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# Integrating automated vehicles into macroscopic travel demand models

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**Abstract**

The development of vehicles with increasing levels of automation will change transport supply and is likely to influence travel demand. The paper looks at ways of integrating characteristics of AV and AV-related mobility services in traditional macroscopic travel demand models based on the four-stage algorithm. It suggests a framework for (1) modelling impacts of AV on network performance and capacity, for (2) modelling impacts of AV on travel demand and for (3) modelling impacts of vehiclesharing systems on empty trips and the bundling of ridesharing trips. To model capacity three approaches are described quantifying capacity in passenger car units, in vehicle units and in time units. For mode choice approaches with a Multinomial Logit model, a Nested Logit model and a Cross-Nested Logit model are compared.


Peer-review under responsibility of the scientific committee of the mobil.TUM 2018 conference.

*Keywords:* Automated vehicles, macroscopic travel demand model, road capacity, vehiclesharing systems

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## 1. Problem Statement

The development of vehicles with increasing levels of automation will change transport supply and is likely to influence travel demand. Currently it seems impossible to forecast the point in time when driverless cars will be ready to serve the entire road network on level 5 according to the SAE standards (SAE 2014). The probability, however, that this time will come is high and the path to fully automated driving already brings major changes. Therefore, transport planning should address the topic of automated vehicles (AV) and connected automated vehicles (CAV). AV and CAV may influence the transport supply in the following ways:

- Road safety will increase. Fewer accidents reduce the number of traffic states with capacity reductions and thus increase travel time reliability.
- The capacity of the road network may increase at least on roads restricted to motorized vehicles. This will increase travel time reliability and reduce delay time.
- AV sharing the same road space with non-motorized traffic may require certain road conditions to operate safely. This could necessitate speed limits in the feeder network.
- CAV of level 5 make carsharing and ridesharing services more efficient as vehicles can be reallocated without driver.
- Driverless buses will reduce operating costs for public transport.

These changes in transport supply will have impacts on the travel behavior and the resulting travel demand:

- Traveling by car becomes more comfortable as in-vehicle time can be used for activities not related to driving.
- Private and shared cars of level 5 can be used by travelers without a driving license or by travelers who are not able to drive a car.
- Taxi-robots, short- and long-distance carsharing and ridesharing services will provide alternative travel options.
- Using a car no longer requires car ownership. This can reduce the threshold for car usage.
- Traveling may become cheaper.

The changes obviously depend on technological developments, on legal issues, on existing and future transport companies and on local conditions. Transport models can help planners and decision makers to gain a better understanding of potential developments and impacts of AV. Until now, modelling research in the context of AV focuses either on microscopic traffic flow models or on microscopic travel demand models. Microscopic traffic flow models are applied to estimate impacts on capacity, e.g. Fernandes & Nunes (2010), Le Vine et al. (2015) or Talebpour & Mahmassani (2016). Microscopic travel demand models are used to analyze the impact of ridesharing systems, e.g. Fagnant & Kockelman (2015) or Bischoff & Maciejewski (2016).

This paper looks at ways of integrating characteristics of AV and AV-related mobility services in traditional macroscopic travel demand models based on the four-stage algorithm, which replicates the trip generation, destination choice, mode choice and route choice processes of travelers. Many cities and regions operate macroscopic travel demand models for forecasting future travel demand and for estimating the impacts of potential measures. Thus, it would be helpful, if model builders and model users could extend existing models for testing scenarios with AV. This paper describes ongoing research of the EU-funded project CoEXist (www.h2020-coexist.eu), which aims at providing AV-ready macroscopic and microscopic transport models. The paper addresses the following topics:

- Modelling impacts of AV on network performance and capacity
- Modelling impacts of AV on travel demand
- Modelling impacts of vehiclesharing systems on empty trips and the bundling of ridesharing trips

The impacts of AV on travel demand depend on several factors, many of which can only be assumed at the moment. Examples of uncertainty include the throughput of cars in shared road space with non-motorized traffic, the operating cost of vehiclesharing with AV, the perception of travel time in AV and the willingness to share a vehicle or a ride in cases where sharing provides seamless travel with times similar to a private car. The paper does not address these uncertainties, but it suggests a modelling framework to examine assumptions and their impact on travel demand.

## 2. Modelling impacts of AV on network performance and capacity

The American Highway Capacity Manual (HCM, 2010) defines road capacity as the maximum sustainable hourly flow rate at which persons or vehicles reasonably can be expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, environmental, traffic and control conditions. This definition treats capacity more or less as a constant value. Brilon et al. (2007) indicate that this assumption is not appropriate as observations show, that the maximum traffic throughput varies even under constant external conditions. They introduce the concept of stochastic capacities to replicate the relationship between traffic flows and traffic breakdown in a better way. Lohmiller (2014) shows that the throughput on a motorway depends on the traffic composition, i.e. the driver population influences the quality of the traffic flow. This leads to two interpretations for the relationship between demand, capacity and performance. The performance, which can be measured by the indicator delay time per vehicle, depends either on variable capacity values or on the ability of a given demand composition (driver / vehicle population) to use a given (constant) capacity.

