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Disaggregated car fleets in microscopic travel demand modelling

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Abstract

Microscopic travel demand models take the characteristics of every individual person of the modeled population into account for computing the travel demand for the modeled region. The real world mobility of individuals strongly depends on the specific available car, if any. However, mode choice models usually take a standard average car as reference. This paper shows an integrated approach to model the travel demand with respect to car specific attributes. The proposed work uses a synthetic population for the German capital of Berlin and simulates the travel demand for different examples that replicate car specific changes in fuel price, fleet distribution and entrance restriction. Some of these car-specific measures influence the travel behavior on a level that cannot be modeled when using an average car at all. Furthermore, the results show significant changes in usage of specific car segments, which would be difficult to model using an averaged car.

*Keywords:*travel demand; microscopic modeling; car fleet; disaggregated cars; agent based modeling

1. Motivation

Classic 4-step transport models have been dominating the operational use for traffic simulation, measure assessment and decision making for a long time. But flow-orientated modelling has certain limits, such as hardly achievable consistencies of trip chains or of shared resources as cars in the same household. This led to the idea, that transport is the sum of trips of individual persons, finally resulting in microscopic demand models[13]. These microscopic approaches maintain personal attributes as driving licenses and manage shared household resources such as the available cars for computing consistent daily activity patterns. Current microscopic travel demand models generate the travel behavior for every person in a synthetic population with respect to the person's household context to determine the population's reactions of changes in costs, travel time and/or demand. Often, an averaged vehicle is used. But the typical usage of an averaged vehicle does not take the individual costs of the vehicle's usage into account, which largely depend on the car's fuel consumption and type of engine. Therefore, growing interest in disaggregated car fleet appears as logical extension for microscopic travel demand models

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and has been implemented in various models[4,11]. However, car-specific attributes are often limited to load capacity and costs but do not extend to fleet distribution and location choice.

Currently travel demand models are increasingly applied to evaluate emission measures in local areas, such as access zones for different engine types[14]. Exempting electric vehicles from parking fees and taxes are also investigated[8], which has a major impact on mode choice and furthermore on the whole trip chain. Such car specific restrictions that have a significant impact on travel demand cannot be modeled adequately using a standard average car.

In this work, an approach to integrate a disaggregated car fleet in a microscopic travel demand model is presented. The simulated persons adopt their mode and location choice with respect to their personal car-specific costs and restrictions. The proposed approach is evaluated in different scenarios with varying prices, fleet structure and accessibility. The results show that the resulting behavior can be better interpreted if cars are not represented by an average standard instance.

The remainder is structured as follows. At first, the travel demand model used within the research is described in section 2. In section 3, the used simulation scenarios are explained. The results are given in section 4. This document ends with a summary, given in section 5.

2. Proposed model

This work presents the integration of a disaggregated car fleet in a microscopic activity based travel demand model called Travel-Activity PAttern Simulation (TAPAS)[9] and shows an application example for vehicle-specific measurements including access zones and fuel pricing.

Fig. 1 shows the flow chart of the simulation model which consists of four parts: population generation, activity generation, location choice and mode choice. The result of a TAPAS simulation mainly consists of a day plan for each person contained in the simulated population. This day plan consists of activities, locations, used modes, as well as travel-times. The final plan is checked for feasibility with respect to the simulated person's time and budget constraints. If the plan gets rejected, plan generation is repeated until an acceptable plan is found.

