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Mobility impacts of automated driving and shared mobility – explorative model and case study of the province of north-Holland

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This paper presents a model specifically developed to explore the mobility impacts of connected and automated driving and shared mobility. It is an explorative iterative model that uses an elasticity model for destination choice, a multinomial logit model for mode choice and a network fundamental diagram to assess traffic impacts. To the best of the authors' knowledge, it is the first model that combines a network fundamental diagram with choice models. A second contribution is the inclusion of automated vehicles, automated (shared) taxis, automated shared vans and new parking concepts in the model as well as the way in which they affect mobility choices and traffic conditions. The insights into the direct mobility impacts are the third contribution. The short computation time of the model enables exploration of large numbers of scenarios, sensitivity analyses and assessments of the impacts of interventions. The model was applied in a case study of the Dutch Province of North-Holland, in which the potential impacts of automated and shared vehicles and mitigating interventions were explored. In this case study, four extreme scenarios were explored, in which 100% of the vehicles have SAE-level 3/4 or 5 and people have a low or high willingness to share. The extremes were chosen to get insights into maximum effects. The results show that if automated vehicles and sharing are accepted, it is likely that there will be considerable changes in mobility patterns and traffic performance, with both positive and problematic effects.

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1. Introduction

In the coming decades, major changes in the transport system are expected, because of trends such as connected and automated vehicles and shared mobility. There is much uncertainty with respect to how soon these changes will happen, and how much the way people travel and goods are transported is impacted. If technology develops further and is affordable, if people are willing to use automated vehicles, and there are clear societal benefits, a 'driverless' future with shared vehicles can be imagined and the traffic and transport system could change drastically.

Traditionally, strategic traffic and transport models have been applied to explore the impacts of trends and socio-economic developments, and to determine which changes are needed in transport networks in terms of network design and capacity. However, as explained in more detail in the next section, the models available are generally not suitable for assessing the impacts of automation and shared mobility because they don't contain new mobility concepts and they have long computation times which makes them unsuitable to explore many different future scenarios. We therefore need dedicated transport models, that can consider new transport concepts, enabled by automation and shared mobility and that can deal with all the uncertainties with respect to implementation, cost and time parameters and acceptance of these new concepts.

This paper presents an explorative iterative model that uses an elasticity model for destination choice, a multinomial logit model for mode choice and a network fundamental diagram to assess traffic impacts of connected and automated driving and shared mobility. To the best of the authors' knowledge, it is the first model that combines network fundamental diagrams with choice models. The network fundamental diagrams replace traffic assignment models that are traditionally used in iterative 4-step traffic and transport models. Since network fundamental diagrams are much more aggregate than network-based traffic assignment models, the presented model contributes to the literature of explorative models. A second contribution is the inclusion of automated vehicles, automated (shared) taxis, automated shared vans and new parking concepts in the model as well as the way in which they affect mobility choices and traffic conditions. The insights into the direct mobility impacts are a third contribution. The model was applied in a case study, in which the potential impacts of automated and shared vehicles in the Dutch Province of North-Holland were examined.

The next section provides an overview of related modelling efforts in literature. Then, the methodology section discusses the set-up of the model – input, models, output. This is followed by a section discussing the application of the model in the North-Holland case study, and a conclusions and recommendations section.

2. Literature review

A comprehensive overview of the implications of automated driving is provided by the ripple model of Milakis et al. (2017), which distinguishes three layers: 1) implications on traffic, travel cost, and travel choices; 2) implications on vehicle ownership and sharing, location choices and land use, and transport infrastructure; 3) wider societal implications. The methodology that we propose in this paper focuses primarily on the first layer, which roughly corresponds to the impacts that can be assessed with a traditional four-stage model (Ortúzar & Willumsen, 2011). This section subsequently discusses how automated driving and car and ride sharing are included in traffic assignment, mode choice, trip and destination choice, and location and car ownership choice models in literature. All these elements are also present in the road transport impact assessment framework of Annamae et al. (2018) and may be impacted by automated driving according to Kuhr et al. (2017).

Throughout this paper, automation levels follow the SAE-levels of motor vehicle automation (SAE International, 2018).

2.1 *Traffic assignment*

For the automated driving adaptation of the Puget Sound regional transport model by Childress et al. (2015), link capacities were adjusted, but no distinction between vehicle classes was added to the model. Levin and Boyles (2015) formulate a static assignment distinguishing between fully automated and non-automated vehicles, where the capacity linearly depends on the penetration rate of automated driving. Levin and Boyles (2016) formulate a similar dynamic assignment where the fundamental diagrams depend on the penetration rate. Bischoff and Maciejewski (2016), Moreno et al. (2018) and Basu et al. (2018) use dynamic agent-based simulations to study the impact of shared autonomous vehicles, explicitly replicating the operation of the shared vehicle system. Zhang and Guhathakurta (2017) and Bischoff and Maciejewski (2017) do this without considering the impact of congestion on link travel times. In their modification of the Dutch national transport model for automated driving, Smit et al. (2017) distinguish between level 4 automated vehicles and other vehicles in the assignment, which is static but heuristically accounts for spillback. The route choice differs due to different values of time and automated driving only being available on part of the network. The assignment considers assumed differences in time headways (road capacity) of both vehicle classes.

To calculate travel times, one may alternatively use a network fundamental diagram, i.e. the relation between vehicle density and speed for a network (Zhang, et al., 2015; Knoop & Hoogendoorn, 2015). Abbas (2016) suggests to adapt the network fundamental diagram to automated vehicles based on microscopic simulations. Lu and Tettamanti (2018) estimated network fundamental diagrams this way for different penetration rates of different automation levels, based on assumed parameters for driving behaviour. Based on Malone et al. (2001), Puylaert et al. (2018) calculate travel times for automated driving scenarios in the Netherlands using a network BPR function per region type, which is made dependent on the proportion of level 0, level 1-2 and level 3 automated vehicles. This capacity effect is made non-linear to account for cooperative driving.

In addition to passenger transportation, Smit et al. (2017) and Puylaert et al. (2018) explicitly consider the presence of both automated and non-automated trucks on the road. Finally, the International Transport Forum (OECD, 2015) uses a mobility dispatcher for ride sharing to assign shared vehicles to users, based on time-minimization-rules. Link travel times are fixed and waiting times and route travel times including detours are minimized.

