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WHO GETS THE KEY FIRST?
CAR ALLOCATION IN ACTIVITY-BASED MODELLING

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Abstract

Decisions concerning household car ownership and the corresponding usage by the household members have significant implications on vehicle usage, fuel consumption and vehicle emissions. In this context, long-term and short-term choices which are strongly interrelated with one another play an important role. The long-term aspects involve the number of vehicles and their different types owned by a household as well as the assignment of a main driver, acting as the primary user, to each vehicle. The short-term dimension is represented by the vehicle allocation within a household at a daily level.

In order to better understand the vehicle allocation process in the household context, the paper at hand investigates the importance of the short-term and long-term aspects in this process and explores several approaches to model them. For this purpose, four different methods for car allocation within a household, which strongly differ in their complexity, are implemented into a microscopic agent-based travel demand model and subsequently evaluated. The respective approaches are the following: (1) random car allocation, (2) car allocation by age, (3) car allocation by main driver assignment, and (4) car allocation by household optimisation. Given a population of a bigger region that is described by a set of attributes, these various models determine which person of a household uses one of the available cars within the household for his/her daily trips. The simulations show that all four implementations of car allocation result in good representations (with deviations of less than 10%) of observed travel behaviour, their results being closer to each other than initially expected. Model (4), which optimises car allocation for the entire household, shows the best results when compared to real-world data, while model (3) allows for the adaptation of changes in car ownership and/or socio-demographic and socio-economic attributes of the population.

Keywords

car allocation, activity-based model, urban context, household travel surveys, discrete choice modelling

Introduction

Decisions concerning household car ownership and the corresponding usage by the household members have significant implications on fuel consumption and vehicle emissions (Angueira, 2014; Golob, Kim and Ren, 1996). In this context, long-term and short-term choices which are strongly interrelated with one another play an important role (Angueira, 2014; Vovsha and Petersen, 2007). The long-term aspects involve the number of vehicles and different types owned by a household as well as the (often implicit) assignment of a main driver, acting as the primary user, to each vehicle. The short-term dimension is represented by the vehicle allocation within a household at a daily level. This means that intra-household car allocation addresses the question, which driver uses which car for which trips (Nam, Lee, Aultman-Hall and Sears, 2013).

The choice context is described by household and individual characteristics, such as household size and structure, income as well as age, gender and occupation of all household members. Furthermore, the available vehicles in a household with their varying attributes, such as model, vintage, type and size as well as fuel type and fuel consumption play an important role. The corresponding vehicle trips are characterised by their purpose, destination, and number of companions, carried cargo as well as distance and duration covered. All these choices have significant implications on the spatial-temporal distribution of congestion, vehicle usage, road safety, emissions and the corresponding environmental impacts, such as noise, air pollution and climate gases.

In order to better understand the vehicle allocation process in the household context, the paper at hand investigates the importance of the short-term and long-term aspects in this process and explores different approaches to adopt them. For this purpose, four different methods for car allocation within a household are implemented into the microscopic agent-based travel demand model called Travel and Activity PAtterns Simulation (TAPAS) (Heinrichs, Krajzewicz, Cyganski and von Schmidt, 2016; Hertkorn, 2005), which is developed at the DLR Institute of Transport Research. Current activity-based travel demand models, such as TAPAS, generate the travel behaviour for every person in a synthetic population with respect to the person's household context in order to determine the population's reactions to changes in costs, travel time and/or availability of mobility options. Households with more potential drivers than cars have to decide who is allowed to take the car first or, more bluntly put, who gets the key first.

The four implemented models for car allocation strongly differ in their complexity, ranging from more trivial to more sophisticated ones. The respective approaches are the following: (1) random car allocation, (2) car allocation by age, (3) car allocation by main driver assignment and (4) car allocation by household optimisation. Various modelling results are compared with one another as well as with real-world data of a household travel survey, and evaluated accordingly with respect to how well they represent car allocation and usage within the household context.

In the next section, car allocation within the household context is characterised, including a description of the various ways of implementation in activity-based modelling. Subsequently, the used microscopic travel demand model TAPAS is presented. The main part of the paper then concentrates on the comparison of the simulation results with one another as well as with observed data. Finally, conclusions are drawn and an outlook on further research is given.

Car allocation within the household context

Vehicle allocation within a household is constrained by the number and types of vehicles in the fleet. Understanding the available fleet composition is therefore one step in explaining the car allocation process (Nam *et al.*, 2013). Households acquire vehicles to satisfy specific travel needs and desires as well as the preferences of the household members (Golob *et al.*, 1996). Therefore, car purchase decisions are associated with both household and individual driver characteristics (Nam *et al.*, 2013).

In order to allocate cars to drivers, different strategies may be applied within a household (Mannering, 1983). First, the allocation may be based on individual members consistently using a specific vehicle, perhaps out of some notion of vehicle ownership within the household (Golob *et al.*, 1996; Vyas, Paleti, Bhat, Goulias, Pendyala, Hu, Adler and Bahreinian, 2012). Second, car assignment may be determined by a process in which household members bargain to obtain access to available vehicles for activities (Anggraini, Arentze and Timmermans, 2007; Anggraini, Arentze and Timmermans, 2008; Petersen and Vovsha, 2005). And third, individual cars may be assigned to the trips that are most compatible with the vehicle attributes (e. g. fuel efficiency, seating and cargo capacity, as well as reliability in terms of possible breakdowns) (Anggraini *et al.*, 2007; Anggraini *et al.*, 2008; Petersen and Vovsha, 2006).

The principal, more or less exclusive use of one of the household's vehicles by each household driver due to personal preference, convenience, habit, and routine forms a long-term commitment to that car. In contrast, the use of different vehicles for different trip purposes represents a shorter-term element in the car allocation process. It requires more flexibility and willingness of household members to use a vehicle they normally would not drive or to accept the inconvenience of changing vehicles in the middle of a travel day.

