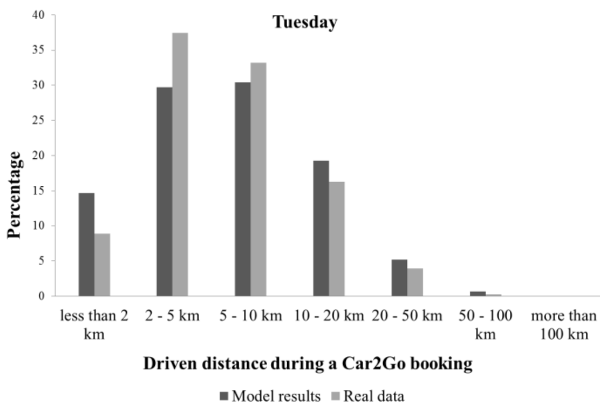
The model results for Stadtmobil show that on Saturday there are more trips of more than 100 km than on a normal weekday. This behavior also reflects the differences in the share of trip purposes between weekdays and weekends. On weekends, for example, there are more leisure trips than shopping trips, and leisure trips tend to be longer on weekends. Other trips include trips to visit someone, which also tend to be longer on weekends. However, this behavior cannot be observed in the results for Car2Go. There are no differences noticeable between weekdays and weekends, neither in the model results nor in the real data.



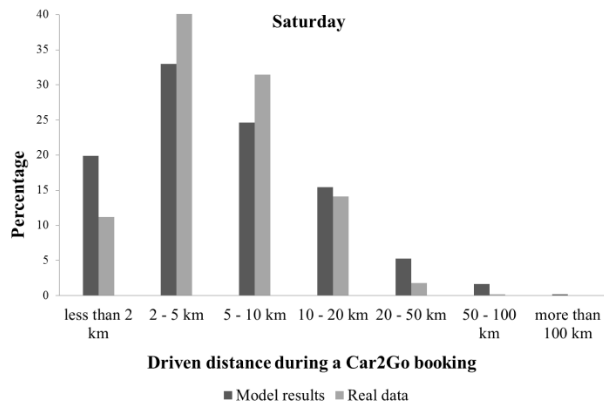
a) Stadtmobil: Tuesday



b) Stadtmobil: Saturday



c) Car2Go: Tuesday



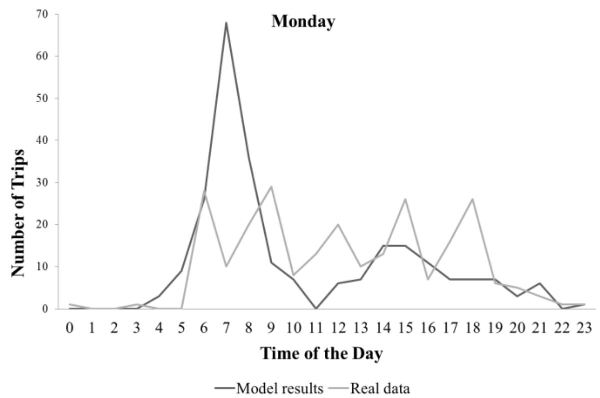
d) Car2Go: Saturday

Figure 3 Distributions of kilometers driven during a carsharing booking: Stadtmobil (a) and (b) and Car2Go (c) and (d)

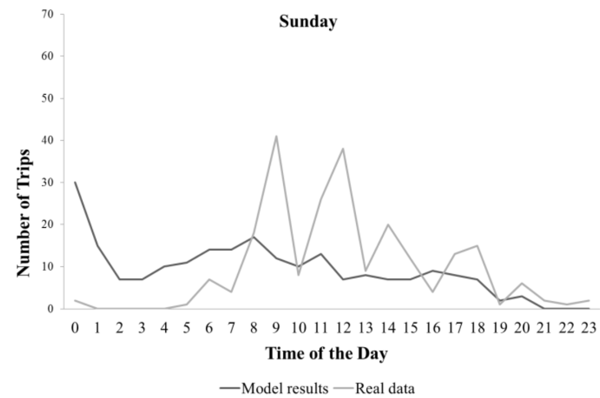
Histogram of Number of Trips

Figure 4 shows the model results regarding the number of bookings and the real number of bookings in the greater Stuttgart area on a Monday and a Sunday for Car2Go as well as for Stadtmobil. The number of real Stadtmobil bookings has been provided by “stadtmobil carsharing AG”, the number of real Car2Go bookings has been collected using the Car2Go-API. Figure 4a) and b) illustrate the usage of Stadtmobil during the day. The histogram of real numbers of bookings is in contrast to the modeled data. This could be due to the fact that the model results are aggregated trip-based data, whereas the real data are based on bookings. It is noticeable that the real data shows peaks around 9 am, 12 am, 3 pm and 6 pm every day, even on Sunday. A reason for this could be the booking process, during which customers have to choose the start of their booking in advance. It is likely that people select distinct times of day more often. Moreover, the model only implies that the beginning of the trip is also the beginning of the booking, not taking into consideration that, people could start the booking in advance and start their trip later. Overall however, the modeled and real total numbers of bookings match in the course of each day.

