ETH zürich

ETH Library

Estimation of carsharing demand using an activity-based microsimulation approach

model discussion and some results

Working Paper

Author(s):
Ciari, Francesco; Schüssler, Nadine; Axhausen, Kay W.

Publication date:
2011

Permanent link:
https://doi.org/10.3929/ethz-a-006804359

Rights / license:
In Copyright - Non-Commercial Use Permitted

Originally published in:
Arbeitsberichte Verkehrs- und Raumplanung

This page was generated automatically upon download from the ETH Zurich Research Collection.
For more information, please consult the Terms of use.

Estimation of Carsharing Demand Using an Activity-Based Microsimulation Approach: Model Discussion and some Results

Francesco CIARI
Institute for Transport Planning and Systems (IVT)
ETH Zurich, HIL F 33.2
CH-8093 Zurich
Phone: +41-44-633 71 65
Fax: +41-44-633 10 57
Email: ciari@ivt.baug.ethz.ch (Corresponding author)

Nadine SCHUESSLER
Institute for Transport Planning and Systems (IVT)
ETH Zurich, HIL F 33.2
CH-8093 Zurich
Phone: +41-44-633 30 85
Fax: +41-44-633 10 57
Email: ciari@ivt.baug.ethz.ch

Kay W. AXHAUSEN
Institute for Transport Planning and Systems (IVT)
ETH Zurich, HIL F 31.3
CH-8093 Zurich
Phone: +41-44-633 39 43
Fax: +41-44-633 10 57
Email: axhausen@ivt.baug.ethz.ch

ABSTRACT

Carsharing is a system that allows individuals to use a car from a fleet on an hourly basis. The growing popularity of carsharing is reflected by a continuous increase in the number of users worldwide. However, the estimation of travel demand for this mode has only sporadically been addressed by researchers and not in a completely satisfactory way. The work reported in this paper introduces a new methodology to estimate travel demand for carsharing: activity-based microsimulation. An existing open source software, MATSim, has been enhanced to allow modeling carsharing. This paper reports the modeling approach and describes the implementation of the carsharing mode in the system. Some results, based on a simulation scenario with about 160’000 agents representing the urban area of Zurich, Switzerland, are presented and validated against customer data of Mobility Switzerland, the dominant carsharing operator active in the study area.

INTRODUCTION

Carsharing is a system that allows individuals to use a car from a fleet on an hourly basis. The Sefage development project in Zurich, which started in 1948, is the first implementation of this concept (*1*). Various other schemes were implemented in the 1970s and 1980s, but most of them operated at a very small scale and none of them survived (*2*). The modern era of carsharing started in the late 1980s, when new schemes, most of them still in operation today, entered the market. Since then, the basic concept of carsharing has evolved in slightly different ways throughout the world, but "neighborhood carsharing" (*3*) is still the predominant operational model, especially in Europe.

In recent years, several new developments have further modified the world of carsharing (*4, 5, 6, 7, 8)*. An extensive discussion of those developments is beyond the scope of this paper, but some important aspects should be highlighted because they are relevant for the work presented here. Carsharing systems and more in general shared-vehicle systems are increasingly popular all over the world. The number of available shared vehicles overall increases both, because new vehicles are added by existing operators and because new operators start their activities. In the case of carsharing, the European market has witnessed an interesting new phenomenon. For the first time, car-makers – i.e. Daimler, Peugeot, BMW, etc. – are directly involved in carsharing operations in the search of new ways to market the product car. At a time when numbers sold vary widely from year to year in most of the western countries and the chance of a surge thanks to developing countries' markets is hindered by the emergence of new car-makers in those same countries (India, China), this is understandable. What impact this will have on the carsharing world will be seen in the future. However, it is reasonable to expect that it will accelerate an already existing trend towards larger carsharing companies (*9*), larger carsharing systems and increased professionalism in their planning and in the conduct of their operations. For this reason, predictive models, instrumental for the estimation of carsharing demand and for the optimization of carsharing operations, are expected to draw more and more attention from

carsharing operators. This resembles what happened to retail location models as their use and importance increased along with the emergence of large retail chains.

The main contribution of this paper is the use of an activity-based microsimulation technique for the modeling of carsharing demand. An implementation of this methodology based on an existing multi-agent, activity-based, travel demand simulator called MATSim (*10*) is proposed. The implementation presented focuses on two particular features of carsharing systems: the access to carsharing cars and the time dependent fee. The results shown, obtained running the model on a large scale scenario, illustrate how the tool works.

The remainder of this paper is organized in four sections. Section two discusses the modeling requirements for the estimation of carsharing demand and explains the potential benefits of using an activity-based micro-simulation approach. It also provides an overview on the modeling framework that has been used, the multi-agent traffic simulation MATSim. Section three presents the implementation of carsharing within the MATSim framework. The model is used in a simulation scenario representing the urban area of Zurich (Switzerland) to estimate carsharing usage. The description of the scenario and the discussion of the results are given in Section four. The paper closes with some conclusions and an outlook on future work in Section five.