The following subsection describes four approaches to determine the main driver for a car in the household context. The first one assigns the driver randomly and, thus, represents a no-model approach. The second one orders household members by their age so that older household drivers are more likely to obtain the available vehicles. The third one represents the longer-term aspect by assigning a main driver to each available vehicle in a household, applying discrete choice modelling in order to obtain a probability function for being a primary driver of a car. The fourth one tries to maximise the day plan acceptance with respect to time feasibility by determining the overall household acceptance of its individual members' day plans and choosing the corresponding combination with the highest acceptance.

It is important to know that within the used simulation system TAPAS, household members are processed subsequently and individually. Consequently, the ones processed first have a greater chance to obtain one of the household's vehicles in case that it matches their mobility wishes. Thereby, all but the last car allocation models work by ordering household members in a specific way.

Random car allocation

The household members are processed unsorted. The drivers assigned to one of the available vehicles within a household are chosen randomly. Thereby, the probability to be chosen first and obtain the vehicle is the same for all drivers.

Car allocation by age

Persons within a household are sorted descending according to their age. As a result, older persons have a higher probability to obtain an available vehicle, because it may get unavailable for the following household members. This model is mainly introduced to avoid overproportioned car usage by younger persons which is observed in random car allocation.

Car allocation by main driver assignment

A further approach to allocate cars to drivers within a household is to determine probabilities for all household members to be a main driver of a car, estimating a corresponding discrete choice model using data from a household travel survey that covers car allocation. The data used to build the model as well as the resulting model itself are described and discussed in the respective following sub-sections.

Data

The corresponding model estimation is based on data of the national household travel survey “Mobility in Germany” (MiD) of the year 2008, which is commissioned by the Federal Ministry of Transport, Building and Urban Development (Bundesministeriums für Verkehr, Bau und Stadtentwicklung, 2010a and 2010b). The MiD survey collects behavioural travel data of entire households for all weekdays using a diary day concept. The sample includes data of nearly 26’000 households with nearly 64’000 household members and approximately 185’000 reported trips. The detailed dataset includes variables on general household and individual characteristics, such as household size and structure, income as well as gender, age and occupation of all household members. With respect to the car ownership of the household, information about the model, vintage, annual mileage, the owner and the main driver is available for the three most used vehicles. For the reported trips, the trip purpose, destination, number of companions, means of transport, including the car used, as well as distance and duration are known, amongst others.

The sample shows a wide structure of car ownership ranging from households with no available car (18%) to one car (53%), two cars (24%), three cars (4%) and more cars (1%). Regarding the ratio of the number of vehicles and the number of driving licence owners within a household, a balanced relationship with an equal number of drivers and cars is observed in 59% of the households. In contrast, the shares of households with fewer cars and more cars than drivers amount to 38% and 3%, respectively.

Assignment of a main driver to a car

Based on this data, a binomial logit model for the identification of a main driver is estimated. Table 1 presents the corresponding results for a model with solely the significant parameters. The explanatory variables include individual and household characteristics. For male respondents, age shows an overall positive influence, whereas for females the opposite applies. After reaching the age of about 30 years, men exhibit a higher probability of being the primary driver than women. This result points to the generally observed lower car ownership and use by females, especially for the elderly, due to a lower availability of driving licences in older age groups (Beckmann, 2013; Beige and Axhausen, 2008). For illustration, Figure 1 shows the summarised utility for being the main driver based on age and gender. Employment of a person has a significant positive effect. To an even greater extent, this also applies to the ownership of a driving licence, consistent with the expectations. When accounting the household context, the household type has considerable impact. In comparison to single parents, all single-person households as well as persons living in households with two adults being older than 60 years are more likely to be primary drivers. All other household types have negative parameters, revealing a certain competition within these households. Likewise, the number of employed household members decreases the probability of being a main driver. At the same time, the household income does not play a significant role. The three variables that describe the ownership of driving licences and cars within a household exhibit a composite interrelationship. Overall, the number of car driving licence owners has a negative and the number of cars a positive effect. As measure for the goodness of fit, the adjusted ρ^2 of the model is shown at the bottom of the table. With a value of 0.660, it is relatively high.

Table 1: Binomial logit model for being a main driver of a car

Explanatory variables	Parameter	Significance
Person related variables		
Age in years	– 0.104	0.000
Age in years natural logarithm	+ 3.530	0.000
Gender: Male	– 1.348	0.000
Age in years * Gender: Male	+ 0.045	0.000
In employment	+ 1.023	0.000
Car driving licence ownership	+ 10.946	0.000
Household related variables		
Household type: Single parents as referential category		0.000
Single-person household and person aged from 18 to 30 years	+ 0.355	0.198
Single-person household and person aged from 30 to 60 years	+ 0.172	0.262
Single-person household and person aged over 60 years	+ 1.225	0.000
Household with two adults and youngest adult aged from 18 to 30 years	– 0.225	0.006
Household with two adults and youngest adult aged from 30 to 60 years	– 0.526	0.000
Household with two adults and youngest adult aged over 60 years	+ 0.003	0.963
Household with three or more adults	– 0.383	0.000
Household with at least one child and youngest child aged under 6 years	– 0.422	0.000
Household with at least one child and youngest child aged under 14 years	– 0.457	0.000
Household with at least one child and youngest child aged under 18 years	– 0.363	0.000
Number of employed household members	– 0.358	0.000
Number of car driving licence owners	+ 1.200	0.000
Number of cars	– 1.698	0.000
Ratio of the number of cars to the number of car driving licence owners	+ 10.662	0.000
Further variables		
Constant	– 25.696	0.000
Number of observations		52080.060
L(0)		– 35835.650
L(max)		– 12176.453
ρ^2 (adjusted)		0.660