2.2 *Mode choice*

Many mode choice models in automated driving literature have the same structure and alternatives as traditional mode choice models, with only modified parameter values and attribute levels accounting for automated driving. For example, Puylaert et al. (2018) use a logit model to choose between car driver, car passenger, train, bus/tram/metro, and bicycle/walking. Malokin et al. (2015) estimate a mode choice model with multitasking attributes using revealed preferences, and then adjust these attributes to quantitatively adjust the model for multitasking possibilities of automated driving. Gelauff et al. (2017) use the same mode choice model as the LUCA model for the Netherlands (Teulings, et al., 2018), but alter the travel time attributes of the alternatives to account for assumed changes in value of time and travel time due to the introduction of automated driving. Smit et al. (2017) adjust their mode choice model by modifying the value of time for owners of automated vehicles and by using the travel times from their modified assignment model. Childress et al. (2015) do the same without distinguishing these user classes. Some literature mentions changing the available modes in the mode choice. LaMondia et al. (2016) add automated vehicle as a third alternative to a mode choice model between car and airplane. Conversely, Correia and Van Arem (2016) consider only level 5 automated vehicles and model mode choice as a choice between car passenger and public transport, removing car driver as a separate option.

While there may be important relations between vehicle automation and sharing (Hao & Yamamoto, 2018; Tillema, et al., 2017), shared vehicle concepts are only sometimes embedded as alternatives in mode choice models for automated driving scenarios. In a multimodal setting, Yap et al. (2016) estimate a mode choice model on stated-preference data that includes an explicit choice between driving a shared vehicle manually and being driven in a shared fully automated vehicle. Bansal et al. (2016) estimate a usage frequency choice model for shared automated vehicles. Pakusch et al. (2018) researched stated preferences among traditional private car, automated private car, traditional shared car, automated shared car, and public transport, but did not include level-of-service attributes in their survey. Moreno et al. (2018) use stated-preference data to calibrate and apply a mode choice model to choose between private car and shared autonomous car, that is dependent on the number of daily trips, but again not on the level-of-service provided by these modes. Basu et al. (2018) add shared automated taxis and the combination of shared automated taxis with rail transport as new options to an existing mode choice model, reusing parameters of existing modes like conventional taxi (Li & Biran, 2017).

In terms of new parking concepts with automated vehicles, Levin and Boyles (2015) add a choice within the mode choice between parking at the destination and having the vehicle drive back empty to the origin and park there, avoiding parking costs. Childress et al. (2015) only reduce parking costs in their model to account for more compact parking of automated vehicles.

2.3 *Trip and destination choice*

The attractiveness of the modes available in the mode choice can in turn impact the destination choice of trips and the choice to make trips. The Dutch national transport model used by Smit et al. (2017) and LUCA used by Gelauff et al. (2017) account for the destination choice effect by combining mode choice and destination choice in a nested logit model (Train, 2002). The Dutch national transport model furthermore uses the expected maximum utility (logsum) of this nested logit model in the trip frequency choice, so that the number of trips also depends on the attractiveness of available destination-mode combinations. Levin and Boyles (2015) base destination choice on the best generalized travel cost of all modes. The reduction of travel time and value of time causes the activity-based model used by Childress et al. (2015) to schedule both more and longer trips. Basu et al. (2018) also have the travel utility feed back into the activity pattern choice.

2.4 *Location and car ownership choice*

Location and car ownership choices are not traditional components of the four-stage model (Ortúzar & Willumsen, 2011). In terms of the ripple model of Milakis et al. (2017), these choices are not directly relevant for first-layer implications of automated driving, but focus on the second layer. Incorporation of location choice would contribute towards closing the land use-transport interaction circle (Wegener & Fürst, 1999). Gelauff et al. (2017) focus on commuter trips and include a home location choice within the same nested logit model as destination (i.e. work location) choice and mode choice, allowing them to analyse relocation effects of automated driving. Car ownership choice is complicated by automated driving in case multiple levels of automation are available to choose from. Smit et al. (2017) inherit a car ownership model from the Dutch national transport model, but assume pre-specified penetration rates for different levels of automation. Puylaert et al. (2018) use penetration rates from Nieuwenhuijsen et al. (2018), who estimate penetration rates of different levels of automation over time using system dynamics, without an explicit model for car ownership choice. As indicated earlier, Pakusch et al. (2018)

embed the choice between an automated and a non-automated vehicle in the mode choice instead of a separate car ownership choice.

2.5 Conclusion literature review

Although there is a growing body of literature with respect to modelling the impact of automated driving and shared mobility, integrated approaches addressing the combined impacts of sharing and automation on travel times, mode choice, destination choice, location choice and car ownership are rare. While the approach of Basu et al. (2018) already includes many of these aspects, it is an activity-based and agent-based approach, resulting in high data requirements and long computation times for large networks. New parking concepts are not included yet.

3. Methodology

This paper presents a model that focuses on mode choice and travel times (via a network fundament diagram) and takes destination choice into account via elasticities. Location choice (spatial effects) and car ownership effects are exogenous inputs to the model. Table 1 describes the model segmentation. The next section describes the model approach in more detail. After that the model convergence and validation are described.

Table 1. Model segmentation

Input	Explanation
12 transport modes (m)	Modes included are car driver (level 0/1/2), car passenger, train, bus/tram/metro, bicycle, walking, trucks (level 0/1/2), automated private car (level 3/4 or 5), automated taxi, automated shared taxi, automated shared van, automated trucks (level 3/4 or 5). Automated private cars are privately owned vehicles with level 3/4 or 5 automated driving functions. Distinctions between the levels can be made by selecting the road types on which the vehicles are allowed to drive automatically, and by changing the cost and time parameters. Automated shared taxis offer a ride sharing service. The same holds for automated shared vans (or buses) but with a higher capacity. In level 3 and 4 a driver is still required for automated taxis (and shared taxis and vans/buses). Automated trucks are level 3/4 or 5 trucks. Finally, with level 5 automation, there is no difference between car driver and car passenger. The car passenger option thus becomes superfluous in level 5 scenarios and is hence removed. Members of the same household can still travel together in an automated private car. Non-automated (shared) taxis/vans are excluded because they have a very low share in the Netherlands.
Level of communication	Share of the fleet that is capable of vehicle-to-vehicle (V2V) communication.
4 road types (s)	Through roads (freeways and highways), distributor roads with separate roadways, distributor roads with mixed traffic, access roads (district and neighbourhood arteries, residential streets).
5 region types (r)	Very highly urbanized areas, highly urbanized areas, other urbanized residential/work areas, rural residential and recreational areas, hubs and mainports.
4 user groups (u)	Car owners with a household income >30000 euro (1) or a household income ≤ 30000 euro (2), no private car available and household income >30000 euro (3) or a household income ≤30000 euro (4).
4 age classes (a)	0-17, 18-35, 36-75, >75 years.
3 parking options (p)	Parking or drop off at location (in case of level 5 automation), valet parking, and parking or drop off at some distance (e.g. park-and-ride locations or centrally located car parks).
3 time periods (t)	Morning peak, evening peak, off-peak period.