MODELING FRAMEWORK

Modeling requirements

In classic travel demand (4-step) models, the mode choice module was typically taking only two modes into account, car and public transport. Some recent efforts have enhanced this to account for other modes (i.e. bicycle and walk travel) but, to the best of our knowledge, the integration of the carsharing mode in that module has not yet been attempted. In fact, the estimation of carsharing demand is a challenging task for various reasons and one could argue that classic modeling tools are not well suited for this. In general, they are estimated on data, which represent the current transportation system and are not based on some general behavioral rules that persons are supposed to follow. Therefore, it is difficult for these

models to make predictions for new transport options. Carsharing is a car mode but also shares attributes with public transport, like access time and the fact that service is not always available. Thus, in order to assign travelers to the right alternative, the description of the modes needs to be detailed enough to include the characteristics that distinguish them. The more similar the modes are the more details are necessary. However, to fully exploit the level of detail, travel should be modeled at the individual level with explicit modeling of modal choice. A precise computation of the access time to the service implies both, high spatial resolution of the model and representation of single travelers. In order to deal with single travelers, individual socio-demographic data is required. In the literature, various reports on themes like estimating carsharing market potential, simulating carsharing operations and estimating the effect of carsharing on car ownership are available. The work of Shaheen and Rodier (*11*) is probably the only example where travel demand and policy effects are forecasted for different scenarios. However, they used a modeling framework that allowed only a very simplistic representation of carsharing. They correctly observed that reliable tools for the estimation of innovative mobility services/policies are missing and overcoming this lack might be crucial for their success. Summarizing, there are three important conclusions:

- Since travel demand models are estimated on data that represents the current transportation system, it is difficult for these models to make predictions for new transport options
- Models with high spatial resolution and many demographic details are needed
- Reliable tools for the evaluation of innovative mobility services/policies might be decisive for their success

As stated in previous work (*12*), a possible way to address these issues is by using a modeling approach that couples the activity-based approach with a multi-agent system. MATSim, the multi-agent simulation that will be used here, is an example of this coupling.

MATSim

MATSim is a fast, dynamic, agent-based and activity-based transport simulation. The basic idea is to let a synthetic population of agents act in a virtual word. The synthetic population

reflects census data while the virtual world reflects the infrastructure such as road network, land use, and the available transport services and activity opportunities. Each agent has its daily activity plan describing the chain of activities that he needs to perform in the virtual world. Each agent tries to perform optimally according to a utility function that defines what is useful for an agent. One virtual day is iteratively simulated. From iteration to iteration a predefined amount of agents are allowed to change some of their daily decisions to search for a plan with a higher utility. The iterative process continues as long as the overall score of the population increases. This point is assumed to be the equilibrium point of the simulated system. The plan that each agent has in use at equilibrium is supposed to be a plausible approximation of the real world behavior of the individual.

More technically, MATSim is an open source toolkit composed of different modules. Each module is responsible for one part of the whole process. A module can have an underlying model (e.g. the traffic simulation, the mode choice, etc.) and can work together with, but also independently from, other modules. In this sense, MATSim can be seen as a comprehensive, flexible framework, which simulates the daily life of persons and produces travel demand as a side product.

Each agent has socio-demographic attributes like age, gender, occupation, home location, car availability, etc. His plan contains information on the daily activities, like where and when those activities will be performed, and which mode of transport will be used to reach the different locations. The underlying activity-chain is assigned to each agent according to its socio-demographic attributes. The plans are executed simultaneously during the traffic flow simulation. Several plans for each agent are retained, given a score, and compared. The plans with the highest scores are kept, and used to create new plans based on the agent's previous experiences. In order to improve their score, the agents can vary their departure time, transport modes, routes and location of some activities. The system iterates between plan generation and traffic flow simulation until a relaxed state is reached (Fig.1).

MATSim's most prominent application is a simulation of the travel behavior of the entire Swiss population, where 7.5 millions of agents are simulated, and about 2.3 million agents are travelling by car on a network with 882'000 links. Additional information on MATSim can be found in (*13*, *14*).

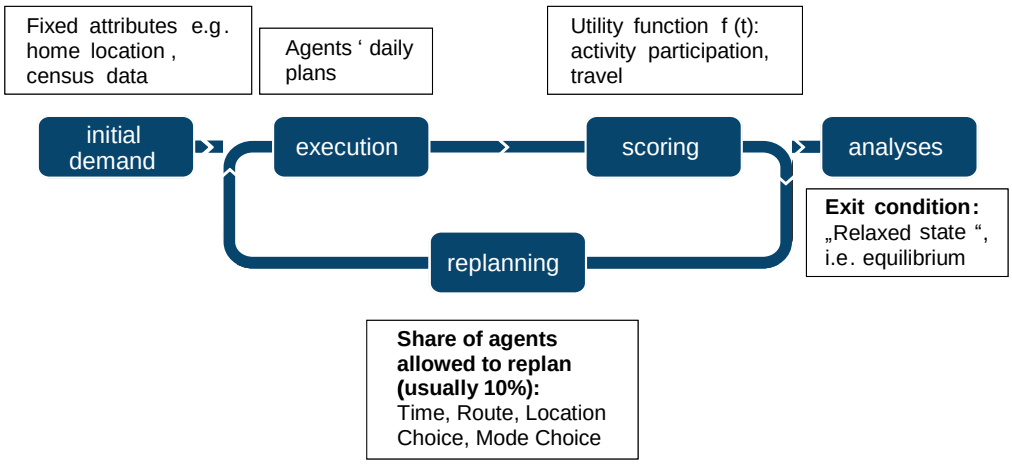

Figure 1 – Graphic representation of the MATSim simulation framework

MATSim utility function

The optimization process described above is based on the evaluation of the plans using a specific scoring function. The MATSim scoring function employed in this paper is based on two ideas: a logarithmically decreasing marginal utility for activity duration and a Vickrey (*15*, *16*) inspired valuation of the timing of the activities and the travel time. Its general form is