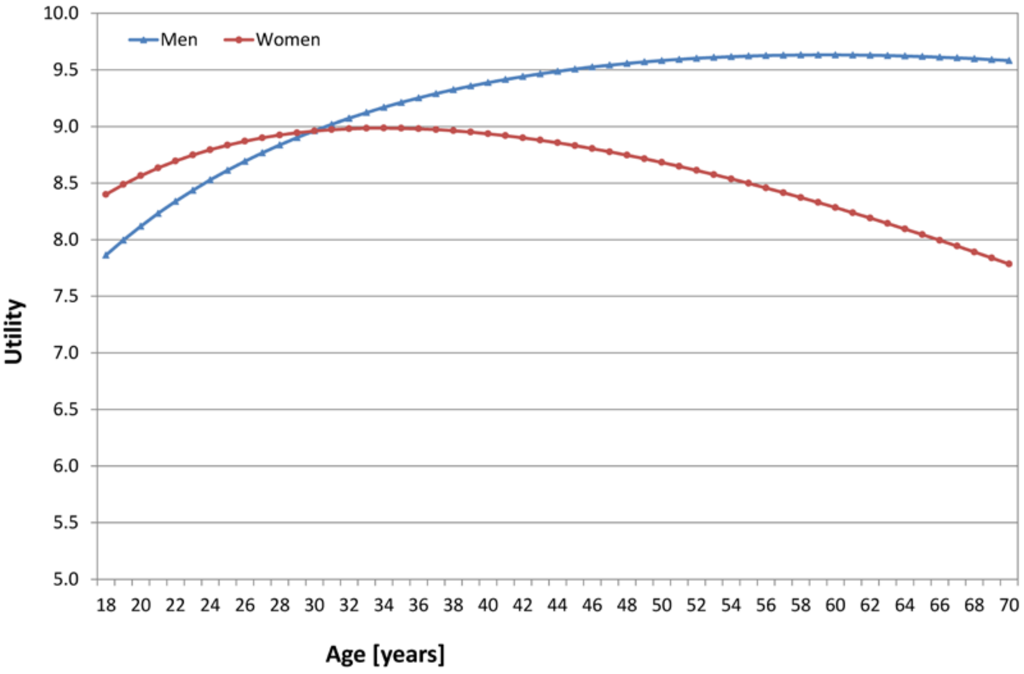


Figure 1: Utility with respect to age and gender

In order to determine the primary driver from two or more candidates in a household, first the probability p of being the main driver needs is calculated as follows

$$p = \frac{1}{1 - e^{-z}}, \tag{1}$$

where z is defined as

$$z = b_1 * x_1 + b_2 * x_2 + \ldots + b_n * x_n + a \tag{2}$$

with b_i being the estimated model parameters and a the constant listed in Table 1, while x_i represent the values of the explanatory variables.

A representation of this logit model is implemented into the agent-based demand model TAPAS. The probability for being a primary driver of a vehicle which is delivered by the logit model is used as a sorting criterion for the household member list. The estimated coefficients are directly embedded into the implementation.

Car allocation by household optimisation

Daily activities are assumed to follow a once decided pattern. When planning the day, the accessibility of activities as well as the costs to reach them are taken into account. One assumes that a household tries to optimise both, its overall accessibility and costs. Both measures highly depend on the available and used modes of transport. Because household members belong to various person groups with different budgets for travelling, mainly in terms of money and time, they perceive these measures differently. Thereby, a proper assignment of available mobility options to distinct household members is necessary to achieve the needed accessibility. The assignment also determines the household's travelling costs.

Being based on the daily activities, this approach represents a rather short-term allocation of vehicles to drivers, even though one can assume that daily usage patterns highly influence long-term decisions, and vice versa. Still, this approach includes short-term aspects, such as reacting to changes in daily plans.

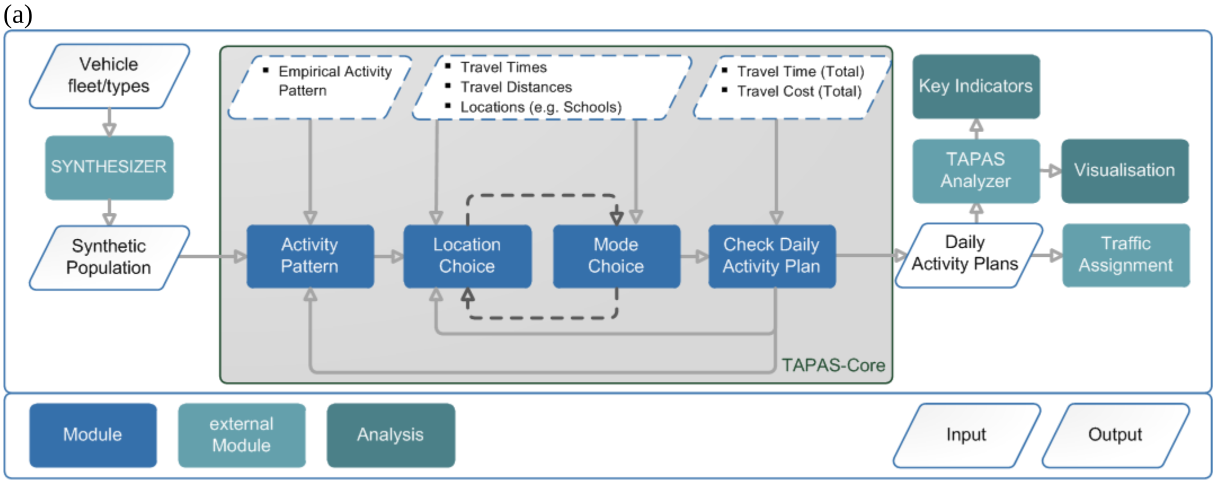
Instead of sorting the persons within a household, the computation of the daily plan is performed with and without car availability for every driver in a household in those cases where the household owns one or more cars. This results in one plan with car usage and one without car usage for every potential driver. All permutations of these daily plans are checked for feasibility with respect to the temporal and financial budget of the individuals, which is calculated based on deviations of the simulated daily plan compared to the reference plan from the household survey. The acceptance function is explained more in detail in the next section. An example for a household with three persons possessing a driving licence but only one available car is shown in Table 2. The picked best permutation in this example is printed in bold..