3.1 Model steps

Figure 1 summarizes the method used. The numbers in the circles refer to the different steps of the method, described below the figure.

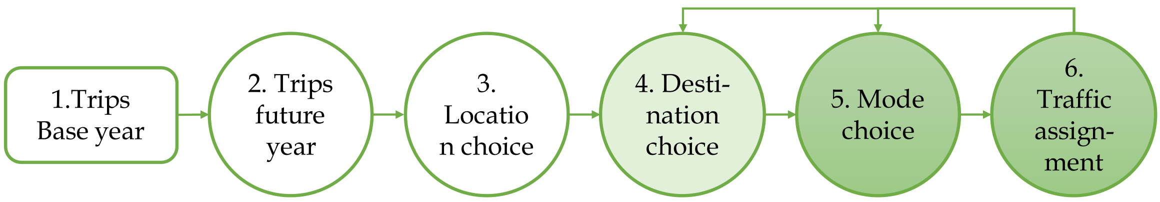


Figure 1. Steps model approach

Step 1: Trips base year

Trips for a base year are exogeneous input. The model was developed for the Dutch situation and passenger trips were derived from the large-scale Dutch survey OVIN (CBS, 2018) which includes trips of about 40 thousand respondents each year. This is about 0.25% of the population. For each respondent, personal characteristics like driving license and age and household characteristics like home location, car ownership and household income are available. For each trip, characteristics like start time, end time, main mode, access and egress modes, estimated travel time and trip distance are available. Weight factors are available to derive information for the entire population. Truck trips are also exogenous input to the model. Truck trips were derived from the Dutch national transport model. The number of trucks does not change (no mode choice effects). The impact of trucks on the capacity can change because of automation and/or communication.

Step 2: Trips future year

The trips for a future year are derived by multiplying the weight factors of the trips with a factor that represents the growth in number of inhabitants according to the long-term future scenarios for the Netherlands (Centraal Planbureau and Planbureau voor de Leefomgeving, 2015). Changes in other socio-economic variables are not considered, nor the impact of changes in travel times on the trip generation. This simplification is justified, because we look at the relative impacts of automation and sharing in several future scenarios.

3.2 Step 3: Location choice

Spatial impacts or location choice effects of automated driving are exogeneous input to our model. Based on literature (see section 2.4) and expert knowledge, it is possible to indicate per region type what percentage of inhabitants relocate and to which region type they are relocating. The weight factor of each trip is multiplied by 1 plus the percentage change in the number of inhabitants of the region type in which the trip starts.

Step 4: Destination choice

Automation and sharing may also affect the destination choice. Destination choice effects are approximated with an elasticity that indicates with what percentage the mileage changes when the generalized travel time changes. An elasticity of -1 is used, which is based on (Herder, et al., 2015).

Step 5: Mode choice

Mode choice effects for each trip are modelled with a multinomial logit model. Similar to (Pakusch, et al., 2018), the choice between automated and non-automated (shared) vehicles is embedded in the mode choice as is explained in section 2.2. Trips are divided over different parking concepts (scenario input) and divided over different user classes that have a different willingness to share (scenario input per user group and age class).

The utility functions for the different modes contain fixed costs (*cf*), costs per kilometre (*cv*), travel time (distance/speed = X/V), parking search time and time to go to the destination (pt), parking costs (*pc*), an extra travel time factor for ride sharing and/or car sharing that represents the extra time needed to pick up or to drop off other passengers or to walk to or wait for a shared vehicle (*tf*). Costs for road pricing per region (*cpr*) and per kilometre (*cpk*) are included for analysing the impact of pricing interventions. Finally, the utility function includes a mode specific constant and age dummies. Equation 1 shows the general form of the utility function for each mode, in which m = mode index, p = parking concept index, r = region type index, s = road type index, a = age class index, t = time index, vot = value of time. The distance per trip is output of the 'destination choice' step. The trip length is split over multiple road types s such that $\sum_s X_s = X$, using road type fractions that are exogenous input. The speeds for the car modes are output of the traffic assignment via the network fundamental diagram (step 6). The speed V for cars, taxis and vans are weighted average speeds. The speeds for these modes vary per road type and region type.

$$U_m = cf_m + cv_m * X + \left(\frac{X}{V_m} + pt_{mp}\right) * vot_m * tf_m + pc_{mp} + cpr_r + \textstyle\sum_s (cpk_s * X_s) + ASC_m + age_a \quad (1)$$

Table 2 summarizes the input. The costs are derived from (Boston Consulting Group, 2016). The costs of automated vehicles are expected to stay equal to the costs of current cars. The purchase costs of automated vehicles are expected to be higher, but the insurance costs and fuel costs are assumed to decrease. In case of sharing, the costs decrease because they are shared with multiple people. In the level 3/4 scenarios, the automated taxi (shared or not) and van is relatively expensive as a driver is still needed. The value of times for the existing modes are based on (KIM, 2013). The values of time for the new modes are derived from (Snelder, et al., 2015). Finally, automation of trains and bus/ tram/metro could also reduce the costs of these modes. However, this has not been implemented. It is assumed that automated taxis, shared taxis and shared vans increase the total travel time with respectively 5%, 20% and 40%, as compared to private cars. When shared concepts become more attractive, the detour time might decrease, because the vehicle fleet will be larger, which allows for further optimization of the system. For automated shared taxis and vans a maximum distance (md) of 35 km is assumed because these vehicles are assumed to stay within a certain range from their 'home region'.

The modes car driver and automated private car (level 3/4) can only be chosen when the person that makes a trip has a car in the household and a driver's license. Automation might have an impact on car ownership, especially when the costs decrease. This is however outside the scope. We assumed that in case of level 5 automation, a driver's license is no longer necessary. A bicycle can only be chosen when the person that makes a trip has a bicycle. The modes automated shared taxi and automated shared van can only be chosen when the person is willing to share.