$$(1) \quad U_{plan} = \sum_{i=1}^{m} (U_{act,i} + U_{travel,i})$$

where the global utility of a plan is maximized. The number *m* is the number of activities and *n* the number of legs included in the plan. The elements included in the second term of equation (1), which is basically the disutility of traveling, are access/egress time, traveling

time and the cost of the trip with a given mode. Thus, the cost of traveling from activity *i*-1 to activity *i* with transport mode *mode* can be expressed as follows:

$$(2) \quad U_{travel,i,\text{mode}} = \alpha_{\text{mode}} + \beta_{tt,\text{mode}} * TT + \beta_{\text{cost},\text{mode}} * Cost_{\text{mode}} * Dist$$

In the basic model, access and egress time are not calculated but assigned to each mode in the form of a non-positive constant α_{mode}. The cost component represents the kilometric cost for the mode considered and is an average based on Swiss values (*17*). It is assumed to be zero for cycling and walking, while their values for the other modes are:

$Cost_{car}$ = 0.12 Sfr/km; $Cost_{pt}$ = 0.28 Sfr/km; $Cost_{pt,\text{season tickects}}$ = 0.14 Sfr/km.

The two different values for public transport take into account the fact that a passenger might own a season ticket of some kind. *Dist* is the distance traveled for the leg calculated with specific methods for each mode. The travel time (TT) is either derived from the simulation or calculated based on the distance and the speed of the mode. The constant average speed of the public transport mode is based on measurements in the city of Zurich while speeds for cycling and walking are based on the National travel diary. They are respectively:

v_{pt}=15.7 km/h; v_{bike}= 14 km/h; v_{walk}=2.8 km/h

The speed for the car mode is the "real" travel time obtained through the simulation. Through this physical representation, based on a queue model, agents interact in the sense that they are competing for the infrastructure. Therefore, travel time and, consequently, the generalized cost of a car trip depend on congestion on the network and, thus, on the mobility behavior of other agents. The constant α_{mode} and the parameters $\beta_{tt,mode}$ and $\beta_{cost,mode}$ are different for each mode and have been estimated using stated preference survey data (*18*). The parameters represent the marginal utility of another unit of time and the marginal utility of another unit of money spent on traveling by *mode*.

Other kinds of out-of-pocket expenses (like parking costs) can be added in the same way, as well as other aspects of travel with a specific mode. The utility function allows the user to

vary the characteristics of different modes and observe the reaction of agents to such variations.

THE IMPLEMENTED MODEL

In the most recent version of the MATSim toolkit, the available modes are car, public transport, bike and walk. Carsharing is not considered as an option. A new transport mode can be added to the simulation tool in various forms and with different levels of detail. In any case, it is necessary to introduce a function that represents the generalized cost of travel with the given mode in a form similar to (2). In the work presented here, two of the fundamental features that characterize the carsharing mode, access to carsharing cars and the fare structure are explicitly modeled. Our assumption is that a model with a correct representation of these two features is able to give plausible estimates of carsharing usage in terms of modal share, and to induce in the agents some of the typical carsharing usage patterns. A convenient access to carsharing cars has been found of particular importance in most of the surveys conducted among carsharing users and, indeed, is often referred as the most important factor for joining a carsharing program. The fare of carsharing is generally the sum of a time dependent part and a distance dependent part. The users are charged for both the distance they travel and the time they keep the car (or more precisely the time they reserved the car). This feature is specific to carsharing and it is known to have a strong influence on usage patterns (*19*). In order to explicitly represent the mentioned features, the model has been enhanced as follows:

- Carsharing stations have been introduced; stations are located at the actual carsharing locations in the modeled area.
- One agent can pick up the car only at one of the predefined stations, and must bring it back to the same one.
- Agents always choose the closest station to the starting facility.
- Agents walk to the pick-up point.
- The agent's utility function is enhanced to account for carsharing. A time dependent penalty is introduced to mimic carsharing fare structure.

Other features, which are also specific to carsharing programs, like membership and reservations, have not been taken into account yet, which means that in the simulation the following applies:

- Carsharing is available to everybody having a driving license (no membership is needed)
- An unlimited number of cars is available at the stations

These are unrealistic assumptions and a better modeling of such features will be addressed in the future work. The function representing generalized cost of travel for car sharing is:

$$U_{travel,i,cs} = \alpha_{cs} + \beta_{\text{cost},cs} Cost_t * RT + \beta_{tt,walk} * (AT + ET) + \beta_{tt,cs} * TT + \beta_{\text{cost},cs} * Cost_d * Dist \quad (3)$$

Compared to (2), equation (3) has five terms instead of three. The first, the constant α_{cs} has a different meaning than the constant in the previous equation since access/egress are explicitly represented in the equation. This is intended to mimic the minimum cost of carsharing, since the minimum reservation length offered by the Swiss operator Mobility is 30 minutes. This term is important to keep agents from using carsharing in the simulation for only few minutes. The second term refers to the time dependent part of the fee. RT is the total reservation time minus 30 minutes (already taken into account) and $Cost_t$ represents the cost for one hour reservation time. The parameter $\beta_{cost,cs}$ represents the marginal utility of an additional unit spent on traveling with carsharing. The third term is the walk path to and from the station and is evaluated as a normal walk leg. The other two terms represent the car route and have the same meaning as in equation (2). The time cost is set to 2 Sfr/h while the distance cost is set to 0.64 SFr/km, which is the standard carsharing fee in Switzerland.

