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Explorative Model and Case Study of the Province of North-Holland

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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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ABSTRACT

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 impact mechanisms and the direct and indirect mobility impacts are the third contribution. The short computation time of the model enables exploration of large numbers of scenarios, sensitivy 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.

Keywords: Automated driving, Shared mobility, Mobility impacts, Mode choice, Network fundamental diagram

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 quickly 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 take into account 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 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 impact mechanisms and the 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.

LITERATURE REVIEW

A comprehensive overview of the implications of automated driving is provided by the ripple model of Milakis et al. (*1*), 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 (*2*). This section subsequently discusses examples of the modelling of automated driving impacts and sharing on traffic assignment, mode choice, trip and destination choice, and location and car ownership choice. All these elements are present in the road transport impact assessment framework of (*3*) and and may be affected by automated driving according to (*4*).

Throughout this paper, automation levels follow the SAE-levels of motor vehicle automation (*5*).

Traffic assignment

For the automated driving adaptation of the Puget Sound regional transport model by Childress et al. (*6*), link capacities were adjusted, but no distinction between vehicle classes was added to the model. Levin and Boyles (*7*) formulate a static assignment distinguishing between fully automated and non-automated vehicles, where the capacity in the BPR function linearly depends on the penetration rate of automated driving. Levin and Boyles (*8*) formulate a similar dynamic assignment where the fundamental diagrams depend on the penetration rate. Moreno et al. (*9*) and Basu et al. (*10*) use dynamic agent-based simulation to study the impact of shared autonomous vehicles, explicitly replicating the operation of the shared vehicle system. Zhang and Guhathakurta (*11*) do the same, but assume fixed travel times.

To calculate travel times, one may alternatively use a network fundamental diagram, i.e. the relation between vehicle density and speed for a network (*13*, *14*). Abbas (*15*) suggests to adapt the network fundamental diagram to automated vehicles based on microscopic simulations. Lu and Tettamanti (*16*) estimated network fundamental diagrams this way for different penetration rates of different automation levels, based on assumed parameters for driving behavior. Based on Malone et al. (*17*), Puylaert et al. (*18*) 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.

Finally, the International Transport Forum (*19*) 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.

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, Malokin et al. (*20*) 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. (*21*) use the same mode choice model as the LUCA model for the Netherlands (*22*), 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. (*12*) 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. (*6*) do the same without distinguishing these user classes.

Some literature mentions changing the available modes in the mode choice. LaMondia et al. (*23*) add automated vehicle as a third alternative to a mode choice model between car and airplane. Conversely, Correia and Van Arem (*24*) 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 (*25*, *26*), shared vehicle concepts are only sometimes embedded as alternatives in mode choice models for automated driving scenarios. In a multimodal setting, Yap et al. (*27*) 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. (*28*) estimate a usage frequency choice model for shared automated vehicles. Pakusch et al. (*29*) 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. (*9*) 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. (*10*) 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 (*30*).

In terms of new parking concepts with automated vehicles, Levin and Boyles (*7*) 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. (*6*) only reduce parking costs in their model to account for more compact parking of automated vehicles.

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. (*12*) and LUCA used by Gelauff et al. (*21*) account for the destination choice effect by combining mode choice and destination choice in a nested logit model (*31*). 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 (*7*) base destination choice on the best generalised travel cost of all modes. The reduction of travel time and value of time causes the activity-based model used by Childress et al. (*6*) to schedule both more and longer trips. Basu et al. (*10*) also have the travel utility feed back into the activity pattern choice.

Location and car ownership choice

Location and car ownership choices are not traditional components of the four-stage model (*2*). In terms of the ripple model of Milakis et al. (*1*), these choices are not directly relevant for first-layer implications of automated driving, but focus on the second layer. Gelauff et al. (*21*) 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 analyze 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. (*12*) 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. (*18*) use penetration rates from Nieuwenhuijsen et al. (*32*), 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. (*29*) embed the choice between an automated and a non-automated vehicle in the mode choice instead of a separate car ownership choice.

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. (*10*) already includes many of these aspects, it is an activity-based and agent-based, resulting in high data requirements and long computation times for large networks. New parking conepts are not included yet.

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. This section describes the model approach in more detail. Table 1 describes the model segmentation.

TABLE 1 Model segmentation

Inputs	Explanation
12 transport modes	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 automated driving functions corresponding to level 3/4 or 5. 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.
Level of communication	Share of the fleet that is capable of vehicle-to-vehicle (V2V) communication.
4 road types	Through roads (freeways and highways), distributor roads with separate roadways, distributor roads with mixed traffic, access roads (district and neighborhood arteries, residential streets, woonerf).
5 region types	Very highly urbanized areas, highly urbanized areas, other urbanized residential/work areas, other urbanized residential/work areas, rural residential and recreational areas, hubs and mainports.
4 user groups	Car owners with a household income >30000 euro, car owners with a household income ≤ 30000 euro, no private car available and household income >30000 euro, no private car available and a household income ≤30000 euro.
4 age classes	0-17, 18-35, 36-75, >75 years.
3 parking options	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).