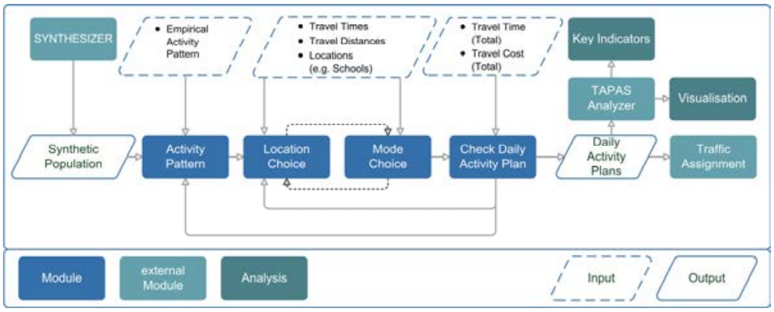

Fig. 1. TAPAS flow chart

The population in TAPAS is generated by combining various statistical data. Therefore the well-known Iterative Proportional Fitting (IPF) approach[3,7] was used to estimate household and person-level joint distributions for 12 different districts of Berlin. Afterwards, these distributions were used within the Iterative Proportional Updating (IPU) algorithm[17] for calculating sample household weights. This weight-based procedure for stochastic drawing of households results in the generation of a synthetic population that closely matches household and person-level distributions[17]. Finally, the households are further spatially distributed over the study area based on population density per block building. Each person of the synthetic population includes socio-demographic characteristics such as age, gender, employment status, mobility budget, public transport ticket, driver license and bike ownership. The associated households' attributes comprise the number of members, a specific total income and an available number of cars. The resulting population is stored in a database and can used for simulating different scenarios.

The car ownership is modelled by assigning an externally specified fleet, which consists of the numbers of vehicles per size, value, and fuel-type. Each household has an affinity to own up to two cars based on household size, income and number of driving licenses. The car affinity is derived from data of the SrV2008[1], one of the large national household time studies (NHTS) in Germany. Shares are expressed by a probability vector for having zero, one or two cars.

TAPAS computes the daily activity plan for each person by finding locations for each activity and determining the mode to get there. The individual persons are processed at household level. All persons from a synthetic household are processed individually but are limited by the household constraints like car availability and mobility budget. Consequently, a car can only be used by different persons, if no overlap in time occurs. The activities are derived from reported diaries stemming from a German time budget survey[18]. The activities are subdivided into education, work, shopping, private matters, leisure and study. To increase the variance of possible day plans persons and plans are grouped to several classes called person groups and activity scheme classes, respectively. Every person group has a probability vector for choosing one of the activity scheme classes. The probability to draw a specific plan from scheme class is equally distributed[15].

After selecting the day plan for each individual, the activities are processed in a hierarchical way (see Fig. 2). Trips of high priority like work or education are processed first. Afterwards, activities of lesser priority are inserted in the trip-chain by splitting existing trips from the previous step whereby limitations in mode- and location-choice are taken into account, especially in case of modes using cars and bikes, which have to be returned at the end of the trip.

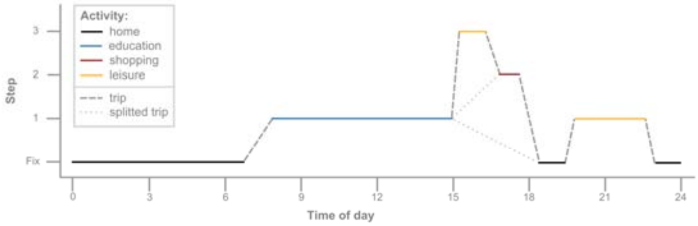

Fig. 2. hierarchy of activities

For each activity, possible destinations are selected based on available transport modes, mode specific accessibility, remaining capacity, previous and next destinations, time budget and an empirically determined search radius. The mode specific accessibility takes vehicle restrictions into account. The access to restricted zones can be prohibited for certain modes or vehicle classes and hence become less attractive for persons possessing restricted vehicles.

Next, a specific mode is chosen, based on the availability of bikes and cars, driving licenses, costs, travel times, local restrictions, a season ticket, age, trip-purpose and the distance to the destination. All these factors are taken into account by a multinomial logit model. The costs for car trips are calculated using the specific cost factors of the used vehicle. Additionally, parking fees for the duration of the stay are added, if parking is charged in the destination area.

Finally the total travel time and costs are compared to the original time and monthly mobility budget. In case of rejecting the proposed day plan a new day plan is selected and the requirements are tested again.

The car fleet can be exchanged separately from the synthetic population. This makes delta analysis possible and specific effects of certain car fleet segments can be modeled. The cars have attributes for size, fuel type, costs per kilometer, maximum range, and restrictions that are specific to certain areas of the simulated region. Every household owning cars is equipped with unique instances of specific cars, enabling vehicle specific cost calculation.