The mode choice module of MATSim is subtour based. A subtour is defined as a sequence of at least two trips starting and ending at the same node. Agents choose the transport mode at this level. This fits well with the way real carsharing systems are functioning since it forces an agent to bring back the car to the starting station.

A last aspect of the model that is worth mentioning is the physical simulation. In the version of MATSim used for this work only private cars are physically simulated. The physical simulation allows taking into account the interactions among agents; basically their competition for the infrastructure. Too many agents on a certain road at a certain time will cause congestion and agents will try in successive iterations to switch time or route in order to obtain a better score. This generates a dynamic assignment of the demand to the network. If an agent uses a mode other than the car mode, the attributes of this travel (distance, time) are calculated independently from the situation on the network. This is equivalent to assuming that such modes neither are influenced by nor influence congestion on the network. In fact, in a real world situation, this is largely true for the walk mode and more or less true for the bike mode. This is, however, a major simplification for public transport travel. A detailed discussion of that feature of the model is beyond the scope of this paper, but, it is important to explain how carsharing is modeled to this respect. It is obvious that it cannot be assumed that the congestion on the network is not influential for carsharing travel. Nevertheless, since car sharing cars make up only for less than 1% of global car travel (the sum of private cars plus carsharing cars) it seems reasonable to assume that carsharing users contribute only very marginally to congestion on the network. They are, however, affected by the congestion that the other car travelers cause. For that reason, carsharing cars are not physically simulated, but travel time for carsharing is calculated on the congested network. Therefore, travel time for carsharing in the simulation does depend on the level of congestion of the network at the time when and on the route where carsharing travel happens.

A TEST CASE: THE AREA AROUND ZURICH

The simulation scenario

The test case scenario used here is a “Greater Zurich” scenario. It is a subset of the Swiss scenario, and covers an area of about 2’800 km^2, obtained by drawing a 30 km circle around the “Bellevue” square in the centre of Zurich. This scenario is built with geo-coded data from the year 2000 population census (individuals, households, commuting matrices), the

year 2000 census of workplaces (facilities by type and capacity) and the national travel survey for the year 2005 (9'429 types of activity chains classified by duration of the activities, their number, types and sequence; eight classes of agents by age and work status are distinguished). The study area has approximately 1 million inhabitants. Moreover, the scenario contains all agents that have plans with at least one activity within the area and all agents crossing the area during their travel. Transit traffic through the country is included based on relevant border survey data. A map of the scenario is presented in Fig. 2.

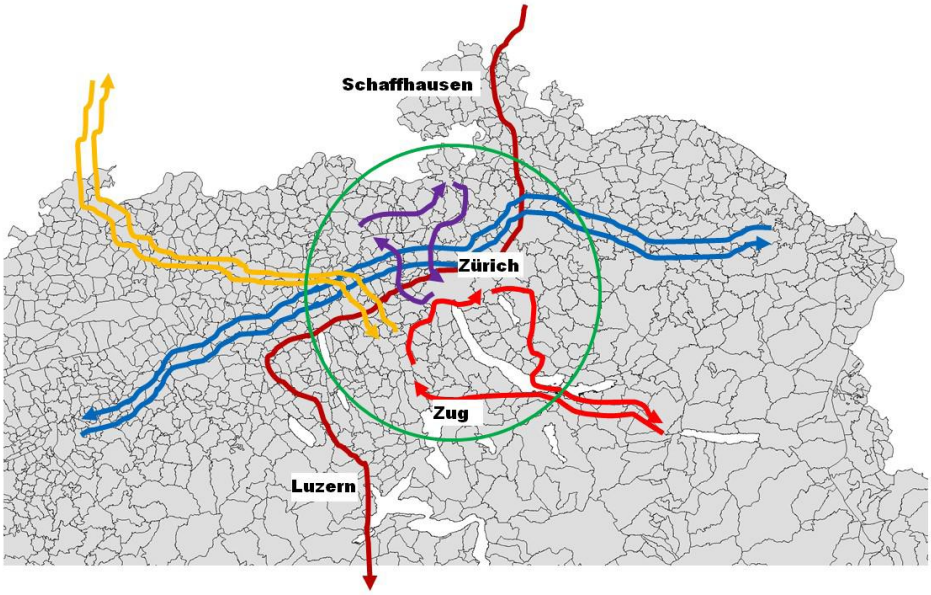

Figure 2 – Map of the Greater Zurich scenario (circle) with graphic representation of types of plans included in the scenario.

The road network model has more than 236'000 directed links and more than 73'000 nodes. It is obtained from the Teleatlas navigation network. The number of facilities for out-of-home activities is 373'155. A MATSim specific subdivision of activities into 4 different types is used: work, education, shop, and leisure. These activity types represent the possible entries in an agent's plan. The transport modes allowed are: car, public transport, bicycle, walk, and carsharing. In this scenario, 276 carsharing stations define the locations where an agent is allowed to pick up and drop off a carsharing car. The locations are the actual locations of the Swiss carsharing operator Mobility CarSharing (*20*) in the study area. Mobility CarSharing is the only operator in Switzerland; it operates 2'350 Cars at 1'200

stations and is one of the leaders worldwide in terms of number of customers. For computational reasons, the simulation is run on a 10% sample of this scenario, which means that 161'810 agents are simulated. The network capacity is also scaled (each link's capacity is set to 10% of the original capacity) in order to have realistic traffic flows on the network links. In the 10% sample, the number of agents crossing the study area while transiting Switzerland is 5'791, linked to 880 home facilities outside Switzerland.