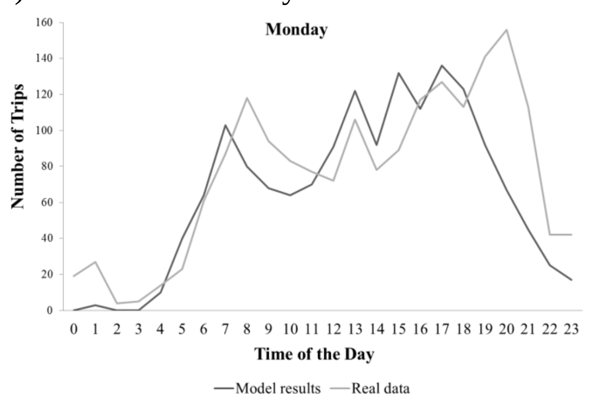
Figure 4c) and d) illustrates the usage of Car2Go during the day. The modeled numbers of bookings match the real numbers during the day. It is noticeable that the numbers on Monday differ from the numbers on Sunday. On Monday there are typical weekday-travel peaks, whereas on Sunday there are less remarkable peaks. On Sunday, the number of bookings around midnight is quite high. A reason for that could be that people substitute the cab to get home by Car2Go.



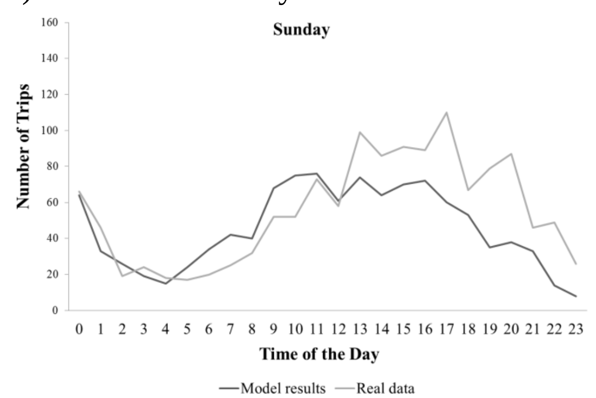
a) Stadtmobil: Monday



b) Stadtmobil: Sunday



c) Car2Go: Monday



d) Car2Go: Sunday

Figure 4 Histogram: number of Stadtmobil bookings on a) Monday and b) Sunday and number of Car2Go bookings on c) Monday and d) Sunday in the greater Stuttgart area

CONCLUSION

In general, a multiple-day model generates more results than a one-day model. It is possible to analyze issues regarding differences in usage between the days of the week. Therefore it is important to model these differences to understand carsharing usage and thus be able to consider the aspects of carsharing usage in the planning process.

In our work, we integrated station-based and free-floating carsharing in the multiple-day agent-based model mobiTopp. For this we estimated and calibrated a carsharing customer model and enhanced the mode choice model by two carsharing modes. Despite a moderate data basis, we succeeded in generating reliable model results. The model results illustrate the variations in trip length between a weekday and a weekend-day as well as the free-floating carsharing usage in relation to the time of the day. The results also show plausible variations in the share of trip purposes like shopping and leisure for both station-based and free-floating carsharing. However, as the model results are trip-based and real data is based on bookings, it is not possible to evaluate the model results regarding temporal usage of station-based carsharing. This gap has to be bridged in future versions of the model by either using more detailed data or by explicitly modeling each booking.

Another key aspect is the spatial resolution. In order to model access and egress trips explicitly, the model needs to use a higher spatial resolution than zones. With the current model version, the impedances between the zones in destination and mode choice are the same no matter where the agent is located within the zone. To improve the model, we plan to use geographical coordinates in the future; this would result in modelling individual access and egress trips as well as in individual impedances for destination and mode choice for every trip.

ACKNOWLEDGEMENTS

This paper presents excerpts of work in the project "eVerkehrsraum Stuttgart". The authors are grateful to the German Ministry of Transport and Digital Infrastructure funding the project under support code 16SBW006A.

Furthermore, the authors thank stadtmobil carsharing AG for providing the booking data and the Innovation Centre for Mobility and Societal Change (InnoZ) for providing data collected in the project "BeMobility 2.0".

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