Table 1: Mode Share comparison for 2008

Mode	SrV2008	MiD2008	TAPAS	Deviation SrV	Deviation MiD
Walk	28.1	27.4	28.9	0.8	1.6
Bike	12.5	12.2	15.5	3.0	3.3
Car	25.1	28.1	27.6	2.5	-0.5
Car passenger	6.4	7.9	5.8	-0.6	-2.1
Public Transport	27.0	24.2	22.2	-4.8	-2.0
Others	0.9	0.3	0.0	-0.9	-0.3
No. of trips	329816	7859	13955041	-	-

The model has been calibrated by adjusting the search-radius of the location choice for each type of activities and their possible destinations to achieve a valid modal split. As reference data for modal split, the survey SrV 2008 and MiD 2008[20] for Berlin have been taken. The results are shown in Table 1. The validation shows an underestimation of public transport (PT) and overestimation of the main competing modes bike and car compared to the SrV. The MiD shows similar results, except, that this survey reports a higher car and car passenger share than the SrV as well as TAPAS. The underestimation of PT is mainly caused by difficulties in properly locating access points and by the used model for PT-travel time calculation: The used PT-network is modelled based on frequencies and not on scheduled times. This results in higher waiting and transfer times compared to the real network. Therefore, the modeled public transport system is less attractive than the reference data. However, the scope of this paper is on car trips and the named shortcome of the model can be ignored for now.

3. Defining the simulated area and example measures

The model has been used to simulate the travel behavior of an average week day for all modes of transport within a regional analysis area[10,12]. In this example, the simulation covers the area of the city of Berlin, Germany, with 3.3 million inhabitants. The population, the car fleet and the fuel prices have been parametrized to meet the values of the reference year 2010 of the official traffic forecast VP2030[16]. The population distribution is sampled from the official German census data[19] and consists of 3.3 million persons living in 1.9 million households. The sample is fitted to meet the distribution of age, gender, status, household size and income . The availability of driving licenses and season tickets is modelled based on gender, status and age using data from the SrV2008. The distribution of age, household size, income and driver licenses of the resulting synthetic population are shown in Fig. 3.

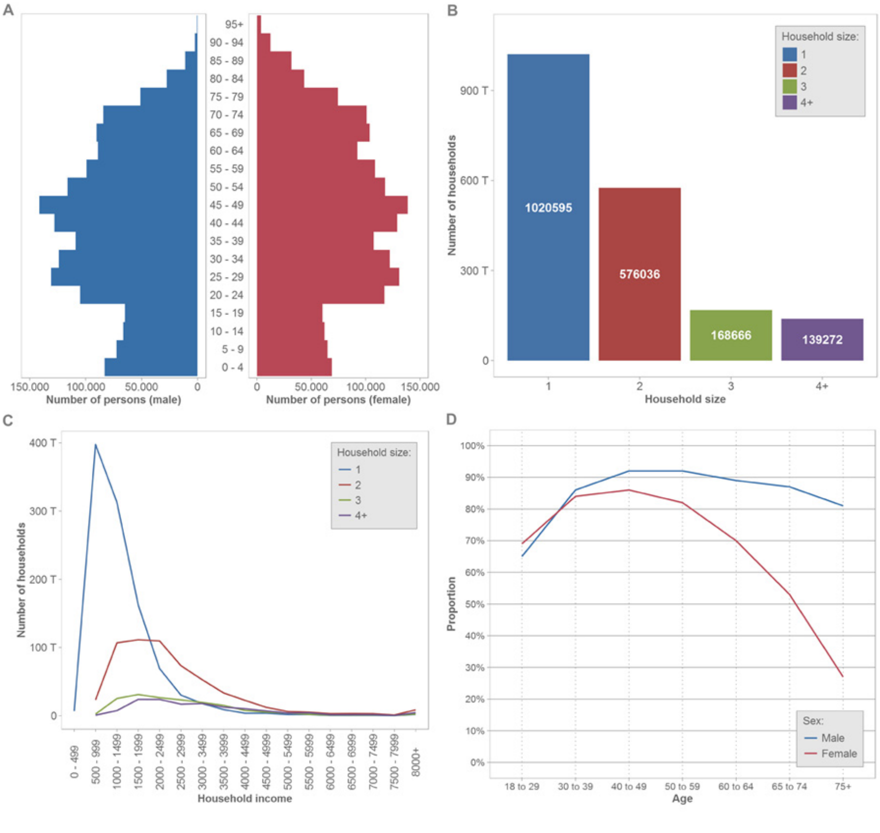

Fig. 3. (a) age pyramid; (b) household size; (c) income; (d) driver license of the synthetic population of Berlin 2010

The car fleet is distributed based on income, household size and driving license availability with a maximum of two cars per household, reflecting the share of less than 1% of households possessing more cars in Berlin. After all, 41% of the synthetic households have no car, 49% have one car and 10% have two cars. Unfortunately, the population density is not integrated in the distribution algorithm because of insufficient spatial resolution of the data. This leads to a slightly overestimated motorization rate in the inner city. The motorization-rate and cars per km² can be seen in Fig. 4.