Macroscopic route choice and assignment models for private transport apply volume-delay functions to determine travel time in the road network. For links, the travel time is computed by multiplying the free flow travel time with a factor that is determined by a volume-delay function (VDF) as shown in equation (1). For nodes, a delay time is added to the free flow travel time as shown in equation (2). Equation (3) presents a simple example of a VDF. The VDF-factor depends on the volume / capacity ratio, i.e. the saturation rate $x_s$ of a supply element *s*, which represents either a link or a node. The relationship between volume and capacity is described in equation (4). It uses the concept of passenger car units (PCU) where capacity and vehicle volumes are converted into passenger car equivalents. Examples for vehicle type specific PCU values are 1.0 for conventional passenger cars, 2.3 for heavy goods vehicles and 0.4 for motorcycles (Kimber et al. 1982).

$$t_{s=link}\left(x_s\right)=t_s^{free}\cdot VDF\left(x_s\right) \tag{1}$$

$$t_{s=node}\left(x_s\right)=t_s^{free}+VDF\left(x_s\right) \tag{2}$$

$$VDF\left(x_s\right)=1+\alpha\cdot x_s^{\beta} \tag{3}$$

$$x_s=\frac{\sum_{i\in VehType} q_{s,i}\cdot f_i^{PCU}}{q_s^{\max}} \tag{4}$$

where

| | |
|---|---|
| $t_s\left(x_s\right)$ | travel time on supply element *s* at saturation rate $x_s$ [sec] |
| $t_s^{free}$ | travel time on supply element *s* at saturation rate $x_s=0$ [sec] |
| $VDF\left(x_s\right)$ | volume-delay function with parameters $\alpha$ and $\beta$ |
| $x_s$ | saturation rate (volume/capacity ratio) on supply element *s* [-] |
| $q_s^{\max}$ | capacity of supply element *s* assuming that all vehicles are conventional pass. cars [PCU/h] |
| $f_i^{PCU}$ | PCU of vehicle type *i* [PCU/veh] |

In the following three methods to incorporate effects of AV on network performance are presented. They differ in their interpretation of capacity:

1. Capacity and demand in PCU: Capacity is assumed as constant value, demand is adapted using specific passenger car unit factors for AV.
2. Capacity and demand in vehicle units: Capacity depends on specific time headways between vehicle types.
3. Capacity and demand in time units: Capacity is a constant value describing the available time, demand is converted in required time depending on the vehicle composition.

*2.1. Capacity and demand in PCU: Adapting passenger car unit factors for AV*

The concept of PCU is a common concept in macroscopic assignment models. It is mainly used to convert heavy goods vehicles (HGV) into PCU. Assuming that AV have a performance that differs from conventional cars (CV) and that the performance additionally depends on the type of supply element, the PCU concept must be extended to AV as well as to road and intersection types (motorway or urban road, grade separated or at-grade intersections, signalized or unsignalized intersections). Since the PCU-factor will be multiplied with the volume of the related vehicle type, it is possible to model the impacts of different penetration rates of AV.

This extension can come in two forms making different assumptions. The first approach assumes a linear relationship between the share of AV and their capacity impact. This requires a specific but constant PCU-factor for each combination of vehicle type and supply element type as shown in equation (5). In this first approach the PCU-factor does not depend on the share of AV. The second approach assumes a nonlinear relationship. In case of a low penetration rate the influence of a single AV is smaller than in cases with a higher penetration rate. To achieve this the PCU-factor must be adapted during an assignment depending on the AV share using equation (6). Its value ranges between the PCU-factors for an AV share of 0% and 100%. In the CoEXist project, the PCU-factors will be estimated by capacities observed in microscopic traffic flow simulations. These simulations will vary driving logics for the AV, the share of AV and the type of road facility.

$$x_s = \frac{\sum_{i \in VehType} q_{s,i} \cdot f}{q_s^{\max}} \qquad \text{where} \begin{cases} f = f_{s,i}^{PCU} & \text{linear impact AV} \\ f = f_{s,i}^{PCU}(p_{s,AV}) & \text{nonlinear impact AV} \end{cases} \tag{5}$$

$$f_{s,i=AV}^{PCU}(p_{s,AV}) = f_{s,i=AV}^{PCU,Max} - p_{s,AV} \cdot \left( f_{s,i=AV}^{PCU,Max} - f_{s,i=AV}^{PCU,Min} \right) \tag{6}$$

where

| | |
|---|---|
| $f_{s,i}^{PCU}$ | PCU of vehicle type *i* on type of supply element *s* [PCU/veh] |
| $f_{s,i}^{PCU}(p_{s,AV})$ | PCU function dependent on the share of AV $p_{s,AV}$ [PCU/veh] |
| $f_{s,i=AV}^{PCU,Max}$ | PCU of vehicle type AV on supply element type *s* for an AV-share of 0% [PCU/veh] |
| $f_{s,i=AV}^{PCU,Min}$ | PCU of vehicle type AV on supply element type *s* for an AV-share of 100% [PCU/veh] |
| $q_{s,i}$ | volume of vehicle type *i* on supply element *s* [veh/h] |
| $q_s^{\max}$ | capacity of supply element *s* assuming that all vehicles are conventional pass. cars [PCU/h] |
| $VehType$ | set of vehicle types: CV, AV, HGV |

### 2.2. Capacity and demand in vehicle units: demand dependent capacities from time headways

Another way to incorporate effects of AV on performance is to adapt the capacities of road facilities. Such an approach is introduced by Wagner (2016, 2017). It determines capacity depending on vehicle headways, vehicle lengths, share of AV and speed. This approach replaces PCU-factors by specific headways between vehicle types.