Each mode can only be selected when the mode is allowed in the region type of the origin and destination. This allows for scenarios in which, for instance, automated private cars are not allowed in very highly urbanized areas or any other region restriction. Restrictions for region types that are merely crossed during a trip are not considered.

The mode choice model is estimated based on OVIN data for the base year 2015. For the new transport concepts including automation and sharing, the parameters cannot be estimated, since they are not included in the data yet. The mode specific constant (ASC_m) and age dummies (age_a) contain mode preferences that are not related to travel times and costs (e.g. comfort). Because people of different ages may have different preferences age dummies are added. The parameters for the automated private car are set equal to the parameters of car driver. For automated taxis, shared taxis and shared buses, these parameters were set to 40%, 80% and 100% of the parameters for bus, tram and metro since these new concepts have more in common with public transport than with cars. It is assumed that automated taxis are preferred over automated shared taxis and buses, because they are not shared with others. Similarly, automated shared taxis are shared with less people than automated shared vans. Therefore, they have a lower disutility.

The costs, value of time and mode specific constants were varied in a sensitivity analysis.

Table 2. Exogeneous variables and parameters

	CF (€)	CV (€/KM)	TF	VOT (€/H)	MD (KM)	ASC	AGE 0-17	AGE 18-35	AGE 36-75	AGE >75
Car driver	-	0.17	1.00	9.00	-	0.0	8.0	0.0	0.0	3.0
Car passenger	-	0.00	1.00	7.20	-	-1.0	-1.0	0.5	0.5	0.0
Train	2.20	0.17	1.00	9.25	-	3.5	2.0	0.0	0.0	12.0
Bus/Tram Metro	0.78	0.10	1.00	6.75	35	5.0	0.0	0.0	0.0	5.0
Bicycle	-	-	1.00	9.00	-	2.5	-3.0	0.0	0.0	4.0
Walking	-	-	1.00	9.00	-	2.0	-2.0	0.5	-1.2	2.0
Automated private car	-	0.17	1.00	L5 7.20 L3/4 8.10	-	0.0	8.0	0.0	0.0	3.0
Automated taxi	-	L5 0.18 L3/4 2.50	1.05	L5 7.20 L3/4 8.10	-	2.0	0.0	0.0	0.0	2.0
Automated shared taxi	-	L5 0.12 L3/4 1.63	1.20	L5 7.65 L3/4 8.55	35	4.0	0.0	0.0	0.0	4.0
Automated shared van	-	L5 0.06 L3/4 0.81	1.40	L5 7.65 L3/4 8.55	35	5.0	0.0	0.0	0.0	5.0

Step 6: Traffic assignment

Travel time impacts are computed with a network fundamental diagram per road type s and region type r for the morning peak, evening peak and off-peak period t. The network fundamental diagram gives a relation between the accumulation (average network density *K*) and the average network speed *V*. If the network density is below the critical density vehicles drive at the maximum or free-flow speed. If the density is above the critical density the speed reduces to 0 km/h.

$$V^{rsp}(K^{rst}) = v_0^s \qquad if\ k^{rs} \le k_{crit}^{rs} \qquad \forall\, r \in R, s \in S, t \in T \tag{2}$$

$$V^{rst}(K^{rst}) = \left(k_{jam}^s - K^{rst}\right) * \frac{w^s}{K^{rst}} \qquad if\ k^{rs} > k_{crit}^{rs} \qquad \forall\, r \in R, s \in S, t \in T$$

$$w^s = \frac{cap^s}{(k_{jam}^s - k_{crit}^s)} \qquad \forall\, s \in S$$

v_0 is the free-flow speed, k_{jam} is the jam density (vehicles/kilometre/lane), k_{crit} is the critical density (vehicles/kilometre/lane), w is the waves peed (km/h) and cap is the capacity (vehicles/lane/hour). *R, S* and *T* are the sets of region types, road types and periods respectively. The free-flow speed and lane capacity of the fundamental diagrams are based on the national model system LMS and are summarized in Table 3. The jam density of 125 veh/km is based on literature.

Table 3. Parameters fundamental diagram

Car	Through roads	Distributor roads	Access roads
Freeflow v_0^{rs} [km/h]	100	60	50
JamDensity k_{jam}^{rs} [veh/km]	125	125	125
Capacity cap^{rs} [veh/hour]	2000	1400	1000

To compute the network density per region and road type and per period (formula 3), the trips i are converted to the number of vehicles that are present in the network in a period based on a weight factor D that shows how many trips with mode m, trip i represents (see step 1). For each trip i, the modal split Dim has been determined by the mode choice model. Only the subset of modes (MR) that use the road network are considered. This implies that cycling, walking, train, bus, tram, metro are excluded. For automated shared taxis and automated shared vans an average occupancy rate *o* is assumed of respectively 2.5 and 5 persons per vehicle. For automated private cars and automated taxis, the average occupancy rate depends on the number of car passengers. Per trip, region and road type, the vehicles are multiplied by a factor (travel time reference case/duration period H^t) that indicates which percentage of the time they are present in the network of that region and road type. The travel time for the reference case is computed by dividing the distance travelled X on each region and road type by the speed from the reference case for that region and road type and period v_b^{rst}. f_i^{rs} is the fraction of the trips driven on road type *s* in region type *r* and *tf* is an extra travel time factor for ride sharing and/or car sharing that represents the extra time needed to pick up or to drop off other passengers or to walk to or wait for a shared vehicle. This factor is exogenous input to the model. The factor can be determined using a vehicle allocation model as is for instance done in (OECD, 2015)(see section 2.1). Finally, the density is computed by dividing by the calibrated total number of lane kilometres LK per region and road type and per period. The number of lane kilometres is used as calibration parameter to correct for the fact that a sample of trips is used as input (see step 1).

$$K^{rst} = \left(\sum_{i \in I} \sum_{m \in MR} \left((D^{imt}/o^m) \left(\frac{f_i^{rs} * X^i * tf_m}{v_b^{rst}} / H^t \right) pce^m \right) + D_{truck}^{rs} * pce^{truck} \right) / LK^{rst} \quad (3)$$

Automated vehicles affect the capacity because they can drive closely together when there is V2V-communication. When there is no V2V-communication (autonomous driving) the headways are expected to stay equal or increase slightly because of larger safety margins. Snelder et al. (2015) present a literature overview of microsimulation studies, e.g. Shladover et al. (2012) and Wang (2014), that indicate how much time headways may change for locations with and without bottlenecks. Based on those studies, we assume that automated private cars, (shared) taxis and vans have a passenger car equivalent (pce) value of 1.05 when there is not V2V-communication and a pce-value of 0.7 when there is V2V-communication.

