MOBILITY IMPACTS OF EARLY FORMS OF AUTOMATED DRIVING - A SYSTEM DYNAMIC APPROACH

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ABSTRACT

Modern cars are increasingly being equipped with automated driving functions. For governments it is important to gain insight in the mobility impacts of automated vehicles. This is important as the introduction of automated vehicles affects current investment decisions about infrastructure projects and other policy measures like road pricing. Quantitative literature with respect to the impact of automated vehicles focuses mostly on capacity implications. Literature about large scale mobility impacts is mainly qualitative. This paper introduces a System Dynamics model (SD-model) to quantitatively explore the impacts of early forms of automated vehicles (level 1, 2 and 3) on mobility. The model is explorative and can be used to evaluate different scenarios in a short time. This model is applied in a case study for the Netherlands to assess the impact of automated vehicles on mode choice, time of day choice and travel times on characteristic relations in the Netherlands. In contrast to other studies the SD-model is able to simulate the effects of AVs over time and to simulate mixed automated vehicle types. A scenario for autonomous driving and a scenario for cooperative driving are considered. The simulations show that car traffic will increase and the level of congestion does not necessarily decrease and might even increase on some relations, especially in the autonomous scenario. Furthermore, in the cooperative scenario the increase in number of trips by car is larger, the average speeds are higher and there is less congestion compared to the autonomous scenario.

Keywords: Automated Vehicles, Self-driving Cars, System Dynamics, Mobility Effects, Large Scale Effects

1 INTRODUCTION

Modern cars are increasingly being equipped with automated driving functions. The Society of Automotive Engineers [1] defined 6 levels of automation, in which level 0 is a vehicle without automation and level 5 a fully self-driving vehicle capable of automated driving under any condition. First versions of automated vehicles (AV) are already on the road: in new luxury models adaptive cruise control and lane keeping are widely available (level 1 / 2). A key distinction is between level 2, where the human driver performs part of the dynamic driving task, and level 3 (conditional automation), where the automated driving system performs the entire dynamic driving task. In level 3, the driver is expected to be available for occasional control of the vehicle, while in high and full automation (level 4 and 5) he or she is not.

The implementation path of automated driving is highly uncertain in the sense that it is unknown when different levels of AV will be introduced, what the penetration rate of the different levels will be in the coming decades and how that varies per region and country. Expected impacts of automated driving on car ownership, car usage, value of time, driving costs, road capacity etc. are also uncertain. By consequence, the expected impacts on demand, vehicle kilometers driven and congestion are uncertain as well. For governments it is important to have insights in these mobility impacts because they affect current investment decisions about infrastructure projects and other policy measures like road pricing.

According to Milakis et al. [2] and Fagnant & Kockelman [3] the scarce quantitative literature with respect to the impact of AV that is available, focuses on local implications on traffic flows such as impact on capacity, capacity drop, stability and shockwaves. Literature about large scale mobility impacts is mainly qualitative [4]–[6]. National and regional governments often use macroscopic traffic and transport models to assess the impact of different policy measures. These models have not been designed to model the impact of automated vehicles. They are often highly detailed in order to capture as many demand decisions as possible. Besides that, the level of service of the different modes is modelled as accurate as possible. The first AV-studies with these models [7], [8], [9] (or unpublished work [10]) indicate that the high level of detail results in high computation times which makes them less suitable for explorations with many uncertainties. Furthermore, they do not distinguish different vehicles types for automated driving, but instead are based on and only allow for changing the attributes of the average vehicle.

This paper presents a macroscopic model to explore the impacts of early forms of automated vehicles (level 1, 2 and 3) on mobility. A System Dynamics model (SD-model) is introduced which is based on the structure of the ScenarioExplorer [11]. It combines scenario and transportation modelling on an abstract network. The main contribution of this paper is that the existing method is extended in such a way that the impact of level 1, 2 and 3 automated vehicles can be modelled on a macroscopic level. In contrast to other macroscopic studies about automated vehicle impacts [7]–[10] the SD- model is able to simulate different vehicle classes and to simulate the introduction of automated vehicles over time.