Table 2: Household acceptance probabilities

Available cars: 1		Driving licenses: 3	
Mode	Person 1(%)	Person 2 (%)	Person 3 (%)
with car	87%	**68%**	76%
w/o car	**88%**	41%	**70%**

Feasible combinations are then weighted by the sum of the individual acceptance of the persons' plans they consist of. The combination with the best overall acceptance is chosen. In contrast to the previous models, the implementation of the household optimisation does not yet consider the possibility to pass a used vehicle to another household member when both are at home during the day. The integration of this extension into the existing simulation system is shown in Figure 2 (b).

(a)



(b)

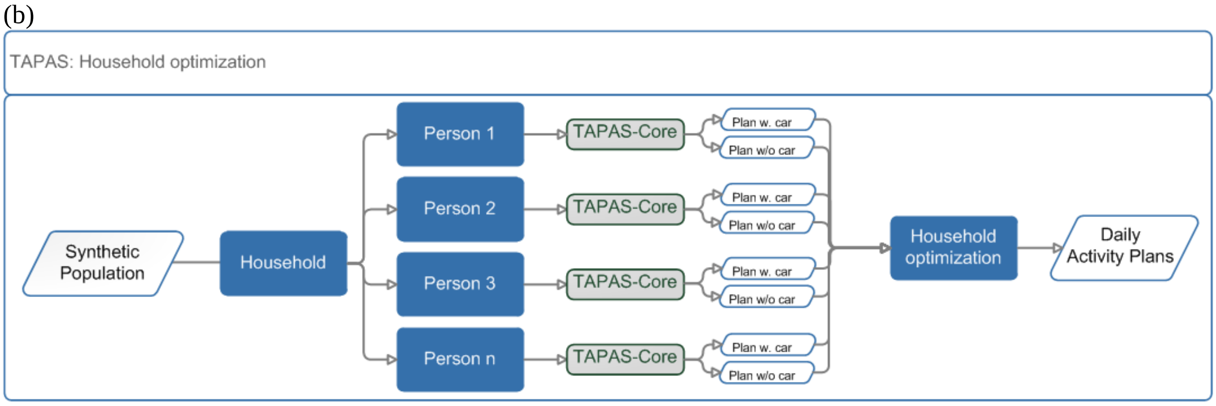


Figure 2: TAPAS flow chart. (a) Core TAPAS functionality. (b) Household optimization extension to TAPAS

Simulation system

In order to analyse the influence of car allocation on travel behaviour, namely the mode choice, the proposed methods for car allocation are integrated in the microscopic activity-based travel demand model (ABM) called Travel and Activity PAtterns Simulation (TAPAS). Figure 2 (a) shows the flow chart of the simulation model.

The synthetic population consists of persons grouped to households. It is generated using the so-called SYNTHESIZER module. During the population generation procedure, households are assigned up to two specific types of cars depending on their household attributes. Hereby, size and structure of the vehicle fleet in the study area is replicated.

For each individual, the demand generation starts with the selection of a base activity pattern from a set of reported activity diaries that is matching the individual's socio-demographic and socio-economic attributes. Subsequently, for each tour in the pattern, an interrelated location and mode choice is executed. Location choice currently follows a gravity-based approach. Mode choice is implemented as a multinomial logit model. Here, the car allocation within the household takes place for determining the availability of a car for the respectively regarded person. Finally, an acceptance probability is computed for the obtained person plan using a two-step approach. First, the deviation between the simulated and the reported travel time of the whole plan is calculated. The so-called EVA-function (Lohse, Lätzsch and Schnabel, 1997) is used as an acceptance function with a turning point at 50% deviation. Therefore, plans with a travel time deviation of more than 50% are most likely to be rejected. Second, the costs for this plan are compared against the average mobility budget on an individual level. If the costs exceed the average mobility budget by 50%, the plan is very likely to be rejected. Plans which cost less than the average budget cannot be rejected according to the budget check but only because of the travel time check.

The main result of a TAPAS simulation is a day plan for each person contained in the simulated population. This day plan includes activities, their locations, the traffic mode used to reach them, as well as the respective travel time and the time of the subsequent activity. Methodological details can be found in Heinrichs *et al.* (2016).

The model is calibrated by adjusting the search radius of the location choice for each type of activity and their possible destinations to achieve a valid modal split. As reference data for the modal split, the two household travel surveys “Mobility in Cities – SrV 2008” (Ahrens, 2009) and “Mobility in Germany – MiD 2008” (Lenz, Nobis, Köhler, Mehlin, Follmer, Gruschwitz, Jesske and Quandt, 2010) for Berlin are considered. The calibration results regarding the modal split are shown in Table 3, indicating solely small deviation between TAPAS and the data of the two household travel surveys. The highest absolute difference observed amounts to only 2.7%.