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

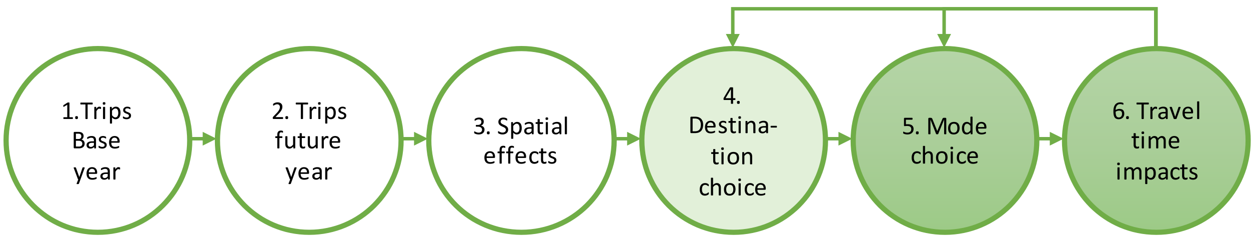

FIGURE 1 Steps model approach.

Step 1
Trips 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 questionnaire OVIN (*33*) 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, the number of cars 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.

Step 2
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 (*34*). 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.

Step 3
Spatial impacts of automated driving are exogeneous input to our model. Based on literature and expert knowledge, it is possible to indicate per region type what percentage of inhabitants relocate and to which region type they are relocating.

Step 4
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 (*35*).

Step 5
Mode choice effects for each trip are modeled with a multinomial logit model. Similar to (*29*), the choice between automated and non-automated (shared) vehicles is embedded in the mode choice. 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 kilometer (*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 kilometer (*cpk*) are included for analyzing 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, *w* = road type index, *a* = age class 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 *w* such that $\sum_w X_w = X$, 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.

$$U_m = cf_m + cv_m * X + \left(\frac{X}{V_m} + pt_{mp}\right) * vot_m * tf_m + pc_{mp} + cpr_r + \sum_w (cpk_w * X_w) + ASC_m + age_a \quad \textbf{(1)}$$

Table 2 summarizes the input. The costs are derived from (*36*). 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 (*37*). The values of time for the new modes are derived from (*38*). 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 not 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 of our research. 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 parameters for these modes are derived from the parameters of the other modes. The mode specific constant and age dummies 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.

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)	asc	md (km)	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	5.0	35	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	4.0	35	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	5.0	35	0.0	0.0	0.0	5.0

Step 6

Travel time impacts are computed with a network fundamental diagram per road type and region type for the morning peak, evening peak and off-peak period. The network fundamental diagram gives a relation between the accumulation (average network density *k*) and the average network speed *V*.

$$V(k) = v_0 \qquad if\ k \le k_{crit} \tag{2}$$

$$V(k) = (k_{jam} - k) * \frac{w}{k} \qquad if\ k > k_{crit}$$

$$w = \frac{cap}{(k_{jam} - k_{crit})}$$

In which v_0 is the maximuma speed, k_{jam} is the jam density (vehicles/kilometer/lane), k_{crit} is the critical densitiy (vehicles/kilometer/lane) and *cap* is the capacity (vehicles/lane/hour). The parameters of these fundamental diagrams were calibrated based on link-level flow, capacity and speed data from the Dutch national transport model. For each link the region type and road type is known.

In order to compute the density per region and road type and per period, the trips were converted to the number of vehicles that are present in the network in a period. For automated shared taxis and automated shared vans an average occupancy rate 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) that indicates which percentage of the time they were present in the network of that region and road type.

Finally, the density is computed by dividing by the calibrated total number of lane kilometers.

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. (*38*) present a literature overview of microsimulation studies (e.g. (*39*); (*40*)) 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.

Iterative proces

The speeds for the car modes are input to the destination and mode choice model. The sub-models iterate until convergences is reached.

CASE STUDY NORTH-HOLLAND

The case study focuses on the Province of North-Holland in the Netherlands (*41*). The largest city in this province is Amsterdam. In 2015, the Netherlands Institute for Transport Policy Analysis (KiM) presented four scenarios for a future traffic and transport system with self-driving vehicles (*42*). 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 travelers 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 60% communicates with each other and 40% is autonomous.

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, travelers 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.

Gelauff et al. (*21*) 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 (*21*). 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.

Results

This section first presents the results for the entire Province of North-Holland and then highlights the main differences per region type. Figure 2a 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.

An extensive sensitivity analysis was done on the on the costs, value of time and mode specific constants for the new modes in all scenarios. By means of example, the three columns on the right show the most important results for L5-sharing. The mode specific constant (*asc*) for automated taxis, shared taxis and shared buses, 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%. The value of time of the new modes (*vot*) and the costs (*cv*) are set equal to the values for car drivers in two separate sensitivity analyses (no reduction). Varying the model 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%.