In a simplified case where the mean net time headway differs from the normal headway only in the case of two consecutive AV, equation (9) is applied to calculate the mean net time headway over all vehicles. It is simply based on the probability of specific vehicle types succeeding others, which in turn depends on the penetration rate of AV. Then the mean gross space headway required by an average vehicle is determined from the net time headway, the speed and the mean vehicle length of the vehicle composition on the considered supply element. This leads to the vehicle density shown in equation (8). Multiplying the vehicle density with the speed determines the capacity as shown in equation (7). Since the capacity depends on the share of AV, it must be updated during an assignment.

$$q_s^{\max} = 3600 \cdot v_s \cdot k_s(v_s) \tag{7}$$

$$k_s^{\max}(v_s) = \frac{1}{v_s \cdot t_s^{mean}(p_{s,AV}) + l_s^{mean}} \tag{8}$$

$$t_s^{mean}(p_{s,AV}) = {p_{s,AV}}^2 \cdot t_{AV} + (1 - {p_{s,AV}}^2) \cdot t_{other} \tag{9}$$

where

| | |
|---|---|
| $q_s^{\max}$ | capacity of supply element *s* [veh/h] |
| $v_s$ | speed limit on supply element s [m/sec] |
| $k_s(v_s)$ | traffic density for speed $v_s$ on supply element s [veh/m] |
| $t_s^{mean}(p_{s,AV})$ | average net time headway between vehicles [sec] |
| $l_s^{mean}$ | mean vehicle length on supply element *s* (possibly including a safety margin) [m] |
| $p_{s,AV}$ | share of AV on supply element *s* [-] |
| $t_{AV}$ | mean net time headway between AV and AV [sec] |
| $t_{other}$ | mean net time headway between all other combinations of vehicles following each other [sec] |

### 2.3. Capacity and demand in time units: constant capacity and demand dependent time requirements

The third approach is equivalent to the second approach of demand dependent capacities, but uses an interpretation which assumes that capacity is a constant value measured in seconds and that the throughput depends on the traffic composition. This can be achieved by inserting the terms for capacity $q_s^{\max}$ from equation (7) and for density $k_s$ from equation (8) into equation (10), which defines the saturation. This leads to equation (13), which includes nothing but the number 3600 [sec/h] in the denominator. This can be interpreted as capacity in time units describing the available time to pass a supply element. Traffic signals reduce and multiple lanes increase this available time. The nominator describes the time required by a specific traffic composition scaled to one hour. Impacts of AV on traffic performance can be included by a different time headway required to pass a supply element compared to CV.

$$x_s = \frac{q_s}{q_s^{\max}} \tag{10}$$

$$x_s = \frac{q_s}{3600 \cdot v_s \cdot k_s(v_s)} \tag{11}$$

$$x_s = \frac{q_s \cdot \left( v_s \cdot t_s^{mean}(p_{s,AV}) + l_s^{mean} \right)}{3600 \cdot v_s} \tag{12}$$

$$x_s = \frac{q_s \cdot \left( t_s^{mean}(p_{s,AV}) + \dfrac{l_s^{mean}}{v_s} \right)}{3600} = \frac{\text{required time}}{\text{available time}} \tag{13}$$

## 3. Modelling impacts of AV on travel demand

Travel demand models replicate the decision making process of individual travelers concerning the choice of destination, mode and route. In each choice situation travelers select from a set of choices. A utility function describes the utility of each choice considering the characteristics of the trip maker (user group) and the trip purpose (activity). These functions consider various time components (access, egress, driving, waiting, parking search), cost and travel comfort. Each component is weighted with a specific factor. For current transport modes, these factors can be estimated by mobility surveys. For choices with AV, the functions as well as the choice set need to be adjusted in a suitable way.

### *3.1. Impact of AV level 3 and 4*

At these levels AV still require a driver as fallback. Consequently, the set of choices remains more or less similar to the situation without AV. However, the attributes of a choice change for the mode car-driver. The value of time experienced in an AV differs from the value of time spent in a CV, because the driver can spend some time of the trip duration on other tasks than driving. If AV of level 3 and 4 can only drive automatically on certain road types or on certified network sections, they probably have an impact on route choice as well as mode choice. Such a behavior can be integrated in existing travel demand models by adding an additional transport system AV with a specific utility function for route choice.

This specific utility function resembles already existing functions for CV but is supplemented by another factor $\beta_s^{t,AV} \leq 1$, which reduces the perception of travel time in an AV. Due to the fact that automated driving is only possible on certain parts of the road network, the factor needs to dependent on the road segment $s$ used by the AV. For road segments that allow automated driving $\beta_s^{t,AV}$ represents the reduced perception of time spent in an AV, whereas for road segments that do not provide the necessary design standard there will be no reduced value of time for AV and therefore $\beta_s^{t,AV}$ is set to one. Equations (14) and (15) show how a weighted travel time $v_{odr}^t$ can be computed for CV and AV using the factor $\beta_s^{t,AV}$.

$$v_{odr}^{t,CV} = \beta^{t} \cdot t_{odr}^{CV} \tag{14}$$

$$v_{odr}^{t,AV} = \sum_{s \in r} \beta_{s}^{t,AV} \cdot \beta^{t} \cdot t_{odrs}^{AV} \tag{15}$$

where

| | |
|---|---|
| $v_{odr}^{t,CV}$ , $v_{odr}^{t,AV}$ | weighted travel time value for CV and AV for the route r from origin *o* to destination *d* [-] |
| $\beta^{t}$ | factor for travel time perception [1/s] |
| $\beta_{s}^{t,AV}$ | factor for travel time perception in an AV on supply element *s* [1/s] |
| $t_{odr}^{CV}$ | travel time with a CV for the route *r* from origin *o* to destination *d* [s] |
| $t_{odrs}^{AV}$ | travel time with an AV on supply element *s* as element of the route *r* from *o* to *d* [s] |