3.3 *Iterative process*

The speeds for the car modes are input to the destination and mode choice model. The sub-models iterate until convergences is reached. In order to make sure that the model converges, the speeds from the previous iteration and the current iteration are combined using a fixed weight α of 0.25 as is recommended by Ortúzar and Willumen (2011)(see formula 4).

$$V_j^{rst} = \alpha V_{j-1}^{rst} + (1 - \alpha) V *_j^{rst} \qquad \forall\, r \in R, s \in S, t \in T \quad (4)$$

Convergence is reached when the weighted average summed speed difference between two iterations j and j -1 is below a threshold value ε (see formula 5). A default value of 0.05 km/h is used for ε. For all presented scenarios convergence is reached in less than 20 iterations.

$$\sum_{r \in R} \sum_{s \in S} \sum_{t \in T} D_j^{rst} \left| V_j^{rst} - V_{j-1}^{rst} \right| / \sum_{r \in R} \sum_{s \in S} \sum_{t \in T} D_j^{rsT} < \varepsilon \quad (5)$$

3.4 *Model validation*

The mode choice model is validated by comparing the mode choice elasticities for changes in costs and times with elasticities found in literature (Wardman, 2012; de Jong & Gunn, 2001; Geilenkirchen, et al., 2010). The elasticity for changes in car travel times is -0.76. Literature reports a value of -0.74. Since the elasticity for changes in car travel times is most important, because it also covers changes in the value of time caused by automated driving and changes in the extra travel time factor for ride sharing and/or car sharing, it is concluded that the mode choice model is valid for usage in exploratory research.

The network fundamental diagrams for distributor and access roads have been validated by making a comparison with a network fundamental that has been derived from Google data for urban roads (Knoop, et al., 2017). The main conclusion is that the network fundamental diagrams are valid for densities up to 35 veh/km. For higher densities the model is a bit too sensitive which results in an underestimation of the speeds of at most10 km/h.

Section 4.3 presents a validation of the model results for four different scenarios with automated driving and sharing.

4. Case study North-Holland

The case study focuses on the Province of North-Holland in the Netherlands (Arcadis and TNO, 2018). The largest city in this province is Amsterdam. Figure 2 shows the province of North-Holland and its region types.

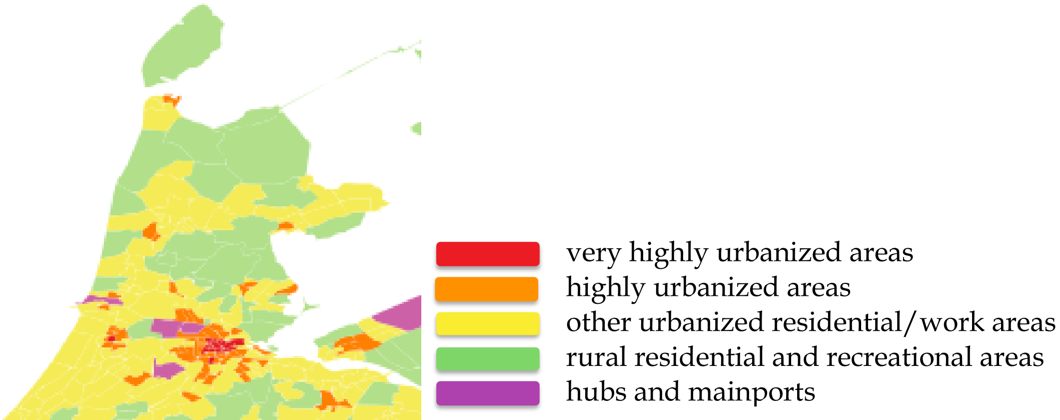


Figure 2. The Province of North-Holland and its region types

In 2015, the Netherlands Institute for Transport Policy Analysis (KIM) presented four scenarios for a future traffic and transport system with self-driving vehicles (KIM, 2015). The scenarios vary in the extent to which vehicles will be automated and how much use will be made of automated vehicles, as well as the extent to which travellers are willing to share a vehicle (in terms of car sharing and ride sharing). The four scenarios were called:

1. Mobility as a Service: Any time, any place (100% Level 5, high willingness to share)
2. Fully automated private luxury (100% Level 5 – no willingness to share)
3. Letting go on highways (100% Level 3/4 – no willingness to share)
4. Multimodal and shared automation (100% Level 3/4 – high willingness to share)

In this case study, extreme scenarios were explored in which 100% of the vehicles is automated L3/4 or L5. The extremes were chosen to get insights into maximum effects. In practice, there will be a long transition phase with a mix of level 0/1/2/3/4/5 vehicles on the road. The transition path is outside the scope of this paper. The presented model can, however, also be used to assess the impact of a mix of vehicles on the road.

It is assumed that in the level 5 scenarios, automated vehicles could drive in automated mode on all road types. There is no abuse such as people stepping in front of a vehicle to make it stop, so reasonable speeds can be achieved everywhere, including residential streets with mixed traffic (e.g. cyclists, pedestrians, stationary delivery vans). For the L3/4-scenarios, it was assumed that on through roads and distributor roads where motorized traffic and active modes are separated effectively, vehicles can drive in automated mode. On mixed use distributor roads and access roads, vehicles need to be driven manually. In the level 5 scenarios, it was assumed that all vehicles communicate with each other and the infrastructure. In the L3/4-scenarios it is assumed that 60% communicates with each other and 40% is autonomous.

4.1 Scenario specific input

Each transport concept was either enabled or disabled. Car and car passenger, as well as automated private car, were disabled in the L5-sharing scenario, except for rural regions. In the L5-no-sharing scenario, automated private cars were enabled but not conventional car and passenger. Automated taxis were enabled for all scenarios and region types; shared automated taxis/vans/buses only in the sharing scenarios. Conventional public transport (train, bus, tram, metro) were enabled everywhere, because disabling them would mean that in the sharing scenarios, for long distances only automated taxis are available (as cycling, walking and sharing concepts were assumed to have a maximum distance associated with them). Cycling and walking were enabled in all scenarios and region types.