The SD-model is strongly explorative and does not make use of an explicit road network. The goal of this model is to capture the most important effects of automated vehicles, but not to model all the details. As the structure is simple and the run time is short, the model can be used to assess different scenarios. Literature indicates two development paths: an autonomous and a cooperative path. Autonomous vehicles only monitor the driving environment, whereas cooperative vehicles also communicate with other vehicles or roadside systems. Both development paths are simulated in a case study for the Netherlands. The model is validated and can be used for explorative research.

Section 2 describes the developed SD-model. The case study for the Netherlands is described in section 3, just as the results of the simulations. The conclusions are presented in section 4.

2 METHOD

2.1 Scope/expected Impact

Our model will focus on mixed traffic of level 0, 1, 2 and 3 [1]. Mikalis et al. [2] have created a ripple model in which they link the different levels of SAE to expected impacts on both the supply and demand side of the transportation system. In this paper level 1 and 2 are seen as a single form of automated vehicles as their expected impacts are similar. Freight transport is modelled exogenously. Only the capacity impact of truck automation is taken into account.

Research of Milakis et al. [2], Litman [4] and Snelder et al. [7] name several effects that AVs have on mobility: capacity effects (maximum capacity, shockwaves, capacity drop, network effects), an effect on the value of time (for the driver), monetary costs (fuel economy, insurance costs), trip length, parking, modal split for freight trips, travel times, congestion, safety and travel time reliability. This paper focuses on the impact of changes in capacity, value of time and monetary costs on the modal split, time of day choice and travel times. These effects are chosen because they are most direct and literature is most explicit about these effects.

The capacity effect is an outcome of four factors from literature (*7*), (*10*): a higher capacity of a road stretch, a lower capacity drop, less shockwaves and a better distribution of vehicles over the network. The second effect is a lower value of time for AVs than for regular vehicles as the driver can do something else while driving. This plays a role in the utility functions used in time of day and mode choice. The third effect is that the monetary cost per driven kilometer of the vehicle decreases, as automation can lead to a higher energy efficient driving, less insurance costs or less maintenance (*4*), (*7*).

2.2 System Dynamic Model (SD-model)

For this explorative phase of forecasting many model runs with different settings are needed, therefore an explorative model is favored over a more detailed model. As explained in the introduction traditional macroscopic models are complex and detailed, which makes them less suitable to deal with uncertainties. In this paper System Dynamics is chosen as method because System Dynamics makes it possible to explore many different scenarios which makes this method suitable for dealing with the uncertainties automated vehicles bring with them [13]–[15]. System Dynamics makes use of causal relationships between elements of a system. By quantifying these relations, the behavior of a system over time can be researched [13]. System Dynamics can be applied in a variety of cases, from simple systems like one company to more complicated ones like the climate effects of a planet [14], [16]. The structure of our model (SD-model) is based on the ScenarioExplorer [11].

The method is extended in such a way that the impact of level 1, 2 and 3 automated vehicles can be modelled endogenously. The Vensim-software is used to implement the model.

2.3 Structure of the SD-model

The goal of the model is to evaluate the mobility effects of early forms of automated driving in the Netherlands from 2013 to 2050. From 2050 onward level 4 is expected to have an impact on most roads [17]. Every time step (one week), the modal split, the amount of people traveling by car in the peak hours and the travel times of cars on 42 relations are calculated.

Figure 1 shows the four steps of the model. There are three main elements in the model:

mode choice, time of day choice and travel time calculation (assignment). Section 2.3.1 to 2.3.3 describe these elements in more detail.

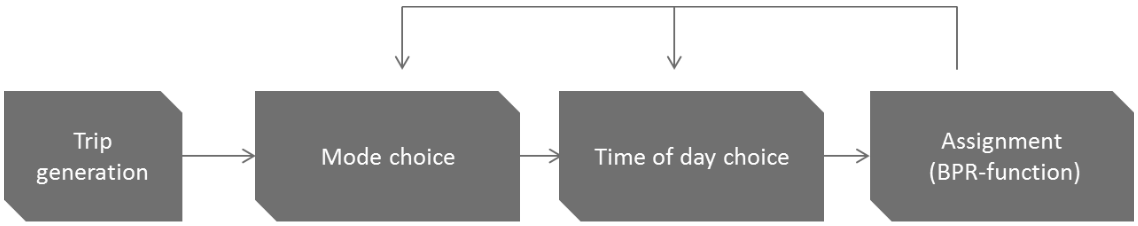

FIGURE 1 Four steps of the model.