With the computer used for the simulation, a shared-memory machine of the type

Sun Fire X4600 M2 with 8 dual-core CPUs and 128 GB RAM, the 10% sample scenario takes about 14 hours of computing time (using 3 cores and 40G RAM) for 40 iterations, which is enough to reach an equilibrium with the settings used.

Results and discussion

The goal of this work is to show that the simple model described in the previous section is able to reproduce a reasonable modal split, and capture some of the usage patterns typical for carsharing. The results of the simulation, whenever possible, are compared to the relevant real world data. In general, they are compared with data obtained from the Swiss National Travel Survey, also known as Microcensus (*21*), or from customer data of the Swiss operator Mobiliy CarSharing. The latter is usage data of 107 of the 276 stations located in the study area collected between August and November 2010. Each station is known with its exact location (coordinates) and the number of cars available. There were 6'700 customers who used a car from those stations in that time period and for all of them slightly randomized coordinates of their home locations are available. The cars were used by these customers for a total of 25'000 trips. For each trip start and end time of the rental and the distance driven are available.

The first analysis compares the modal split obtained from the simulation, with the modal split reported in the Microcensus by respondents living in the study area (Fig.3).

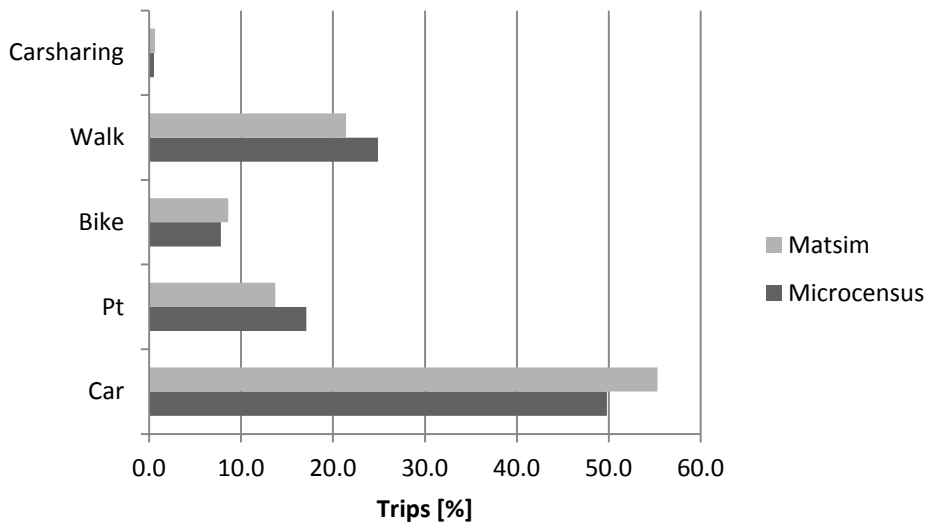

Figure 3 – Shares of the transportation modes, at the trip level, for the simulation scenario "Greater Zurich" and for the corresponding area in the Swiss Microcensus.

The modal split values are the percentage of trips travelled with a certain mode disregarding the distance. The share of agents using carsharing in the simulation is 0.6%. Since carsharing is not a reported mode in the Swiss Microcensus, its share was derived from a national study on carsharing usage (*22*). According to this the current nationwide modal share of carsharing is 0.1% of all trips. An estimate for the simulated area can be obtained considering the number of carsharing cars available at national level and the number of carsharing cars available in the area and assuming that all carsharing cars are used, on average, for the same number of daily trips. This results in an estimate of 0.5% of the trips in the simulation area. This means that the simulation delivers good results. To some extent, they are even better results than expected considering that the current specifications of the model – the unlimited number of cars at the stations and the fact that membership is not taken into account in the model – would have suggested a larger overestimation. A possible interpretation is the fact that we are simulating a week-day where the capacity of the carsharing system is less an issue than on weekends. In other words the use of carsharing is rather limited by the structure of typical week-day activity-chains than by the capacity of the system.

The next analysis checks that the two features of carsharing that were explicitly introduced in the model are inducing the correct behavior in the agents. First, the influence of the time dependent fee is verified. For this, the rental time in the simulation (subtour length) is compared with that of real carsharing customers in Switzerland. Additionally, in order to show that subtours made with carsharing are, on average, shorter than subtours made with the other modes, the distribution of subtour durations in the Microcensus is also reported (Fig.4).