As an input for travel time values and comfort of AV, one can think of using the values for high-speed trains or survey based values. A study of de Looff et al. (2017), for example, focuses on the impacts of AV on the value of travel time for commute trips in the Netherlands. As a result for an AV with an office interior they find a lower value (4.99 €/h) than for the conventional car (7.99 €/h). As indicated by Trommer et al. (2016), the perception of time spent in AV may vary for different user groups and activities. Additionally, reduced travel times from higher capacities and a reduced amount of time for parking because of valet parking options for AV should be considered in the utility functions.

Integrating AV into an existing travel demand model can be achieved by replacing the travel time matrix of CV by a travel time matrix $V^{t,Car}$ which is derived from the weighted travel time matrix of AV and CV. As presented in Fig. 1 and in equation (16) the aggregated weighted travel time for mode car driver is derived by weighting the transport system-specific times with the share of AV in the car fleet $p_{AV}$ . This share is an input value defined by the model user. Assuming that time usage depends on the duration of the fully automated section a certain threshold value $t^{\varepsilon}$ (e.g. 10 minutes) can be set by the model user.

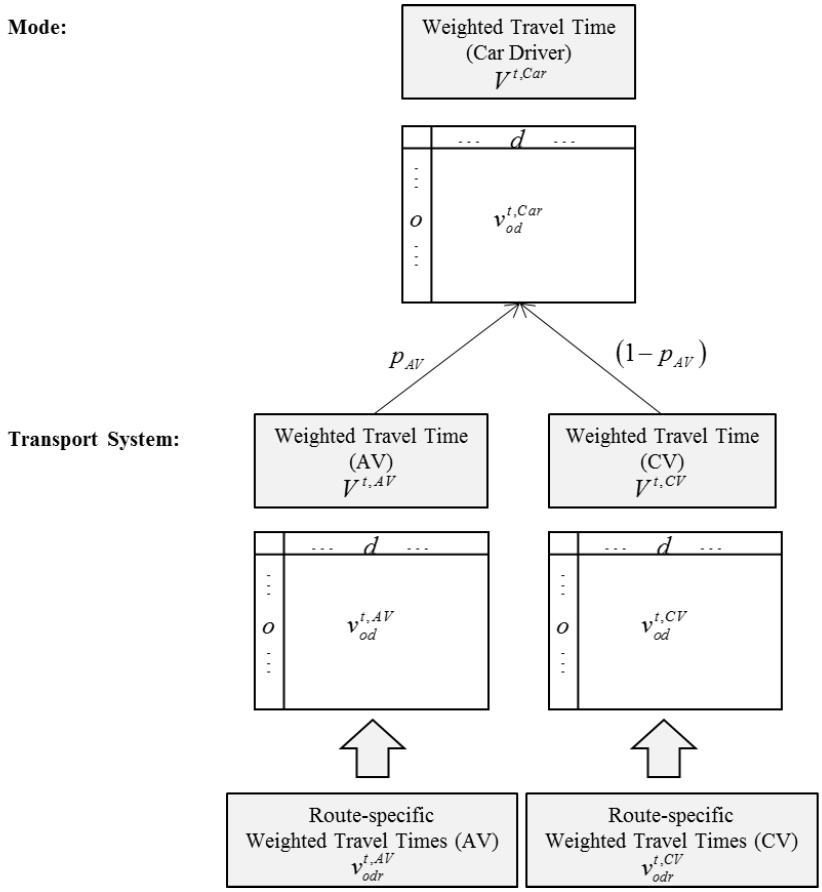


Fig. 1. Derivation of the weighted travel time for the mode car driver from the transport systems AV and CV

$$v_{od}^{t,Car} = \begin{cases} (1-p_{AV}) \cdot v_{od}^{t,CV} + p_{AV} \cdot v_{od}^{t,AV} & \text{, if } t_{od}^{AV,automated} \geq t^{\varepsilon} \\ v_{od}^{t,CV} & \text{, if } t_{od}^{AV,automated} < t^{\varepsilon} \end{cases} \tag{16}$$

where

| | |
|---|---|
| $v_{od}^{t,Car}$ | weighted travel time value for the mode car driver from origin *o* to destination *d* [-] |
| $p_{AV}$ | share of AV in the car fleet [-] |
| $v_{od}^{t,CV}$, $v_{od}^{t,AV}$ | weighted travel time of CV and AV respectively from origin *o* to destination *d* [-] |
| $t_{od}^{AV,automated}$ | part of the travel time of AV driven in automated mode on an od-pair [min] |
| $t^{\varepsilon}$ | threshold travel time to perceive an advantage for driving in automated mode [min] |

### *3.2. Impact of AV level 5*

Concerning level 5 AV, the big change is the redundancy of a driver. This will increase the set of choices for all travelers in three ways. (1) User groups like children or elderly people can now choose to go by car on their own. This has to be considered when editing the mode choice set for the user groups. (2) Car travelers no longer need to take their car back to the origin of the trip (or where else it is needed next), as the AV can relocate on its own. (3) Fleets of shared AV will facilitate new mobility options with carsharing and ridesharing. These new means of transport can provide direct connections between origin and destination or can serve as last-mile service for public transport. If they are operated as part of public transport, this will lead to an improved quality of public transport, which can be reflected in the utility matrices of the travel demand model. But with new fleets of AV for carsharing and ridesharing operating independently from public transport, the mode choice set needs to be extended.