As System Dynamics works with aggregated relations, the model does not make use of an explicit network, but models characteristic relations between zones instead. For these relations the model takes the demand, supply and feedback between them into account. As feedback the mode choice and time of day choice models use the exponentially smoothed travel times of the past half year. This assumes that people have habits which gradually change over the past half year. The time step of the model is a week.

The mobility impacts are analyzed in two simulation environments: a 'Ceteris Paribus environment' and a 'Real World environment'. In the Ceteris Paribus environment all factors except the introduction of automated vehicles stay equal. In the 'real world environment' changes in population, car ownership, variable costs for the car and public transport, speeds of public transport, the number of trucks and the road infrastructure are considered as well.

2.3.1 Mode Choice Model

The base year of the mode choice model is 2013. Estimation of the choice model is based on data of the mobility survey OViN [18]. The amount of trips will stay constant till 2050 in the 'Ceteris Paribus environment', and will rise according to PBL forecasts [19] in the 'real world environment'. Six types of areas are distinguished: 1) Large cities in the Randstad, 2) Satellite towns of large cities in the Randstad, 3) Cities in the Randstad, 4) Rural areas of the Randstad, 5) Cities in the rest of the Netherlands and 6) Rural areas of the Netherlands. This results in 36 relations of which 6 relations are split in local traffic (i.e. within cities) and traffic between cities, leading to a total of 42 relations. The SD-model does not make use of user or age classes, only of car type class (level of automation).

To calculate the amount of people travelling with a certain mode a logit model is used (equation 1). The utility function is shown in equation 2. The utility functions are calibrated based on OViN data (mobility survey in the Netherlands) of 2010-2013. For cars of level 1, 2 and 3 the monetary costs per kilometer are expected to be lower than for normal cars. For level 3 also the value of time differs.

$$T_{m,r} = P_r \frac{e^{V_{m,r}}}{e^{\sum V_{m,r}}} \quad (1)$$

$$V_{m,r} = -\mu_m \left(TT_{m,r} * VoT_m + Var_{m,r} * d_{m,r} + C_{m,r}\right) \quad (2)$$

Where:

V	=	Utility [-]	*VoT*	=	Value of time [€/hour]
μ	=	Scale factor [1/€]	*C*	=	Constant [€]
TT	=	Travel time [hour]	*d*	=	Distance [km]
Var	=	Variable costs [€/km]	*T*	=	Trips [#]
P	=	Production [# trips]	*m*	=	Index modes
r	=	Index relation			

In the mode choice model the trips are categorized into 4 groups: people who have no car available for their trip, people having a regular car available (level 0), people having a level 1 or 2 vehicle available and people having a level 3 vehicle available. The first category (no car) can choose between traveling as car passenger, by train, by BTM or by active modes (cycling and walking). The other three categories can also choose to travel as a driver of the available vehicle. The distinction of no car available is made based upon OViN data, the amount of people per SAE-level is based on research of Nieuwenhuijsen [17]. In the real world scenario, the percentage of people owning a vehicle differs per year.

For trucks the mode choice and time of day choice are set constant. The amount of trucks is 8% of the normal traffic in 2013, this assumption is made based on loop detector data on main roads in the Netherlands [20]. 6% of these trucks drives in the peak hours [20]. The amount of trucks per level of automation is based on the same percentages as for passenger cars.

2.3.2 Time of Day Choice Model

For the trips made by car, a time of day choice is made with a logit model having two alternatives: driving during peak hours and driving outside peak (off-peak). The logit model uses the value of time, the travel time in and off-peak and a constant. The constants and travel times are estimated based on OViN data from 2010-2013. The value of time can be adapted per level of automation. The utility function is shown in equation 3.

$$V_{p,r} = -\mu \left(TT_{p,r} * VoT + C_r\right) \quad (3)$$

Where:

V	=	Utility [-]	*VoT*	=	Value of time [€/hour]
μ	=	Scale factor [1/€]	*C*	=	Constant[1] [€]
TT	=	Travel time [hour]	*p*	=	Index period (peak or off-peak)
r	=	Index relation			