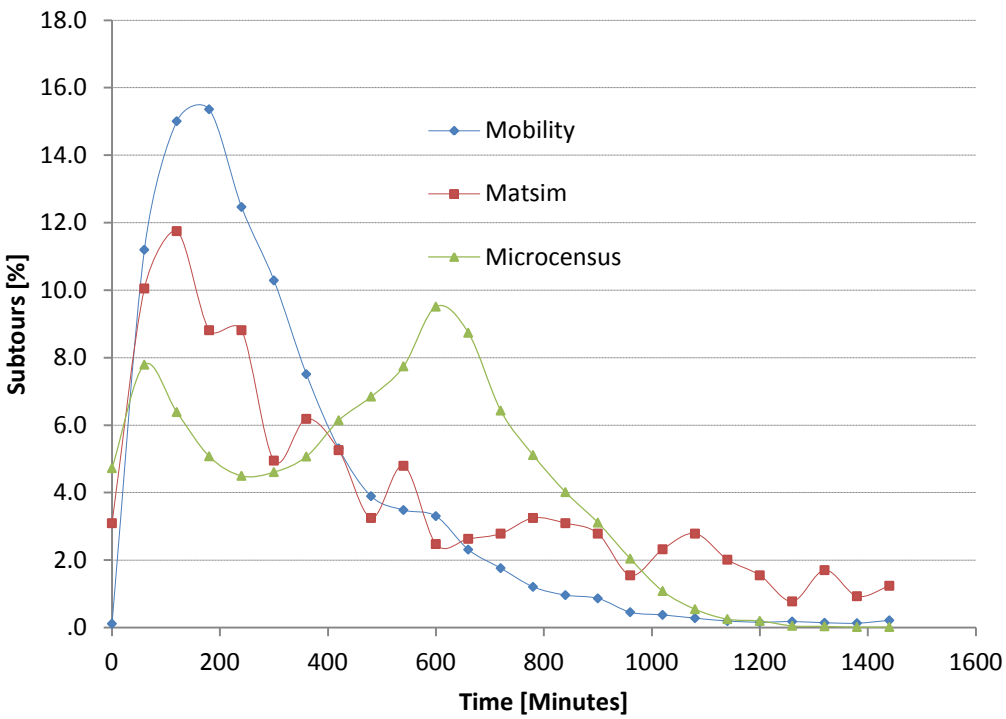

Figure 4 – Comparison of the rental time in the simulation with the real rental time of mobility customers and with subtours time length in the Microcensus.

It can be observed that the general shape of the distribution derived form the simulation is very similar to that derived from Microcensus. Shorter rentals are prevalent, and very long rentals are much less common, though the simulation underestimates the rentals between two and three hours. The second comparison with the distribution of all subtours makes clear that the similarity is not a pure coincidence but a consequence of the fee structure. In fact, on average, subtours reported in the Swiss Mobility Survey are longer and also their distribution

is different. There is a peak for very short tours and another one, more pronounced, for subtours of about ten hours, which reflects the schedule of people commuting to work. This confirms that the agents in the simulation are reacting as expected to the time dependent fee introduced. The next analysis aims to verify that the agents are reacting correctly to the explicit modelling of access/egress distances. To show this it is analysed, if distances between the starting points of carsharing subtours and the stations are similar in the simulation and in reality (Fig.5).

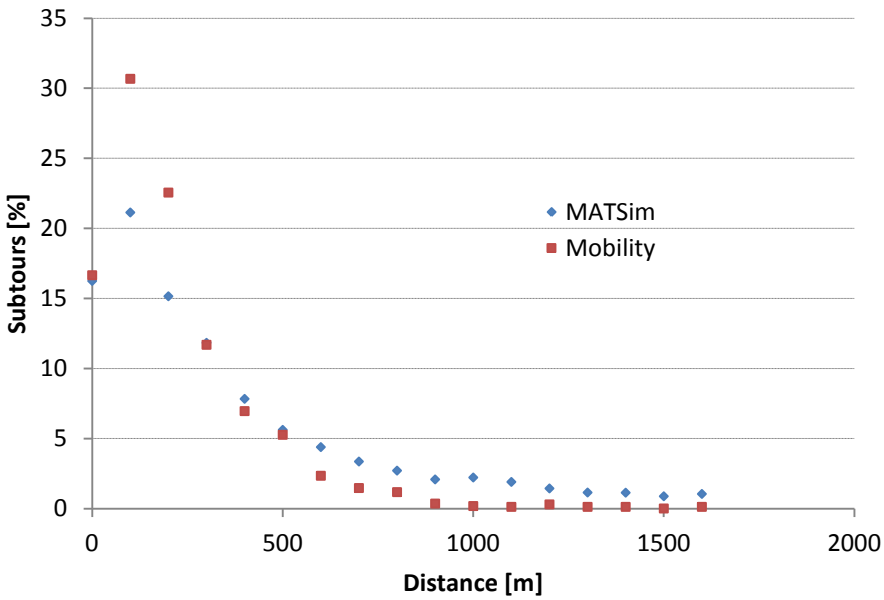

Figure 5 – Comparison of the distance between start location and station used in the simulation and for Mobility customers.

In this case, the two distributions are matching well, the shapes are the same and most of the values are quite close. It means that the agents in the simulation choose the "right" stations to pick up carsharing cars. Specific data about the transport mode used by Mobility CarSharing customers to pick up carsharing cars is not available.

So far it was shown that the model works reasonably well among the dimensions that are explicitly modeled. The next step is to verify that the explicit representation of access to the stations and the time dependent part of the fee are sufficient to induce other typical carsharing usage patterns in the simulation. The first one is the purpose of the trips for which carsharing is used. It is well known that carsharing is used mostly for travel that is not made

on a regular basis and in many cases involves leisure and shopping activities. Since no specific information regarding the trip purpose of carsharing users in Switzerland is available, Fig.6 compares the distribution of trip purposes for carsharing users in the simulation to the distribution for all modes in the Swiss census.