Table 3: Calibration results of TAPAS in comparison to SrV 2008 and MiD 2008 data

Modal split	TAPAS 2008	SrV 2008	Difference SrV 2008	MiD 2008	Difference MiD 2008
Walking	27.4%	28.1%	– 0.7%	27.4%	+ 0.0%
Cycling	12.6%	12.5%	+ 0.1%	12.2%	+ 0.5%
Car driver	25.4%	25.1%	+ 0.3%	28.1%	– 2.7%
Car passenger	9.0%	6.4%	+ 2.6%	7.9%	+ 1.1%
Public transport	25.6%	27.0%	– 1.4%	24.2%	+ 1.4%
Other modes	0.0%	0.9%	– 0.9%	0.3%	– 0.3%

With respect to car allocation, every household member holding a driving licence is generally allowed to use household cars. When the mode choice procedure is called at the beginning of a tour, the availability of a remaining household car is determined. Once a specific car is chosen for a tour, it is marked as unavailable for other users until it returns home at the end of the tour. Thus, multiple household members may use the same car in the course of the day if there is no time conflict. At the same time, car availability depends strongly on the within-household competition, given by the number of potential car drivers competing for the set of cars at hand. As individuals processed first may choose amongst all of the households' cars, the latter become more and more unlikely to be available for the subsequently processed household members. Consequently, car availability depends heavily on the order in which persons are handled.

Before finishing the processing of a person, the constructed activity plan is checked for feasibility with respect to the simulated person's time and budget constraints as described above. If the plan is rejected, first new locations and modes are tried. If this does not result in acceptable plans, new activity patterns are chosen until an acceptable plan is found or a prior defined threshold of retries is reached. If a rejected plan contains a car trip, the car is released to be available for other household members. Details on the validation procedure are given in the next section.

For this case study, a model set up for the city of Berlin, Germany, with 3.4 million inhabitants in 1.9 million households owning 1.3 million cars, is used. Figure 3 shows the car ownership of the households forming the synthetic population in TAPAS, grouped into car deficient and car sufficient households. Car deficiency is observed in households with less available cars than potential drivers, so that a certain competition exists within the household. In contrast, car sufficiency is defined by an equal number of drivers and cars or even more cars than drivers. Car sufficiency is observed in 56% of the households, while the share of households with fewer cars than drivers amounts accordingly to 44%. For car deficient households, the shares of households with no or only one car are significantly higher than for car sufficient ones.

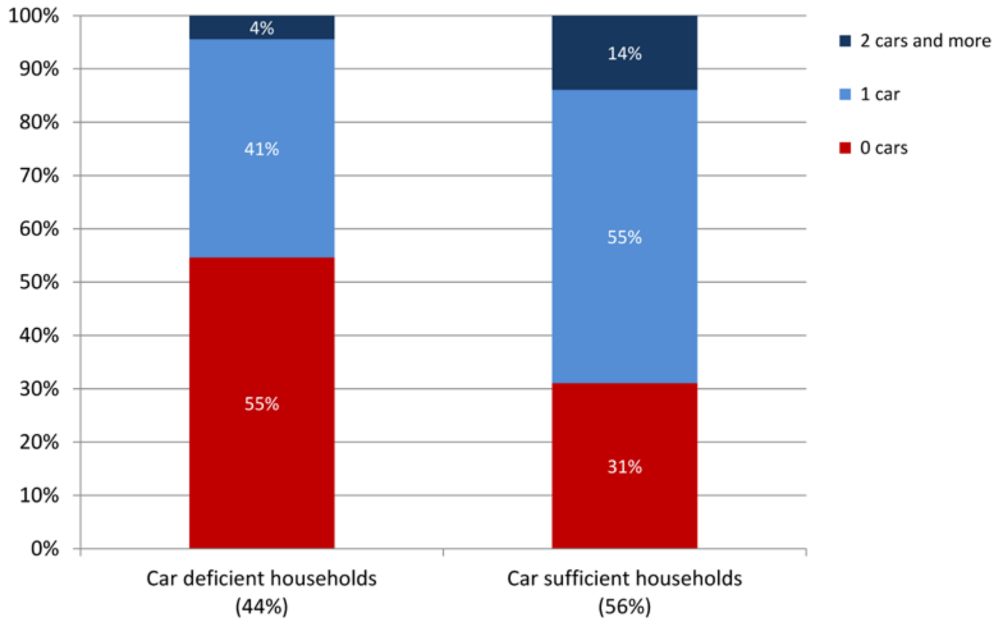


Figure 3: Household car ownership of the synthetic population in TAPAS

Comparison of car allocation methods

In the following, the simulation results for the four implementations of car allocation in TAPAS are compared with one another as well as with data of a household travel survey, namely the so-called system of representative travel surveys “Mobility in Cities” (SrV), for Berlin from the year 2008. The SrV survey collects behavioural data for weekday mobility and travel in various cities. The results are presented by discussing different performance indicators used for measuring the travel demand model’s quality in terms of resembling reality.

Modal split

In a first step, the general modal split is analysed. Overall, the modal splits for the various implementations of car allocation are quite similar and only small deviations occur. This especially applies to the first three simulations, with shares of car use ranging between 25.2% and 25.5% for driver and being 9.0% for passengers. Comparing these three models to the mobility survey data (24.7% car drivers and 7.6% car passengers), the shares of the two car modes are slightly higher. For the model where car allocation is implemented by optimising the acceptance rates of all plans for the entire household, the occurring differences in the modal split are somewhat higher. Here, trips as driver are underrepresented, while trips as passenger are overrepresented, compared to the real-world data.

In a second step, the car usage as driver is differentiated by age and gender. Figure 4 illustrates on the one hand the shares of car use for the four different implementations of car allocation and for the SrV 2008. On the other hand, it shows the differences in these shares with respect to the household mobility survey data. Concurrent with the expectations, car use as a driver strongly rises starting with the age of 18 years when individuals are able to acquire driving licences and therefore drive cars themselves. This increase continues until the age of about 45 years when it reaches its maximum share of approximately 35%. From the age of about 55 years onwards, a strong decline is observed.