Typical macroscopic travel demand models distinguish the modes car-driver, car-passenger, public transport, cycling and walking. The mode choice is often computed by a Multinomial Logit model (MNL). Fig. 2 and equation (17) illustrate the procedure. As stated by many authors, e. g. Ben-Akiva et al. (1999), an important property of the MNL model is the independence of irrelevant alternatives (IIA). This means that the ratio of the choice probabilities of any two alternatives is independent of the choice set. Therefore, similarities of different alternatives cannot be taken into account.

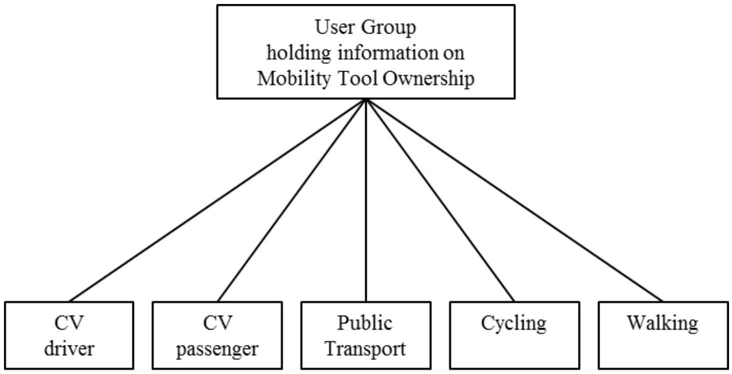


Fig. 2. Multinomial Logit model for mode choice without AV

If the new AV modes, namely AV private, AV carsharing and AV ridesharing, were simply added to the existing choice set in an approach with a MNL model as illustrated in Fig. 3 two major problems occur. The first one is caused by the IIA property of the model, as the new AV modes are not entirely independent from each other and the already existing modes. The second difficulty is caused by the innovative nature of the introduced modes, as traditional methods of identifying user group properties are not applicable.

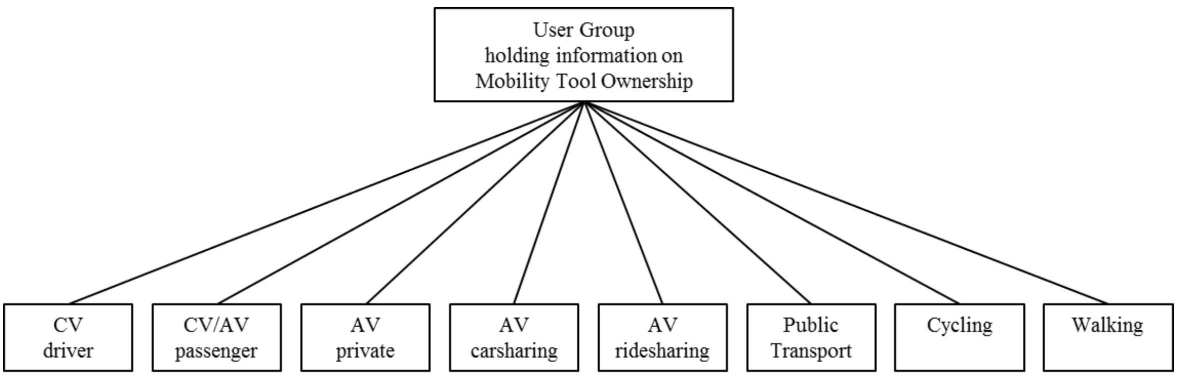


Fig. 3. Multinomial Logit Model for mode choice including AV

Disaggregated travel demand models consider that the utility of a mode depends not only on the service quality of the mode but also on the characteristics of the traveler and the ownership of certain mobility tools (private car, private bicycle, season ticket for public transport). This leads to a segmentation of the demand into user groups. Under the assumption that everyone has access to a bicycle people can choose between the following possibilities:

- Owning a car and a season ticket (CT),
- Owning a car but no season ticket (CN),
- Owning no car but a season ticket (NT) or
- Owning neither car nor season ticket (NN).

In traditional four-stage models the mobility tool ownership is an input value coming from a survey for the base year and from assumptions for future years. But with AV providing new alternatives in mode choice people may reconsider their mobility tool ownership. For the MNL model the user groups need to contain information about mobility tool ownership. This can be achieved by adding a mobility tool ownership model (see Weis et al. (2010) for an example). The results of this model can be implemented in user groups and serve as input for a MNL mode choice model. Another approach is the use of a Nested Logit model.

The Nested Logit model is an extension of the MNL model which enables the user to capture correlations between alternatives (Ben-Akiva et al. (1999)). Fig. 4 shows the concept of a Nested Logit model. In the Nested Logit model each alternative consists of a mode that is associated with a nest. The usage of nests creates hierarchy levels. Ben-Akiva et al. (1985) and Dugge (2006) use these levels for destination and mode choice. Fig. 4 shows an application case in which the nests represent the alternatives of mobility tool access CT, CN, NT and NN. For each nest a different set of mode choices is given. For the nests NT and NN, the mode choice of travelling by a private car as driver (CV) or as the owner of a private AV (AV) is omitted. For nests CT and NT the utility of travelling by public transport is much higher compared to CN and NN. Based on Ben-Akiva et al. (1985) and Dugge (2006) the computation of choice probabilities for the mode and mobility tool ownership combinations can be computed as shown in equations (18), (19) and (20). It is possible to set differing nest and mode specific values. The scaling parameters $\mu^n$ and $\mu^m$ scale the values of the nests *n* and the modes *m* respectively. The ratio of the two parameters determines the impact of the hierarchy levels (Dugge (2006)).