The preference for parking concepts has been specified for each scenario and region type. For the L5-sharing scenario, travellers are always dropped off at their destination in all region types. In L5-no-sharing, valet parking has a large share in mainports and hubs. In urbanized areas, parking is mostly at the destination or valet parking, with a tiny share for parking at a distance. For the most urbanized areas in Amsterdam, parking is assumed to be mostly at the edge or just outside these areas, with a small share for valet parking and a tiny share for parking at the destination. In rural regions, most parking is still done at the destination. In the L3/4 scenarios, valet parking has a very small share. In the rural regions, parking at the destination is still dominant. In L3/4-sharing, parking at a distance and parking at the destinations have equal high shares for urbanized regions; for the most urbanized areas, parking at a distance is dominant.

Some shifts were assumed in spatial distribution, in terms of where people choose to live. Gelauff et al. (2017) indicate that "more productive time use during car trips because of automation results in population flight from cities. The efficiency gain in public transport because of automation has an opposite effect. It leads to further population clustering in urban areas where public transport efficiency is primarily expected to increase. A combination of these two components may result in concentration of the population in the largest most attractive cities and their suburbs at the cost of smaller cities and non-urban regions." Both shifts were applied, taking the order of magnitude of the effect from (Gelauff, et al., 2017). No changes were assumed for L3/4-no-sharing; changes in the order of 0.5-1% for L3/4-sharing (shift towards more urbanized areas) and L5-no-sharing (shift towards less urbanized areas); and finally, in the L5-sharing scenario shifts in the order of 2-3% shift towards highly urbanized areas.

4.2 Results scenarios

This section first presents the results for the entire Province of North-Holland and then highlights the main differences per region type. Figure 3 describes the modal split effects in terms of number of trips. In L5-sharing there is a large modal shift of all modes mainly to automated taxis, because the costs for this mode are relatively low and the value of time is lower as well. 8% of the trips are made with shared concepts. In L5-no-sharing the private car and automated taxi are the dominant concepts. The total share of car trips increases from 41% to 68%. L3/4-no-sharing resembles the reference scenario the most. The differences between L3/4-no-sharing and L3/4 sharing are small because a professional driver is still needed for shared taxis and vans and the costs are therefore relatively high.

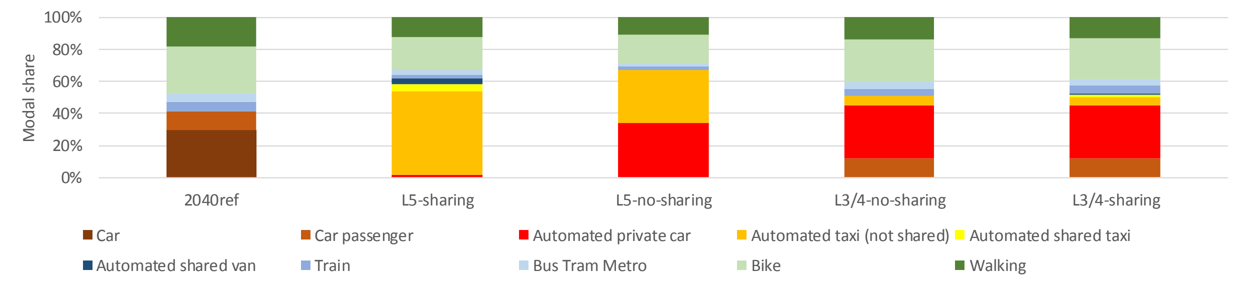


Figure 3. Modal split effects

Figure 4 shows that the number of vehicle kilometres increases in all scenarios compared to the reference scenario. In L5-no-sharing the increase in the number of vehicle kilometres is 69%. This is partly explained by the modal shift towards automated taxis and partly explained by longer distances travelled. By consequence, the number of vehicle hours of delay increases considerably resulting in severe congestion in the L5-scenarios. The total number of vehicles required increases in all scenarios but L5-sharing, where the number of vehicles required decreases with 58% because automated taxis can complete multiple trips per day. The parking revenues increase in the L3/4-scenarios and decrease in the L5 scenarios. In L5-sharing it is assumed that people are dropped off at their destinations. Vehicles must park themselves sometimes during the day when they are inactive. This might give some revenues, but they are not considered in this case study.

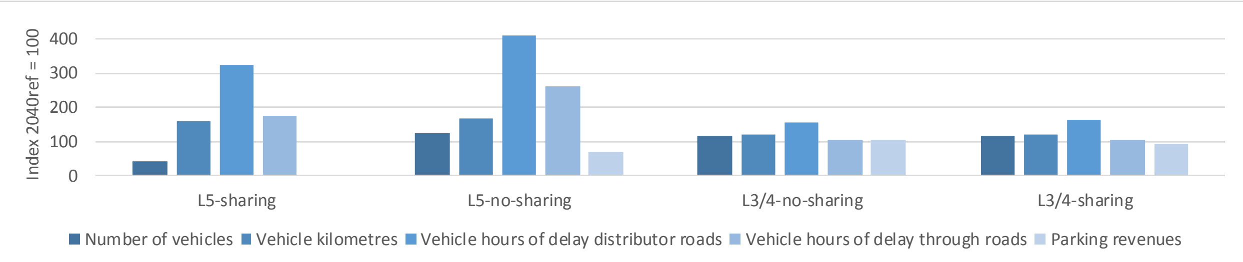


Figure 4. Traffic effects and parking revenues

The abovementioned results are an average for the entire Province of North-Holland. Since the region type 'Other urbanized residential/work areas' is the most frequently occurring region type, the results for this region type are closest to the average results. In (very) highly urbanized areas, the relative increase in mileage and delay is the largest (up to +150% in very highly urbanized areas in L5-no-sharing), because people switch from walking, cycling and public transport to car modes. In rural areas and in mainports and hubs the share of car trips is already high in the reference case, because of the lower spatial density and a lower level of public transport services, so the relative increase in mileage is lower. Since there is more spare road capacity in these regions, the increase in mileage will have less impact on delay. Nonetheless, in L5-no-sharing the delays still increase in rural areas. In the other scenarios, the delays stay more or less equal or even decrease in rural areas and near mainports.

4.3 Comparison with literature

Since automated vehicles of level 3 and beyond are very rare at present time, and comprehensive studies of their impacts are limited and differ in assumptions, our model is difficult to validate. To the best of our ability, we compare results from each of our four model scenarios with results from relevant literature below. While a thorough assessment remains difficult, our model appears reasonably adequate for its explorative purpose.