The car fleet is segregated in three engine classes: gasoline, diesel and a combination of compressed natural gas (CNG) and liquefied petroleum gas (LPG) vehicles. The German market share of other engine types was marginal in 2010 and is therefore not accounted for. The average costs are shown in Table 2 and are calculated based on fuel prices, consumption, taxes and distribution costs[5].

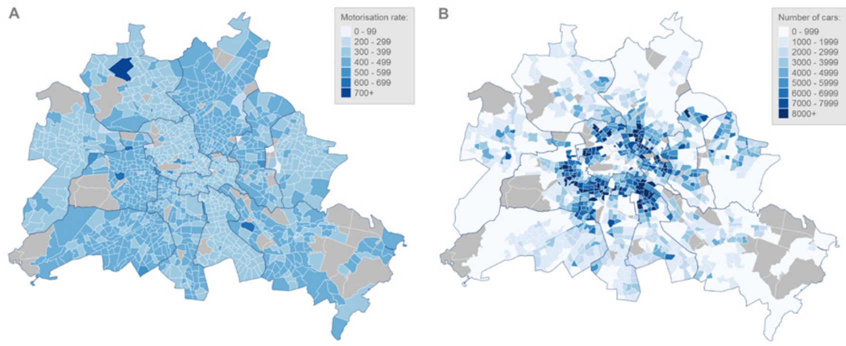

Fig. 4. (a) cars per 1000 persons; (b) number of cars, per km²

Table 2: Kilometre costs by fuel type

Scenario	Gasoline	Diesel	Gas
Scenario 1	11.6ct/km	8.9ct/km	5.5ct/km
Scenario 2-4	11.6ct/km	11.6ct/km	5.5ct/km

The distribution of engine types is based on the official registration statistics for 2010[6]. The total number of cars is taken from the SrV2008 and not from the official registration office, because the SrV2013[2] reports that 20% of the cars owned by the population of Berlin are registered elsewhere and therefore the official numbers of registered vehicles do not represent the real number of cars used in Berlin. The numbers are shown in Table 3.

Table 3: Number of cars and fuel type distribution

Scenario	Total	Gasoline	Diesel	CNG/LPG
Scenario 1-2	1300333	962246 (74.0%)	323913 (24.9%)	14174 (1.1%)
Scenario 3-4	1300333	976172 (75.1%)	194472 (15.0%)	129689 (9.9%)

Four scenarios are simulated for examining the effects of different car fleets:

1. The reference scenario for 2010
2. The same fleet with different fuel prices (Table 2)
3. A different fleet where diesel cars owned by people in the inner city are replaced by CNG/LPG vehicles (Table 3)
4. Same as 3 but with an access restriction for diesel cars of the city centre (see Fig. 5).

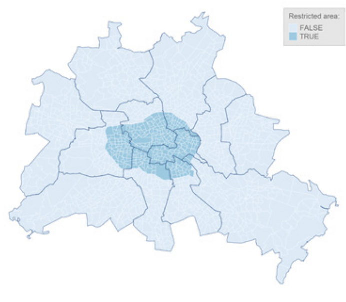

Fig. 5. restricted area in Berlin

The last two scenarios show the effects of using disaggregated vehicle fleet distributions in conjunction with access restrictions. Due to fine particulate regulations high polluting cars have been banned in the city center since 2008. This might happen again for regulating NO_x emissions and the scenarios three and four replicate variants of such a measure. In the third and fourth scenario the fleet in the model is distributed differently: In these scenarios we assume that 10% of the diesel-share is transformed to CNG/LPG and gasoline cars. Within the city center only CNG/LPG and gasoline cars are distributed, while the remaining diesel cars are distributed in the outer areas only. Furthermore, the remaining diesel fleet in the outskirts cannot access the city center in the fourth scenario, which heavily influences mode and location choice for the affected households. Finally, the reference scenario is calculated 3 times to analyze the stability of the results.