Comparing the different models and the data of the mobility survey, the implementation via household optimisation is closest to the observed data. However, the variations in car use on the plateau between the ages from 45 to 55 years are only reproduced to a small extent. These up- and down-turns are better represented by the two models considering age (car allocation by age and main driver assignment), while the random approach lies above these two models with no observable variations at all. Larger differences occur when gender is taken into account. The data of the SrV 2008 for Berlin shows considerable deviations between the male and female respondents of the survey, in particular for the older age groups. These deviations are not represented to this extent by the various models, especially for the persons aged from 45 to 65 years. For men, the random approach gives the best results, while the household optimisation shows the highest differences. For women, the opposite applies. Regarding the older individuals, the deviations diminish.

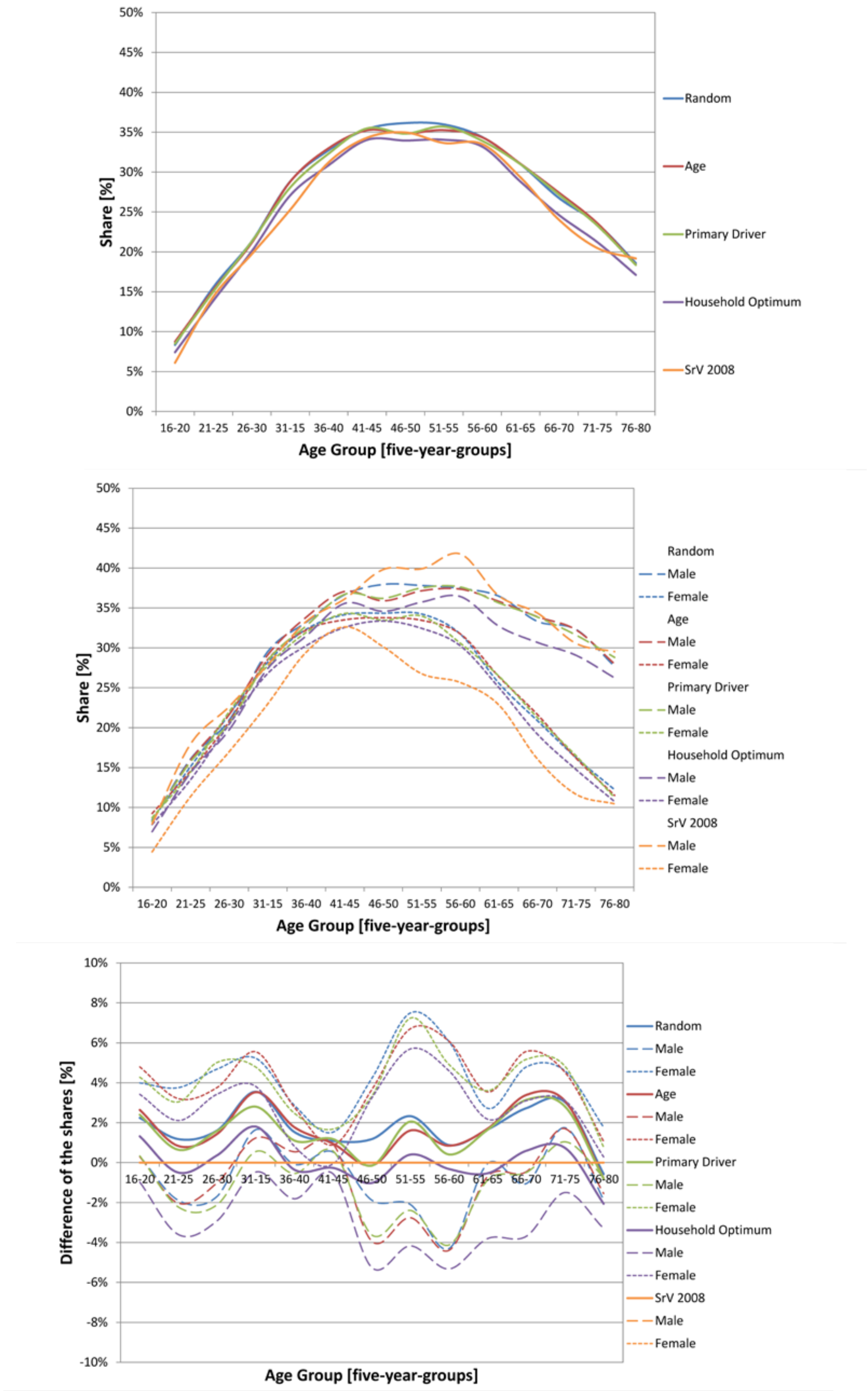


Figure 4: Comparison of the shares of car use differentiated by age and gender for the four models of car allocation and the SrV 2008. (a) Shares of car use as driver differentiated by age. (b) Shares of car use as driver differentiated by age and gender. (c) Differences of the shares of car use as driver with respect to the SrV 2008. Source: "Authors own analyses based on "Mobility in Cities – SrV 2008'', sample Berlin, Senatsverwaltung für Stadtentwicklung und Umwelt Berlin, Abteilung Verkehr

The overall standard deviations for the four models, weighted by the number of persons in each age group, are presented in Table 4, confirming the results shown in Figure 4. The lowest overall standard deviation is observed for the implementation of the household optimisation, amounting to only + 0.1%. When differentiated by gender, the values of the standard deviations increase from left to right for men, while they decrease for the female population. This indicates that household members might have different weights, when it comes to the household optimisation process. This aspect is currently not taken into account yet.