L3/4-no-sharing: Unlike the considerable changes our model predicts for the L3/4-no-sharing scenario, Smit et al. (2017) report only very small changes in the outcomes of the Dutch national transport model after automating about one-third of the vehicles up to level 4 when driving on trunk roads. Contrary to Smit et al., Puylaert et al. (2018) do predict a modal shift to cars, but the impacts are smaller than in our model. A possible explanation is that our L3/4-no-sharing scenario has 100% penetration and further adds automated taxis as a new mode.

L3/4-sharing: Basu et al. (2018) model a scenario for a virtual city where automated shared taxis are introduced. We can roughly compare this with our L3/4-sharing scenario, keeping in mind that Basu et al.'s virtual city also has a human-driven taxi mode and that no changes are made to privately-owned cars. Compared to the respective reference scenarios, both models predict that ridership of traditional public transport will drop (-21% for us versus -7% for Basu et al.) and that the number of car passengers will drop (-2% versus -9%). However, the effect on the number of car drivers of privately-owned cars differs (+13% versus -7%), likely due to the different assumption about automation.

L5-no-sharing: Levin and Boyles (2015) model a scenario in Austin, Texas where motorists can send their automated vehicle back home to avoid parking it at their destination. We can roughly compare this with our L5-no-sharing scenario where travellers also have various parking options and can additionally opt for automated taxis. Compared to the respective reference scenarios, the results turn out to be surprisingly similar: parking at the destination drops considerably (-56% for us versus -66% for Levin & Boyles), public transport ridership also drops considerably (-67% versus -61%), and the network-average speed also reduces (-10% versus -8%).

L5-sharing: Boston Consulting Group (2016) conducted a stated-choice survey among Amsterdam travellers of various modes, asking them whether they would switch to new modes utilizing automated driving. Table 4applies the resulting mode changes to our 2040 reference modal split for metropolitan areas and compares it to our L5-sharing modal split for metropolitan areas. Our model predicts much higher automated taxi use (41%) than the survey forecast (5%). However, contrary to the Boston Consulting Group survey, our L5-sharing scenario does not allow travellers to use private cars; if the private car use according to the survey (23%) is added to the automated taxi use, the difference becomes much smaller. The survey predicts more use of shared vehicles (10% versus 6%). The results for traditional public transport and bicycle are similar. Finally, note that our model predicts a reduction in walking (from 29% to 19%) whereas Boston Consulting Group assumed this wouldn't change.

Table 4. Modal split in metropolitan areas

	2040-reference	2040-reference with BCG mode changes	L5-sharing
Car	14%	6%	0%
Automated car	0%	17%	0%
Automated taxi	0%	5%	41%
Automated shared taxi/van	0%	10%	6%
Train	8%	4%	3%
Bus/tram/metro	8%	2%	4%
Bicycle	41%	28%	27%
Walk	29%	29%	19%

4.4 Sensitivity analysis

Figure 5 shows the results of a sensitivity analysis on the costs, value of time, mode specific constant and occupancy rate. The mode specific constant for automated taxis, shared taxis and shared vans, was respectively 40%, 80% and 100% of the mode specific constant for bus, tram and metro. In the sensitivity analyses they are all set equal to 100% (run 'asc 100%'). In another run the costs of automated taxis, shared taxis and shared vans are set equal to the values for car drivers (run 'costs 17ct'). The run 'costs+fixed costs' is a run in which 20 cent per kilometre divided by the occupancy rate was added to the costs per kilometre. In this scenario the owner of the vehicle, charges the ownership costs to the user(s) of the vehicle. In the runs 'Costs+10%/20%/30%' the costs for automated taxis, shared taxis and shared vans are increased with respectively 10%, 20% and 30%. In the run 'vot 9.00 euro' it was assumed that the value of time does not reduce because of vehicle automation. Finally, in the run 'occupancy rate' the occupancy rate of shared taxis and shares vans was set to 2 and 4 instead of 2.5 and 5.

The results show that varying the mode specific constant has the largest impact. If the new concepts appear to be less attractive than we assumed their total modal share might reduce from 62% to 44%. Charging the ownership costs to the user (run 'costs+fixed costs') also makes a large difference. It reduces the modal share of the new modes to 46%. It is likely that owners of the automated (shared) taxis and vans will do this at least to some extent. Finally, the runs in which the costs are increased with 10%, 20% and 30%, show that some non-linear effects occur.

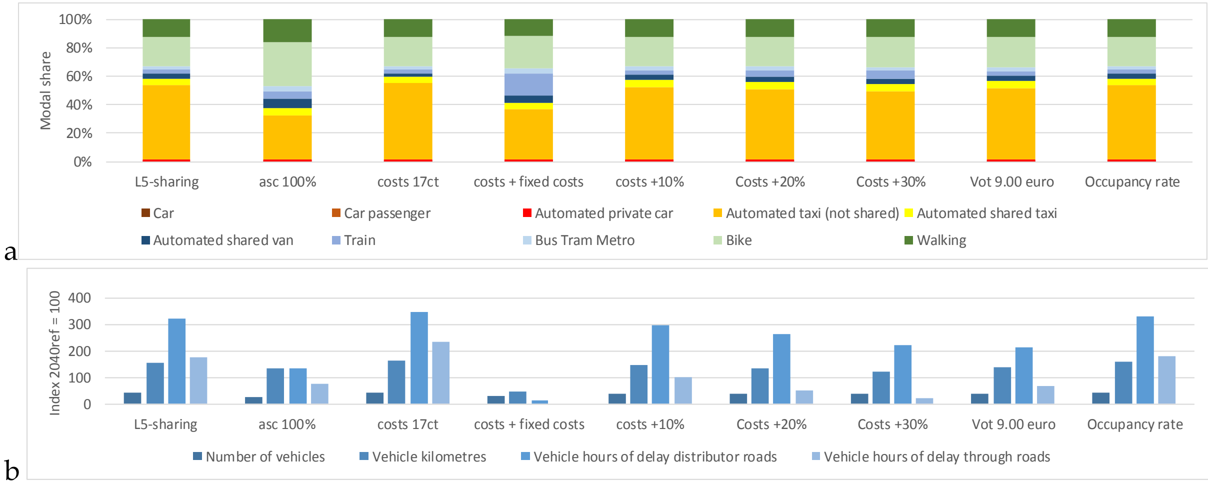


Figure 5. Results sensitivity analysis

4.5 Interventions

Governmental interventions can, on the one hand, accelerate a transition to a self-driving future. On the other hand, the Province and the Amsterdam Transport Region can intervene to mitigate potential negative impacts (e.g. expected severe congestion in (very) highly urbanized areas), in their role as road authority and public transport concession provider. In the case study, the model is further applied to explore the effect of interventions. By means of example, Figure 6 shows the modal split results and traffic effects for a selection of interventions that are relevant in L5-no-sharing (column 4-8) and that are relevant in L5-sharing (column 9-12). The three columns on the left are the same as in figure 3. They are included to make comparisons easier.