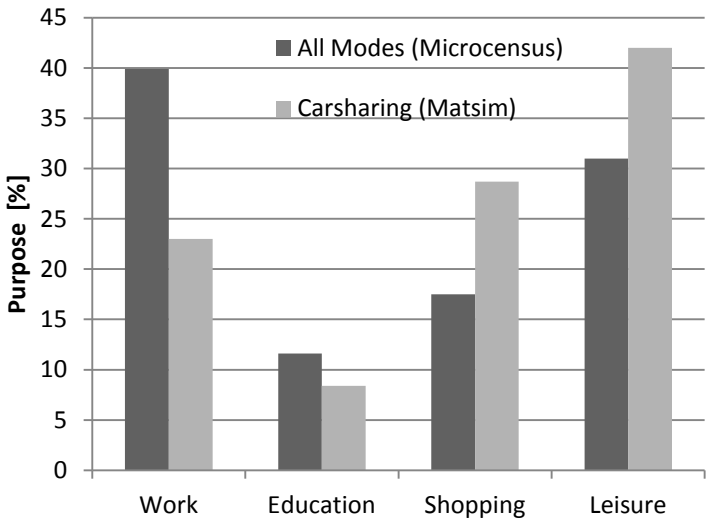

Figure 6 –Distribution of carsharing trips with respect to their purpose in the simulation compared to that of all Microcensus trips.

As expected, carsharing is preeminently used for shopping and leisure activities in the simulation, and this to a much larger extent than other modes are used. This indicates that the usage pattern in the simulation is correct. Nonetheless, the share of legs with work as purpose, appears to be high and casts some doubt; but an analysis of the tours in the simulation showed that about 70% of those work legs are part of a work-work chain. This means that those trips have been made by agents that were already at work somewhere and needed a car to go somewhere else as part of their working activity. This is consistent with how business carsharing is functioning, which is indeed offered by Mobility, and this number might reflect this type of carsharing usage. However, the specific usage data by Mobility is unavailable and, therefore, a direct comparison is not possible. Moreover, even without counting those trips, the residual share of trips with work purpose, about 7% of the total, might be an overestimate. An improvement of the model to this respect depends on the

future availability of relevant data. The aim would be to find out how many work trips are actually made using carsharing and how an eventual overestimate in the simulation could be prevented. In any case, the important fact here is to show that the fee structure with its time dependent part pushes the agents to use carsharing cars prevalently for the "right" activities and not for commuting.

Finally, the distribution of departure times in the simulation is compared to departure times of Mobility customers. Again, in order to show that these distributions are peculiar to carsharing, the distribution of subtour departure times with any mode is also reported (Fig.7).

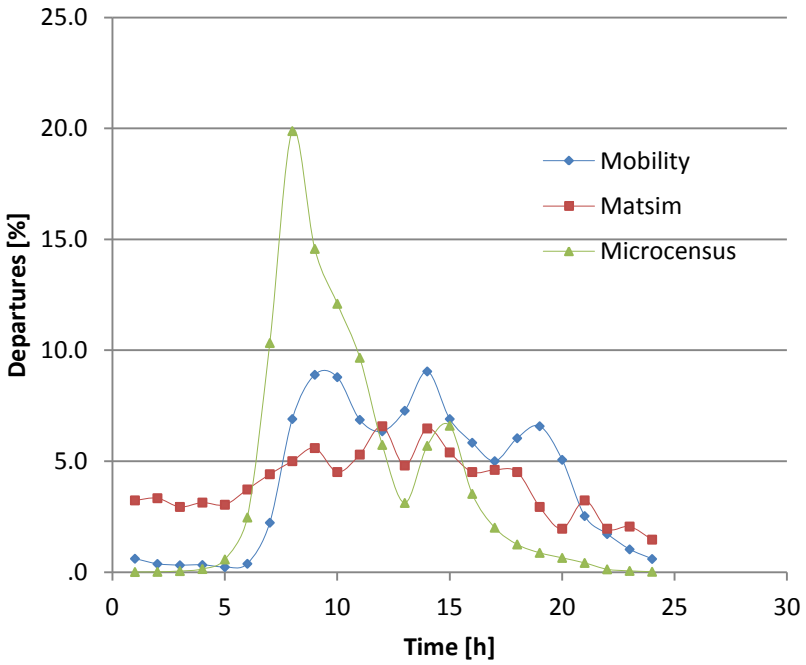

Figure 7 –Carsharing departure times compared to those of Mobility customers and to subtours departure times of Microcensus.

Figure shows that in the simulation too many departures occur in the evening or very early in the morning. Nevertheless, the general shape of the distribution generated by the simulation is similar to that of Mobility customers and, more importantly, is considerably different from the global one, where the characteristic morning peak can be seen. Thus, the simulation is able, although without high accuracy, to reproduce a pattern that is observable in reality.