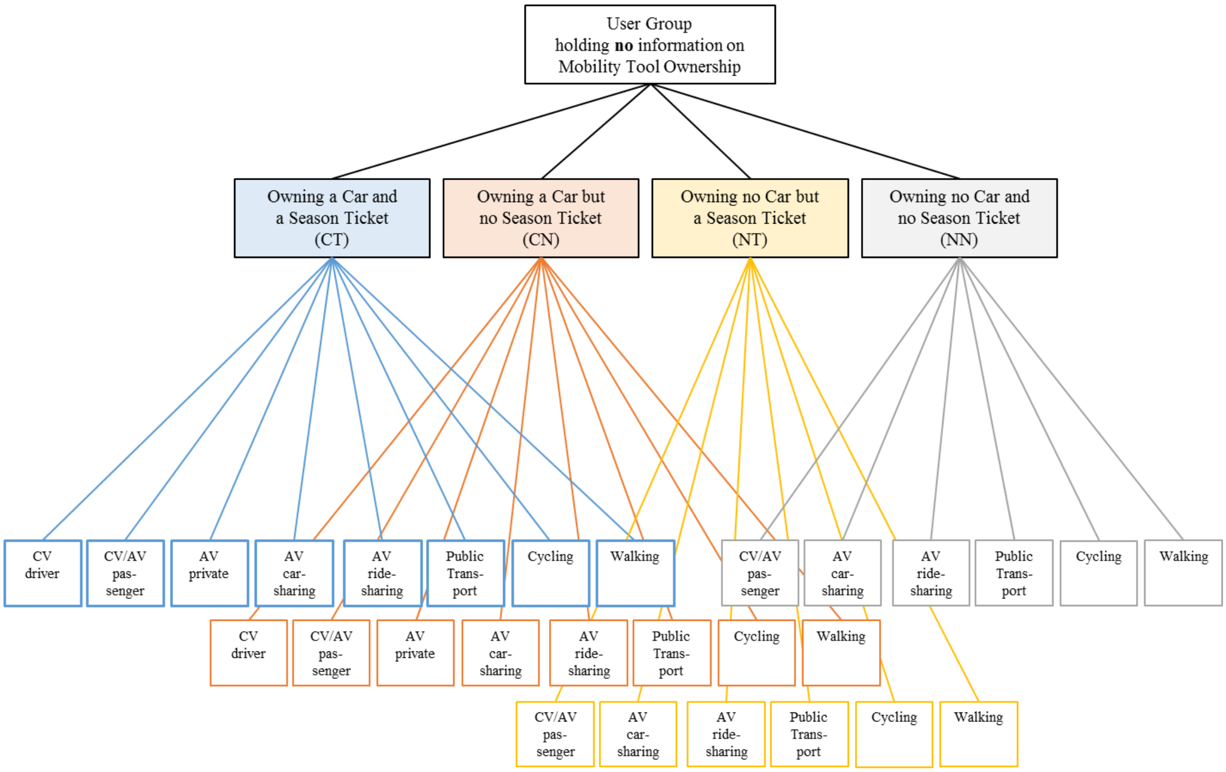


Fig. 4. Nested Logit model for mode choice including AV

Another, closely related model is the Cross-Nested Logit model. As stated by Ben-Akiva (1999) it is a direct extension of the Nested Logit model, where each alternative may belong to more than one nest. For each alternative mode and each nest (mobility tool ownership), allocation parameters $\alpha_{nm}$ represent the degree of "membership" of a mode to the particular nests. If each mode is allocated to exactly one nest, so all $\alpha_{nm}$ equal either 0 or 1, the Cross-Nested Logit model is equivalent to a Nested Logit model. Fig. 5 shows the Nested Logit model of Fig. 4 transformed into a Cross-Nested Logit model. In conformity with Ben-Akiva (1999) and under the assumption of a unit scale parameter $\mu^m$ the probability to choose a mode, no matter which mobility tool ownership led to this decision, is shown in equations (21), (22) and (23).

Estimating the scale and allocation parameters of Nested and Cross-Nested Logit models is an additional difficulty compared to the MNL model. Especially regarding AV modes, estimating parameters in a proper way presents a major challenge since AV are not yet available on the market. Thus, the model builder may have to assume parameters or rely on stated preference surveys with the shortcoming that respondents have to evaluate options they have no experience with.