Interventions L5-no-sharing

'Park at distance' refers to a scenario in which parking or drop/off at location is forbidden in highly urbanized areas. 'Road pricing <30/15/5> ct/km' refer to road pricing scenarios and 'improved public transport' refers to a scenario where the frequencies of train, but, tram and metro are increased with a reduction of about 20% of travel time as a result. The figure shows that in L5-no-sharing only high road pricing charges (15 and 30 cent/kilometre) can keep the number of car related trips, the number of vehicle kilometres and the vehicle hours of delay more or less at the same level as in the reference scenario. The number of bicycle and walking trips increases with all interventions, but the level of the reference scenario will not be reached. For the traditional public transport modes (train, bus, tram and metro) high road pricing charges are needed to reach the level of the reference scenario. The impact of 'Park at distance' is close to zero when all area types are considered. In very highly urbanized areas, the impact is larger (e.g. 9% reduction in automated private car trips).

Interventions L5-sharing
'100% sharing' refers to a scenario in which 100% of the people is willing to share. In the reference scenario for L5-sharing it is assumed that 100% of the people younger than 18 year is willing to share. For others it this percentage is assumed to be between 5%-75% depending on age, household income and car ownership. In 'Reduced time factor' it is assumed that the extra travel time factor for automated shared taxis and vans is reduced with 50% enabled by a larger vehicle fleet. In 'no automated taxi' these vehicles are just like private cars not allowed except in rural areas. 'Mix sharing' combines all these interventions and reduces the travel times by train, bus/tram/metro with 20%. The last 2 scenarios have the largest impact. They reduced the number of vehicle kilometres with respectively 88% and 79%.

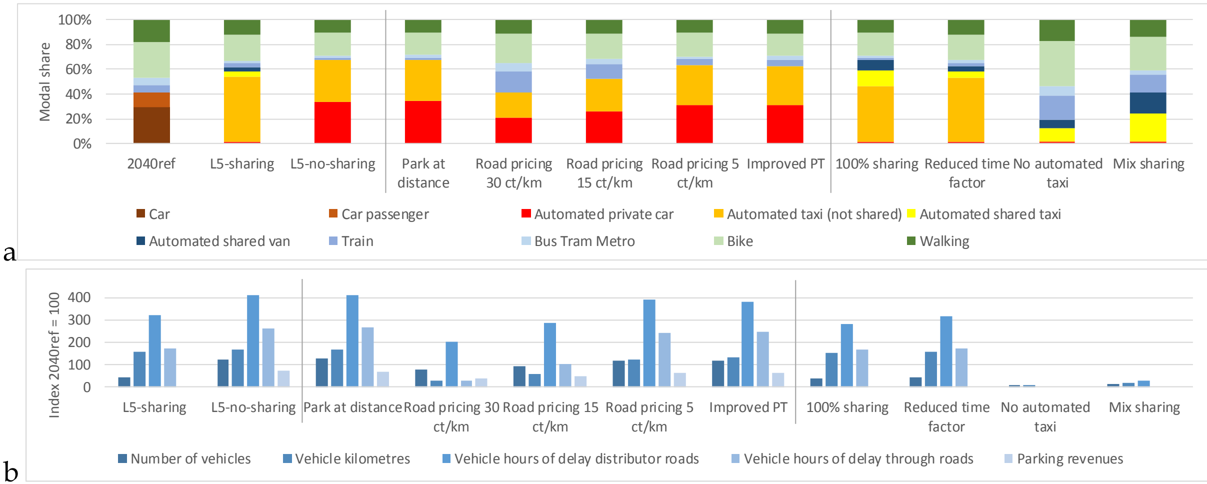
a
b


Figure 6. Modal split effects (a) and traffic effects and parking revenues (b) interventions

Based on the results described above it can be concluded that a strong mix of interventions is needed to keep vehicle kilometres at the same level as in the reference scenario. This is especially the case in (very) highly urbanized areas. In other areas, the interventions can be more modest.

5. Discussion, conclusions and recommendations

This paper presented a new modelling approach that can be used to get insights in the combined impacts of automated driving and shared mobility.

With respect to the results: the case study showed the order of magnitude and types of modal split and traffic effects that can be expected in extreme scenarios. A shift to automated private cars, automated taxis can be expected and to the sharing concepts when sharing becomes popular. This increases the accessibility of many regions for many people; also, those who are not allowed to drive. In the most extreme scenario, L5-no-sharing, the amount of car trips including new modes increases from 41% to 68%. The increased mobility has negative effects on congestion. Note that the impact of congestion on mode choice has been considered. A strong mix of interventions is needed to keep delays at the same level as in the reference scenario. This is especially the case in (very) highly urbanized areas. In other areas, the interventions can be more modest.

With respect to the model: it can be concluded that the model is suitable to get first insights in mobility impacts of connected automated and shared mobility. New transport concepts and parking concepts are included in the model as well as the way in which they affect mobility choices and traffic conditions. The innovative approach that combines choice models with a network fundamental diagram, gives clear insights into the impact mechanisms, despite uncertainties with respect to implementation path, time and costs parameters and user acceptance. The short computation time of the model (less than one minute) enables exploration of large numbers of scenarios, sensitivity analyses and assessments of the impacts of interventions.

The methods used for each sub-model can all be replaced by more detailed methods, like a land-use model, a discrete choice model or gravity model for destination choice, a nested logit model for mode choice, a dynamic traffic assignment model and an optimization model for shared mobility solutions. The level of detail that was chosen in this paper matches the limited amount of empirical evidence regarding the input attributes and parameters and makes it possible to explore many different scenarios within a short computation time. It is recommended to develop more details models, to model de most relevant scenarios in more detail. It is also recommended to include other phenomena in the model like zero-occupant vehicle demand and the impact of automation on car ownership.

Another recommendation is to reduce the uncertainties with respect to the costs, value of time and user acceptance of automated vehicles and sharing concepts, by carrying out stated preference research and by initiating pilots. Finally, it is recommended to get a clearer view on the transition towards a self-driving future and associated scenarios, and subsequently assess the impacts during the transition phase. This allows the development of adaptive policies that will be needed in an era with connected, automated and shared mobility.

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