CONCLUSIONS AND OUTLOOK

This paper reports on the development of a simulation tool that should be able to estimate the travel demand for carsharing and evaluate different scenarios and policies. The main motivation for the work is the expected increase in importance of tools for the evaluation of innovative transport modes in the near future. Such tools are not yet available and the one presented in this paper is an important step in this direction. The methodology proposed is both activity-based and agent-based and builds on an existing open source project called MATSim. This type of model is known to allow for a very rich description of both persons and infrastructure, and MATSim is no exception. This comes at the cost of being computationally intensive. Additionally, the richness of detail does not imply the accuracy of the model, in particular at the micro-scale. However, it is important that such a level of detail is possible because it allows introducing simple behavioral rules at the micro level that determine the macro behavior of the system. The key is to use behavioral rules that are easy enough to observe from real world experience but also "fundamental" enough to induce a plausible behavior in the agents not only for a particular activity or for a particular mode of transport, but in general. This results in the really important feature of showing an emerging behavior at the macro-scale that is caused, but not directly implied, by the rules at the lower level. This emerging behavior is the main reason why agent-based simulation is a suitable tool for modeling innovative transport systems. Moreover, this kind of modeling tool does not rely too much on past information to make predictions. The implementation described in this paper focused on two of the most important aspects of carsharing, the access to the cars and the time dependent fee structure. These two aspects are known to be of great importance for carsharing users and a model aiming to predict carsharing demand should take them into account. The model presented has been tested for this purpose and shown to be able giving plausible results in terms of overall carsharing usage and also with respect to the two

mentioned features. In addition, some typical carsharing usage patterns not directly implied by the model have emerged from the simulation, as hypothesized. The model can be improved in many ways; two of the most obvious are the introduction of the physical simulation of carsharing cars and of a reservation system with a limited number of cars available at each station. The long term goal is to build a predictive and policy sensitive model that can be used by practitioners and policy makers in order to test different carsharing scenarios. The model is still not quite ready for that use, but it is, in our opinion, a very promising advance in the search for reliable predictive models of carsharing demand.

REFERENCES

1. Harms, S. and B. Truffer (1998) The emergence of a nationwide carsharing co-operative in Switzerland, report for the EAWAG (Eidgenossische Anstalt für Wasserversorgung, Abwasserreinigung und Gewässerschutz), Dübendorf.

2. Shaheen, S. A., D. Sperling and C. Wagner (1998) Carsharing in Europe and North America: Past, Present, and Future, *Transportation Quarterly*, **52** (3) 35–52.

3. Barth, M. and S.A. Shaheen (2002) Shared-Use Vehicle Systems Framework for Classifying Carsharing, Station Cars, and Combined Approaches, *Transportation Research Record*, **1791**, 105-112.

4. Shaheen, S.A. and A.P. Cohen (2007) Growth in Worldwide Carsharing An International Comparison, *Transportation Research Record*, **1992**, 81-89.

5. Maire de Paris (2011) Portail Paris, webpage, January 2011 http://www.paris.fr.

6. Car2go (2011) Car2go, webpage, January 2011, *www.**car2go**.com*.

7. Brooks, D. (2010). And what if, instead you share your car? Next generation carshairng hits the street. Webpage, May 2010 http://newmobilityagenda.blogspot.com/2010/05/and-what-instead-if-you-share-your-own.html.

8. RelayRides (2011) RelayRides, webpage, January 20110, http://relayrides.com/.

9. Shaheen, S.A, A.P. Cohen and M. Chung (2010) North American Carsharing 10-year Retrospective, *Transportation Research Record*, **2110**, 35-44.

10. Balmer, M., K. Meister, M. Rieser, K. Nagel and K.W. Axhausen (2008) Agent-based simulation of travel demand: Structure and computational performance of MATSim-T, paper presented at the *2nd TRB Conference on Innovations in Travel Modeling*, Portland, June 2008.

11. Shaheen, S.A. and C. Rodier (2004) Carsharing and Carfree Housing: predicted travel, emission, and economic benefits, paper presented at the *the 83th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2004.

12. Ciari F., M. Balmer and K.W. Axhausen (2009). Concepts for a large scale carsharing system: Modelling and evaluation with an agent-based approach. Paper presented at the *88th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2009.

13. MATSim (2011) MATSim, webpage, May 2011, *www.matsim.org*.

14. Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, R.A. Waraich and K.W. Axhausen (2010) Large-scale agent-based travel demand optimization applied to

Switzerland, including mode choice, paper presented at the *12th World Conference on Transportation Research*, Lisbon, July 2010.

15. Charypar, D. und K. Nagel. (2005). Generating complete all-day activity plans with genetic Algorithms. *Transportation*, **32** (4) 369–397.

16. Vickrey, W. S. (1969). Congestion theory and transport investment. *The American Economic Review*, **59** (2) 251–260.

17. Kickhöfer, B. (2009). Die Methodik der ökonomischen Bewertung von Verkehrsmaßnahmen in Multiagentensimulationen. *Diplomarbeit*. Berlin: Technische Universität Berlin.

18. Vrtic, M., N. Schüssler, A. Erath, M. Bürgle, K.W. Axhausen, E. Frejinger, M. Bierlaire, R. Rudel, S. Scagnolari and R. Maggi. (2008). Einbezug der Reisekosten bei der Modellierung des Mobilitätsverhaltens. Final report for SVI 2005/004, *Schriftenreihe*, **1191**. Bern: Bundesamt für Strassen, UVEK.

19. Millard-Ball, A., G. Murray, J. ter Schure, C. Fox and J. Burkhardt (2005) Car-Sharing: Where and how it succeeds, *TCRP Report*, **108**, TRB, Washington D.C.

20. Mobility (2011). Mobility Carsharing AG, webpage, June 2011, http://www.mobility.ch.

21. ARE and BfS (2007) Mobilität in der Schweiz, Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten, Bundesamt für Raumentwicklung, BFS Statistik der Schweiz, Neuchâtel.

22. Haefeli, U. (2006) Evaluation of Carsharing, Bundesamt für Energie BFE, Bern.