Table 4: Standard deviation of the shares of car use with respect to the SrV 2008 for the four models of car allocation

	Random car allocation	Car allocation by age	Car allocation by main driver assignment	Car allocation by household optimisation	SrV 2008 – Berlin
Overall	+ 1.7%	+ 1.5%	+ 1.4%	+ 0.1%	± 0.0%
Male	– 0.5%	– 0.7%	– 0.9%	– 2.4%	± 0.0%
Female	+ 3.8%	+ 3.6%	+ 3.6%	+ 2.5%	± 0.0%

Overall, the results of the four car allocation models and the SrV 2008 are quite similar. However, when considering only car deficient households with at least one available car (merely 20% of the households in the synthetic population in TAPAS), a slightly different picture arises, as shown in Figure 5. In this context, the data of the national household travel survey “Mobility in Germany” (MiD 2008) is incorporated, once for the entire German population and once solely for the inhabitants of Berlin. With respect to the Berlin data, the curve strongly fluctuates, due to a rather small number of cases in each age group. In general, the car use is considerably higher when only looking at car deficient households with at least one car. The lowest shares are observed for the SrV 2008, followed by the MiD 2008 for Berlin, while the data of the MiD 2008 for Germany mostly displays the highest values, especially for persons aged under 55 years. The four models for car allocation also show greater car use. The first three models, i. e. assigning cars randomly, by age and by primary driver, behave very similar, with an offset of about 10% in comparison to the SrV 2008 data. For the fourth model which is based on household optimisation, the differences are slightly lower. This means that in car deficient households with at least one car, i. e. households with a certain competition with respect to the use of the available vehicles, the four models generally overestimate car usage in comparison to real-world data.

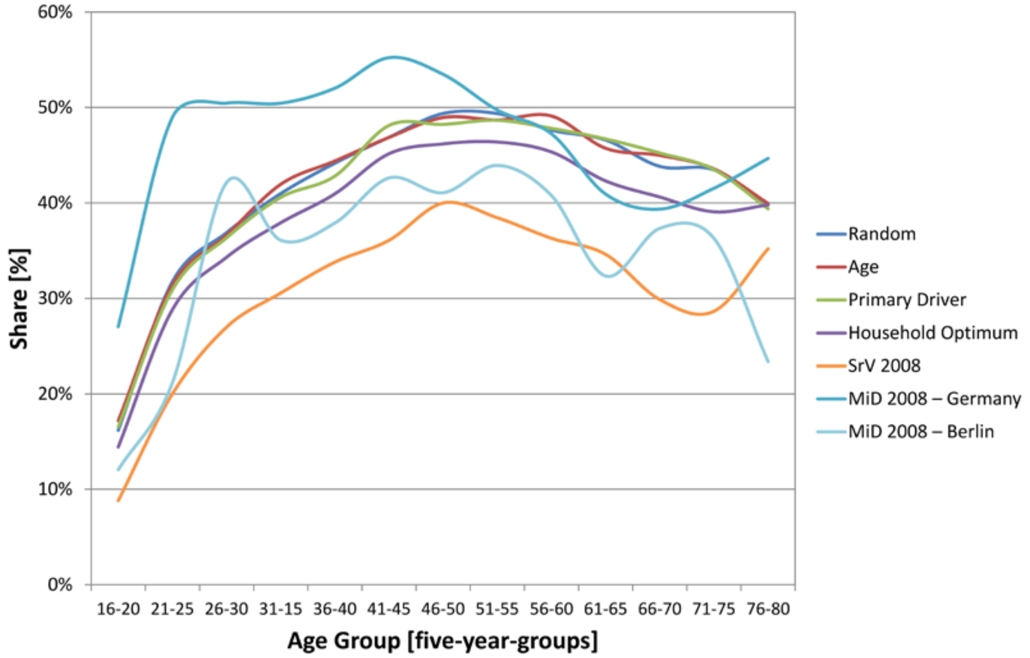


Figure 5: Comparison of the shares of car use in car deficient households with at least one car for the four models of car allocation, the SrV 2008 and the MiD 2008.

Acceptance rates

The acceptance probability of a day plan with respect to the temporal and financial budget is based on the product of two terms. First, the deviation of the modelled travel times from the ones reported in the underlying survey called “Zeitbudgeterhebung 2002” (time use survey), from which the simulated day plans are retrieved. Second, additional costs of the actual trip are compared to the average daily mobility budget. The average acceptance rate of a day plan is a good indicator of how good the model is able to find an appropriate plan.

The average acceptance rates of all persons living in households with at least one car as well as of all persons with at least one car trip, as obtained from the different models, are shown in Table 5. The car allocation used during calibration (see Table 3) was done by age. The acceptance rates for the random, age and primary driver assignment implementations are almost identical, but the household optimum strategy finds much more suitable plans for the household. Looking at the rates of the persons who actually drive a car, the difference is even larger. This indicates that the first three approaches do not identify the person who profits the most from car usage. Furthermore, the household optimum model finds a set of plans which is more acceptable for all household members.

Table 5: Average acceptance rates for the four models of car allocation

Model	Acceptance rate for all persons in households with a car	Acceptance rate for all persons with a car trip
Random car allocation	76.85%	79.00%
Car allocation by age	76.94%	78.96%
Car allocation by main driver assignment	76.87%	78.96%
Car allocation by household optimisation	82.10%	86.06%

Conclusions and outlook

In summary, all four implementations of car allocation in the activity-based model TAPAS represent car use well, replicating the dependency on age and gender, with relatively small deviations of less than 10% maximum. Still, they have difficulties reproducing the modal split to its full extent. This is especially true for the various maxima and single peaks occurring in the mobility survey data, which cannot be modelled due to generalisation. Overall, the four approaches behave very similar to one another, contrary to expectations. Nonetheless, the model which optimises car allocation for the entire household shows the best results when compared to real-world data. Between the other three models, namely the random car allocation, car allocation by age and main driver assignment, only very small differences appear. This is partly caused by the effect that only 20% of the households compete for cars (see Figure 3), while the mode share for car driver amounts to 25.4% (see Table 3). Therefore, only about 5% of all trips are sensitive to the car allocation models.

While on a general level results do not differ strongly between the four approaches, opposing trends for men and women are observed. With regard to the shares of car use as a driver, the male population is better fitted than the female one, though men are underrepresented to a small extent by all four car allocation models.