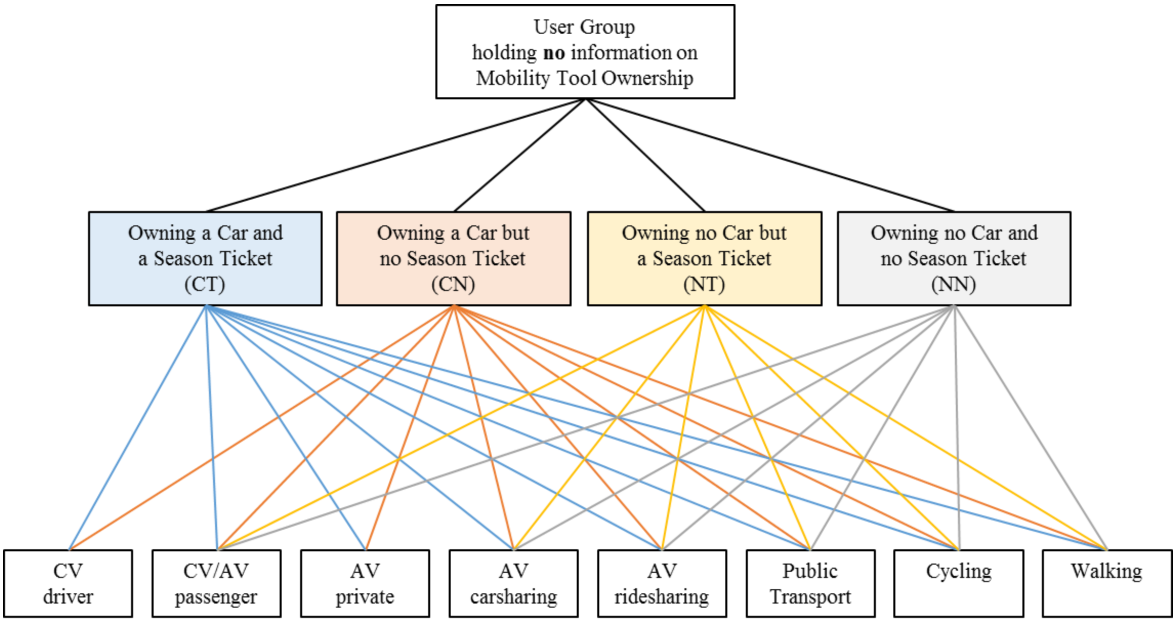


Fig. 5. Cross-Nested Logit model for mode choice including AV

Multinomial Logit Model:

$$p(i) = \frac{\exp(v_i)}{\sum_{i'} \exp(v_{i'})} \tag{17}$$

Nested Logit Model:

$$p(i) = p(n,m) = p(n|m) \cdot p(n) \tag{18}$$

$$p(m|n) = \frac{\exp\left(\left(v_{nm} + v_m\right) \cdot \mu^m\right)}{\sum_{m' \in M_n} \exp\left(\left(v_{nm'} + v_{m'}\right) \cdot \mu^m\right)} \tag{19}$$

$$p(n) = \frac{\exp\left(\mu^n \cdot \left(v_n + \frac{1}{\mu^m} \cdot \ln \sum_{m' \in M_n} \exp\left(\left(v_{m'} + v_{nm'}\right) \cdot \mu^m\right)\right)\right)}{\sum_{n' \in N} \exp\left(\mu^n \cdot \left(v_{n'} + \frac{1}{\mu^m} \cdot \ln \sum_{m' \in M_{n'}} \exp\left(\left(v_{m'} + v_{n'm'}\right) \cdot \mu^m\right)\right)\right)} \tag{20}$$

Cross Nested Logit Model:

$$p(i) = p(m) = \sum_{n' \in N} p(m \mid n') \cdot p(n') \tag{21}$$

$$p(m \mid n) = \frac{\alpha_{nm} \cdot \exp\left(v_m\right)}{\sum_{m' \in M_n} \alpha_{nm'} \cdot \exp\left(v_{m'}\right)} \tag{22}$$

$$p(n) = \frac{\exp\left(\mu^n \cdot \left(v_n + \ln \sum_{m' \in M_n} \alpha_{nm'} \cdot \exp\left(v_{m'}\right)\right)\right)}{\sum_{n' \in N} \exp\left(\mu^n \cdot \left(v_{n'} + \ln \sum_{m' \in M_{n'}} \alpha_{n'm'} \cdot \exp\left(v_{m'}\right)\right)\right)} \tag{23}$$

where

| | |
|---|---|
| $i$ | alternative in universal choice set |
| $n$ | nest indicating mobility tool ownership |
| $N$ | nest choice set, set of options for mobility tool ownership |
| $m$ | mode |
| $M$ | universal mode choice set |
| $M_n$ | mode choice set that is feasible for a person having access to mobility tools of nest *n* |
| $p(i)$, $p(n)$ | probability that alternative *i* and nest *n* is chosen |
| $p(n,m)$ | probability that a combination of *n* and *m* is chosen |
| $p(n \mid m)$ | probability that *m* is selected conditional on *n* being chosen |
| $v_i$ | value of alternative *i* |
| $v_n$ , $v_m$ | value common to all alternatives *i* using nest *n* and mode *m* respectively |
| $v_{nm}$ | the remaining value of i specific to the combination (*n*, *m*) |
| $\mu^n$ , $\mu^m$ | scaling parameters for hierarchy levels *n* and *m* respectively; $0 \le \frac{\mu^n}{\mu^m} \le 1$ |
| $\alpha_{nm}$ | allocation parameter for mode *m* towards nests *n*; $0 \le \alpha_{nm} \le 1$ and $\sum_{n' \in N} \alpha_{n'm} = 1$ |

## 4. Modelling vehiclesharing systems

The introduction of driverless vehicles opens up new business models, since some of the major problems of carsharing and ridesharing would disappear. Relocating vehicles would be possible at lower cost, as for ridesharing or rideselling systems drivers become obsolete. Offering inexpensive door-to-door trips for everyone will have a major impact on the modal and spatial pattern of travel demand. Previous studies already examined some impacts of ridesharing systems for selected cities. Examples are OECD (2015) for Lisbon and for Helsinki (2017), Friedrich & Hartl (2016) for the Stuttgart Region. These examples are similar to other studies (e.g. Fagnant & Kockelman (2015) or Bischoff & Maciejewski (2016)) that worked with microscopic travel demand data from agent-based models. Here, travel demand always has integer values. This is different in macroscopic travel demand models, where demand volumes are non-integer. Modelling vehiclesharing systems in a macroscopic model requires several model extensions:

- Prices: Modelling AV requires modified pricing models for public transport without driver and new pricing models for sharing services. Bösch et al. (2017) carried out a detailed cost based analysis of AV mobility services as well as current transport modes in Switzerland. Fig. 6 shows the results of the cost analysis. One of the key findings is that with the automation of vehicles the cost difference between buses and taxis or carsharing, respectively, is reduced substantially. In urban areas AV-carsharing will be only 71 % and AV-ridesharing only 21 % more expensive than automated buses, compared to 415 % and 204 % before automation. In a regional setting, based on operating costs, even AV-buses and trains loose competitiveness.

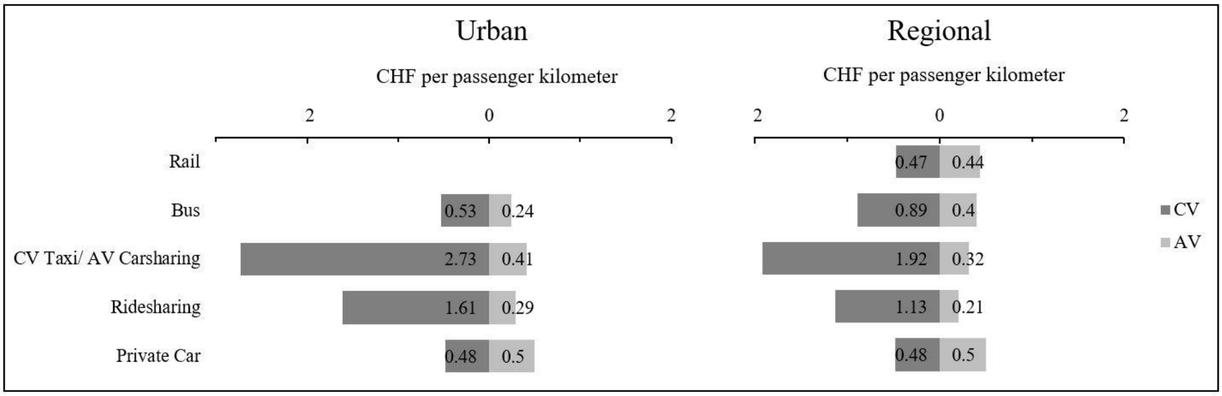


Fig. 6. Cost comparison of different modes with and without AV technology (Bösch et al. 2017, own representation)

- Generating intermodal routes and considering capacity limits resulting from fleet sizes in assignment models: Such assignment procedures are described in Friedrich & Noekel (2015) and have been implemented in the commercial software package PTV Visum.
- Methods for forming carpools (= ridesharing) for non-integer demand: Ridesharing bundles person trips with similar origin and destination. This requires an algorithm for matching the trips of suppliers (today typically drivers of conventional vehicles, in the future mobility-as-a-service providers) and demanders (travelers). Friedrich et al. (2018) present a matching algorithm, which can be integrated in existing travel demand models. The algorithm works likewise with integer demand, which is typical for agent-based microscopic models, and with non-integer demand occurring in travel demand matrices of a macroscopic model. The algorithm compares two path sets of suppliers and demanders. The representation of a path in the road network is reduced from a sequence of links to a sequence of zones. The zones act as a buffer along the path, where demanders can be picked up.

- Methods for operating shared fleets with empty runs between drop-off and pick-up locations: Estimating the required fleet size requires a vehicle-blocking algorithm which concatenates vehicle trips. The authors are currently working on a blocking algorithm handling non-integer demand. For this they adapt the FURNESS method which is often used in doubly constrained trip distribution models. This algorithm works on the level of zones and uses cars waiting or arriving in one time interval as produced trips and the outgoing vehicles as attracted trips. An impedance matrix describes the required time for empty trips and identifies od-pairs which cannot be reached.

## 5. Conclusion

Travel demand models – as all models – only do what the modeler wants them to do. Current travel demand models have proven to be helpful in making decisions, if built and validated in an appropriate way. In the past, uncertainty of travel demand forecasts resulted primarily from uncertainties with respect to population growth, future prices and car ownership levels. In the coming years we expect a revolution in car technology which changes the way of driving and which may – similar to the smartphone – generate new services we cannot yet think of. This makes forecasting more difficult, especially as the impact of social networks and word of mouth on the adoption of new technology is hard to capture in travel demand modelling. Nevertheless, even with a large number of assumptions, modelling probable technical developments like the introduction of AV can help planners and decision makers to better understand the potential impacts on urban and interregional transport and travel demand.

The paper suggests a modelling framework to integrate AV into existing macroscopic travel demand models. At the moment the work is still in the state of model specification. In the next step of the CoEXist project the framework will be implemented and tested. Parameters describing the impact on traffic flow will be estimated by capacities observed in microscopic traffic flow simulations. These simulations are partly based on observations from experiments with AV and partly on assumptions. Parameters used in the utility functions can only be assumed based on parameters of current models or on parameters derived from stated preference surveys. Future price structures for public transport and sharing systems require assumptions as well.

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