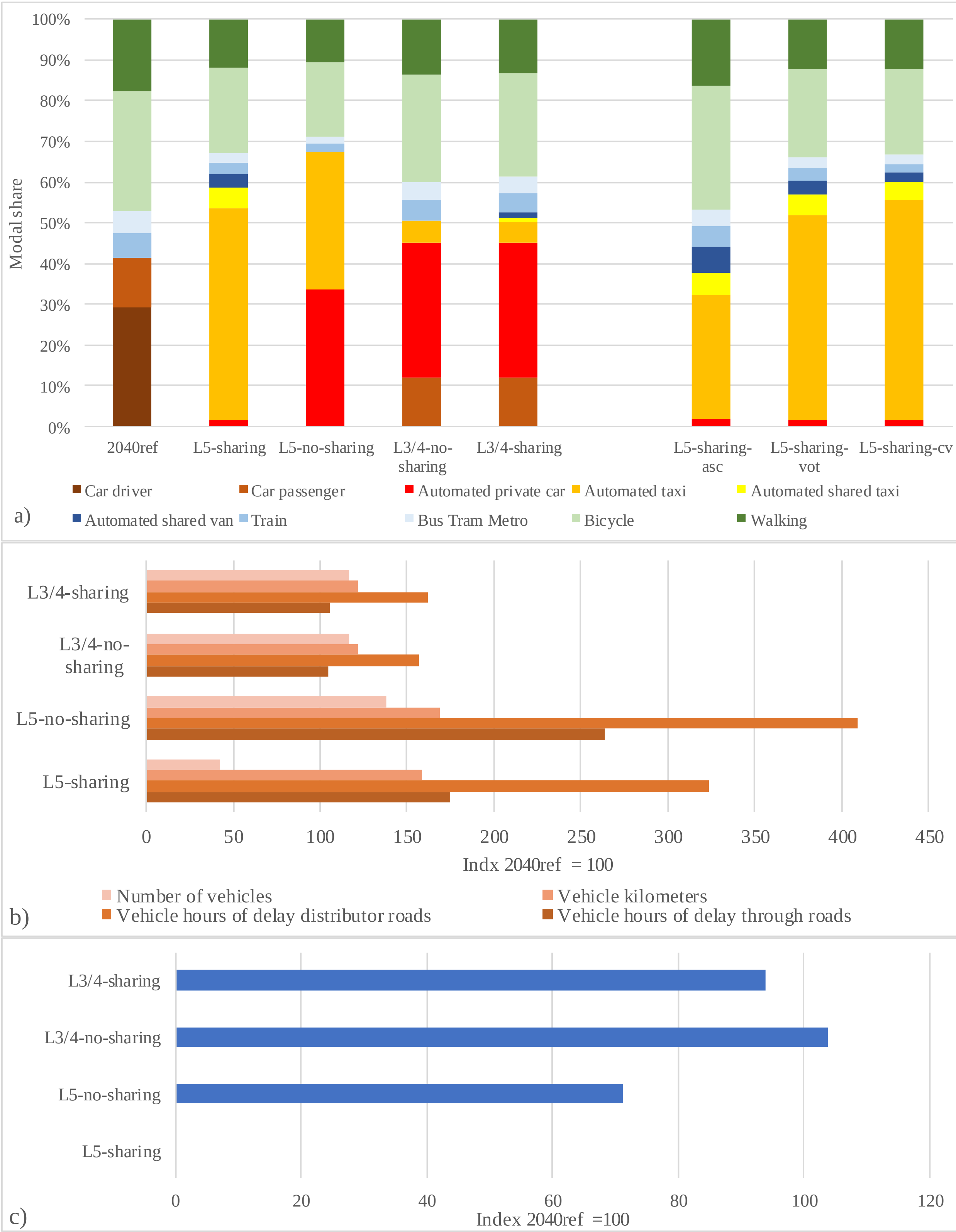

FIGURE 2 a) Modal split effects, b) traffic effects (index 2040ref = 100), c) parking revenues (index 2040ref = 100).

Figure 2b shows that the number of vehicle kilometers increases in all scenarios compared to the reference scenario. In L5-no-sharing the increase is the largest (+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.

Figure 2c shows that 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 have to park themselves sometimes during the day when they are inactive. This might give some revenues, but they are not considered in this case study.

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 was further applied to explore the effect of interventions such as banning parking near destinations in (very) highly urbanized areas, encouraging shared mobility, improving public transport (automation) and road pricing. It was concluded that a strong mix of interventions is needed to keep delays on the same level as in the reference scenario.

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. Based on the mobility impacts other direct and indirect impacts such as safety, sustainability/ livability, social aspects, economic developments and spatial developments can be assessed qualitatively as is shown in (*41*).

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, sensitivy 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 matches the limited amount of empirical evidence regarding the input attributes and parameters. It is also recommend to include other phenomena the model like zero-occupant vehicle demand and the impact of automation on car ownership.

It is recommended 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, by initiating pilots and by further studying the business models to get a better understanding of the user costs. 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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The authors confirm contribution to the paper as follows:
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literature review: Van der Gun, J.P.T.;
model development and analysis results: Snelder, M., Wilmink, I.;
draft manuscript preparation: Snelder, M., Wilmink, I., Van der Gun, J.;
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