As already found for the modal split, the household optimum model performs best as well with respect to the drivers' acceptance rates. Still, the household optimum model does not represent the overall modal split so well and the corresponding reasons need further investigations, e. g. the calculation of the household optimum may use different weights for each household member based on the probability of being the main driver. Likewise, further improvements to the household optimum model can be performed. As an example, the possibility to pass a vehicle to another driver within a day can be added.

So far, only the car driver is considered in the car allocation process, while the vehicle itself with its varying attributes, such as vintage, type, size, fuel type and fuel consumption, is not taken into account. The vehicles and their attributes can be included by expanding the discrete choice modelling approach. For example, a nested logit model can be estimated, which identifies on the first level the main drivers, while on the second level, conditionally on being a main driver, one of the available household vehicles is chosen. The corresponding modelling results of such a model are described in detail in Beige and Cyganski (2015). An implementation of this approach will be investigated in future research.

Overall, the household optimum model seems to be the most exact solution. It can also be assumed to be the most robust one, because it is sensitive to changes in daily plans as well as to their weightings. However, this approach increases computation time by 85% in the used

ABM compared to the other ones due to the need to compute multiple plans per driver. Since the changes between the different presented models are small, this has to be considered when computing time is a critical issue.

While the fourth model based on optimising car usage of an entire household at a daily level performs best, the third model which considers long-term aspects by assigning a main driver to each available vehicle in a household allows for the adaptation of changes in socio-demographic and socio-economic attributes of the population as well as in driving licence and car ownership. This approach is therefore better suited for forecasting car allocation and usage in various scenarios, in which, for instance, the availability of driving licenses increases due to demographic change and the ownership of vehicles is reduced. Both developments lead to a stronger competition for the available cars within households.

References

Ahrens, G.-A. (2009) Endbericht zur Verkehrserhebung "Mobilität in Städten – SrV 2008" und Auswertungen zum SrV-Städtepegel, Institut für Verkehrsplanung und Straßenverkehr, TU Dresden, http://tu-dresden.de/die_tu_dresden/fakultaeten/vkw/ivs/srv/dateien/staedtepegel_srv2008.pdf.

Anggraini, R., T. A. Arentze and H. J. P. Timmermans (2007) Modeling car allocation decisions in automobile deficient households, paper presented at the *European Transport Conference*, Noordwijkerhout, October 2007.

Anggraini, R., T. A. Arentze and H. J. P. Timmermans (2008) Car allocation between household heads in car deficient households: A decision model, *European Journal of Transport and Infrastructure Research*, **8** (4) 301-319.

Angueira, J. R. (2014) An exploration of short-term vehicle usage decisions, Master's Theses, University of Connecticut.

Beckmann, K. J. (2013) Entwicklungslinien der Mobilität im Alter − Bedingungen und Veränderungstendenzen, in B. Schlag, and K. J. Beckmann (eds.) *Mobilität und demografische Entwicklung*, 41-75, TÜV Media GmbH, Köln.

Beige, S. and K. W. Axhausen (2008) The ownership of mobility tools during the life course, paper presented at the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2008.

Beige, S. and R. Cyganski (2015) Long-term and short-term aspects of car allocation within the household context, paper presented at the *4th Symposium of the European Association for Research in Transportation*, Lyngby, September 2015.

Bundesministeriums für Verkehr, Bau und Stadtentwicklung (2010a) *Mobilität in Deutschland 2008 – Methodenbericht*, Bonn und Berlin.

Bundesministeriums für Verkehr, Bau und Stadtentwicklung (2010b) *Mobilität in Deutschland 2008 – Ergebnisbericht*, Bonn und Berlin.

Golob, T. F., S. Kim and W. Ren (1996) How households use different types of vehicles: A structural driver allocation and usage model, *Transportation Research Part A: Policy and Practice*, **30** (2) 103-118.

Heinrichs, M., D. Krajzewicz, R. Cyganski and A. von Schmidt (2016) Disaggregated car fleets in microscopic travel demand modelling, paper presented at the *7th International Conference on Ambient Systems, Networks and Technologies*, Madrid, May 2016.

Hertkorn, G. (2005) Mikroskopische Modellierung von zeitabhängiger Verkehrsnachfrage und von Verkehrsflußmustern, Dissertation, Institute of Transport Research, German Aerospace Centre.

Lenz, B., C. Nobis, K. Köhler, M. Mehlin, R. Follmer, D. Gruschwitz, B. Jesske and S. Quandt (2010) Mobilität in Deutschland 2008 – Kurzbericht, Institute of Transport Research, German Aerospace Centre, http://elib.dlr.de/68010/.

Lohse, D., L. Lätzsch and W. Schnabel (1997) *Grundlagen der Straßenverkehrstechnik und der Verkehrsplanung*, Beuth Verlag, Berlin.

Mannering, F. L. (1983) An econometric analysis of vehicle use in multivehicle households, *Transportation Research Part A: Policy and Practice*, **17** (3) 183-189.

Nam R. H., B. H. Y. Lee, L. Aultman-Hall and J. Sears (2013) Exploration of intra-household motorized vehicle allocation using the 2009 National Household Travel Survey, paper presented at the *92nd Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2013.

Petersen, E. and P. Vovsha (2005) A framework for a joint mode choice - household car allocation model, paper presented at the *European Transport Conference*, Strasbourg, October 2005.

Petersen, E. and P. Vovsha (2006) Intra-household car type choice for different travel needs, paper presented at the *85th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2006.

Vovsha, P. and E. Petersen (2007) Incorporating car-type preferences and intra-household car allocation into travel demand models, paper presented at the *86th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2007.

Vyas, G., R. Paleti, C. R. Bhat, K. G. Goulias, R. M. Pendyala, H. Hu, T. J. Adler and A. Bahreinian (2012) A joint vehicle holdings (type and vintage) and primary driver assignment model with an application for California, paper presented at the *91st Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2012.