4. Results

In this section, the results from the simulation of the travel demand from the four scenarios are shown and discussed. First, the variation of runs with same parameters is analyzed to quantify the stability of the proposed model. Second, we briefly discuss the overall model results. Third, a car-specific analysis of the results is given, pointing out how it delivers more insight to the modelled scenarios.

Several simulation runs of the same parameters in Table 4 show that a difference of 0.1% in mode share and 25 meters in the average trip length are caused only by random factors of the trip generation. Deviations of this magnitude cannot be distinguished from random noise in the simulation.

Table 4: Variation of different runs of the same scenario

	Scenario 1, Run 1		Scenario 1, Run 2		Scenario 1, Run 3	
	No. of trips: 13972214		No. of trips: 13967214		No. of trips: 13976654	
Mode	Modal Split	Avg. length	Modal Split	Avg. length	Modal Split	Avg. length
Walk	28.92%	1364.12	28.93%	1365.16	28.90%	1365.20
Bike	15.62%	4261.02	15.56%	4263.73	15.55%	4265.99
Car	27.59%	6874.43	27.62%	6899.43	27.62%	6901.31
Car pas.	5.80%	6969.53	5.80%	6985.93	5.80%	6985.30
PT	22.08%	7228.79	22.10%	7245.76	22.12%	7253.98

The overall scenario results for modal split, trip lengths per mode and activity type are shown in Table 5. Surprisingly, no significant change can be found in the numbers of trips, mode shares or trip lengths within the first three scenarios' results. The moderate price changes for diesel and fleet distribution seems to have only little effect on mode and location choice, if any. Only the fourth scenario has a small reduction of 0.58% car trips compared to the scenario 1 but no significant changes in trip-lengths.

Table 5: Number of trips, modal split and trip lengths of different scenarios

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	No. of trips: 13972214		No. of trips: 13970441		No. of trips: 13967901		No. of trips: 13967088	
Mode	Modal Split	Avg. length	Modal Split	Avg. length	Modal Split	Avg. length	Modal Split	Avg. length
Walk	28.92%	1364.12	28.94%	1364.11	28.93%	1364.94	28.95%	1364.24
Bike	15.62%	4261.02	15.61%	4266.60	15.60%	4259.84	15.71%	4276.17
Car	27.59%	6874.43	27.48%	6875.20	27.57%	6872.65	27.03%	6861.01
Car pas.	5.80%	6969.53	5.83%	6991.12	5.80%	6974.51	5.96%	7037.66
PT	22.08%	7228.79	22.15%	7244.77	22.10%	7231.00	22.34%	7254.53

For achieving further insight, the trip lengths and volumes per car type for each scenario were analyzed. The trip lengths of other modes are not shown, because they do not differ significantly. The results are shown in Fig. 6. In scenario 1, diesel and CNG/LPG cars show a higher average trip-length compared to gasoline ones, because of the lower costs per kilometer. This is an expected effect since mode choice is related to the actual trip costs, which are calculated using the costs of the available car.

The prices of diesel and gasoline fuels are set equal in scenario 2. Hence, the costs per trip during the mode choice are the same. As a result, the trip-length of these two fuel types does not differ significantly in this scenario. The average trip length of diesel cars drops by 5% compared to scenario 1. Furthermore the number of trips with diesel cars drops by 5%, resulting in a total decrease of traffic volume by diesel cars by 19%.

In the third scenario all diesel cars are assigned to households outside the city center. The prices are not changed compared to scenario 2. Still, the average trip length of diesel cars increased by 14% and the trip length of CNG/LPG cars drops slightly, due to the reassignment of diesel cars to the outer city region. If the comparison base in scenario 2 is limited to trips starting in the outer area, the trip length of diesel cars does not differ anymore to scenario 3 (see Table 6 row "2 – outer city"). Households in these outer areas have fewer opportunities and therefore longer distances to travel. Furthermore the other two car types are concentrated in the city center, which results in slightly shorter trip lengths.

The fourth scenario shows three effects compared to scenario 3. First, the mode share of car trips decreases by 0.54%, which results in less car trips (see Table 5). Second, the number of diesel car trips is dropping by more than 34%. This is caused by the inaccessibility of locations in the restricted zone, which makes trips by diesel cars less attractive. Third, the lengths of the remaining diesel trips decreased by 1.7% or respectively 119m in average. Longer trips could have been expected, because of inaccessible inner city locations, but the remaining accessible locations for diesel cars are either local or too far away, resulting in a preference for short local trips. As a result, the traffic volume of the total diesel fleet drops 35.0% compared to scenario 3. Trip numbers and lengths of the two other engine types show no significant difference in behavior between the last two scenarios.

Table 6: Results of car segments

Scenario	Car type	Number of trips	Avg. Trip length in m	Traffic volume in 1000km
1	gasoline	2631989	6856	18045
1	diesel	1167222	6913	8069
1	CNG/LPG	55189	6934	383
2	gasoline	2634248	6869	18095
2	diesel	1150246	6882	7916
2 - outer city	diesel	788989	7158	5648
2	CNG/LPG	54752	7031	385
3	gasoline	2826412	6804	19230
3	diesel	634328	7169	4547
3	CNG/LPG	390437	6889	2690
4	gasoline	2949548	6827	20135
4	diesel	419206	7050	2955
4	CNG/LPG	406756	6916	2813

Finally, the change in trip distribution of diesel cars for scenario 2 to 4 is analyzed. Since the total number of trips differs, the coloring of Fig. 6 is based on the trip volume of diesel cars going to each cell, normalized by the maximum value within the respective scenario. Thus, coloring does not reflect the absolute trip numbers but the proportion compared to all other cells. Scenario 2 (Fig. 6-a) shows the typical concentration of trips towards the city-center. Scenario 3 shows a significant reduction of trips by diesel cars in the inner city, because only diesel car trips being outside of the zone are possible. In the fourth scenario (Fig. 6 –c) one sees the concentration of the outer areas, because of the access restriction of the inner city.

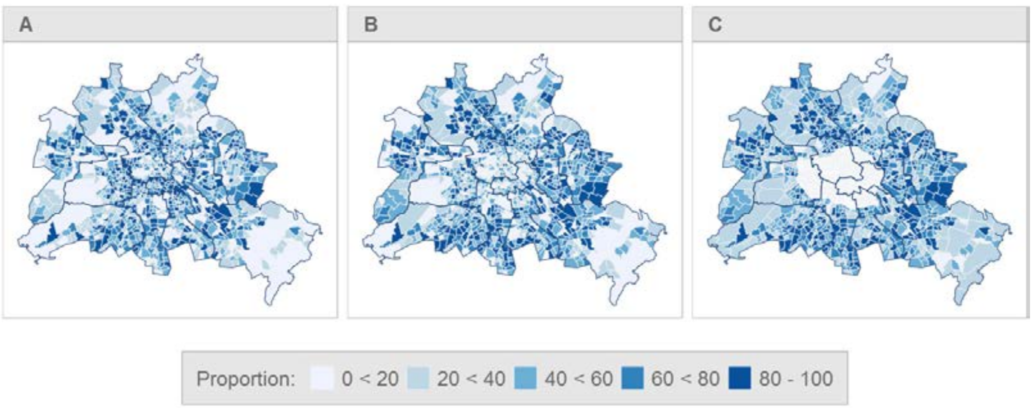

Fig. 6. traffic distribution of diesel car-trips for scenario 2-4 (a-c)

5. Conclusion

The presented work illustrates the benefits of disaggregated car fleets in microscopic travel demand modelling. It has been shown that car-specific costs and restrictions might result in unnoticeable changes of the total traffic volume and the low mode share changes between the scenarios hide the existing shifts that can be observed for different car fleet segments. Only models that distinguish between different car types are capable to reproduce such changes. This enables analysts to assess effects of specific measures more accurately, especially if only smaller fractions of the car fleet are affected.

The correct parametrization of a used car within the simulation makes the simulated travel behavior reacting on specific price changes. Changes in the car fleet structure can be thereby evaluated, especially if type specific changes in availability, costs, access and parking fees are part of municipal measures. Future extensions like car specific ranges, road charges, or parking spaces can be better modeled and analyzed.

However the question, who owns, buys, sells or changes a specific car type has to be investigated more deeply to make better long-term predictions of travel demand possible.

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