2.3.3 Assignment - Travel Time Calculation

For the trips made in the peak hours the travel time is calculated. This is not done via a traditional assignment to a network, but by making use of a BPR-function (speed flow relation) as shown in

[1] For the off-peak trips the value of the constant is zero

equation 4 and 5.

$$S_r = \frac{S0_r}{1 + \beta_r * (IC_r)^4} \qquad (4)$$

$$IC_r = \frac{\sum_l (I_{rl} + HGVI_{rl} * PCU) * PCUA_l}{Cap_r} * OF \qquad (5)$$

Where:

S	=	Speed in period p [km/h]	*PCU*	=	Passenger car unit for trucks
S₀	=	Free-flow speed [km/h]	*PCUA*	=	Passenger car unit for automated passenger vehicles
I	=	Flow passenger cars [veh/hour]	*β*	=	Urbanization factor
HGVI	=	Flow trucks [veh/hour]	*l*	=	Index level of automation {l ϵ 0, 1/2, 3}
Cap	=	Capacity [veh/hour]	*OF*	=	Overlap factor
p	=	Index period (peak or off-peak)	*r*	=	Index relation

This BRP-function is derived from the ScenarioExplorer [11]. The free flow speed S0 is derived from nightly trips from OViN. β is taken from the ScenarioExplorer. Per level of automation a different PCU factor is used. If automation has a positive effect on capacity this factor has a value lower than 1, if it is expected that automation has a negative effect, this factor will be higher than 1. For trucks the same PCU values for automation are used. A regular PCU value of 1.8 is used to transfer the trucks to passenger cars, this is the same value as the LMS (Dutch national model system) uses.

Literature indicates that (for the cooperative scenario) the PCUA per level is not constant over time, but depends on the penetration rate of cooperative vehicles. Figure 2 shows the assumed relation based on latter micro simulation [21]–[23] studies between the penetration rate and PCUA for the autonomous and cooperative driving scenario. PCUA combines two effects: the effects of automated driving (arising from the first car on the road) and cooperative effects (arising from a certain threshold and increasing afterwards). This PCU graph differs for level 1 & 2 and 3 as for level 3 higher impacts are expected.

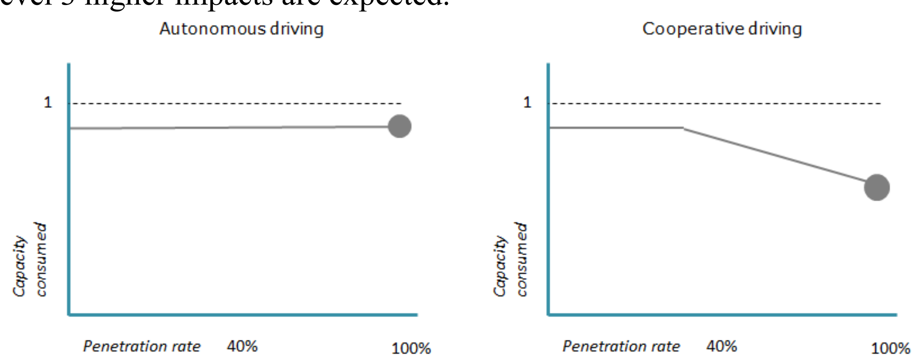

FIGURE 2 ***PCUA*** **value for different penetration rate for autonomous and cooperative driving (based on** ***19, 20, 21*** **and** ***22)*****.**

The travel time calculated with the BPR-function is fed back to the mode choice and time of day choice.

2.4 Validity of the Model

The validity of the model is tested by performing several tests. Among others the internal validity, the structure, extreme values, boundaries and comparisons with 'classical' models are made for the real world scenario and an automated vehicle scenario. These tests are the most relevant ones from the book Business Dynamics of Sterman [14]. The main conclusion over all tests is that the model can be used to make explorative forecasts for early forms of AV.

3 CASE STUDY THE NETHERLANDS

The SD-model is applied in a case study for the Netherlands to model the expected impact of automated vehicles from 2013 till 2050. Figure 3 shows the allocation of municipalities to the six area types. These six types are the same as the ScenarioExplorer uses.

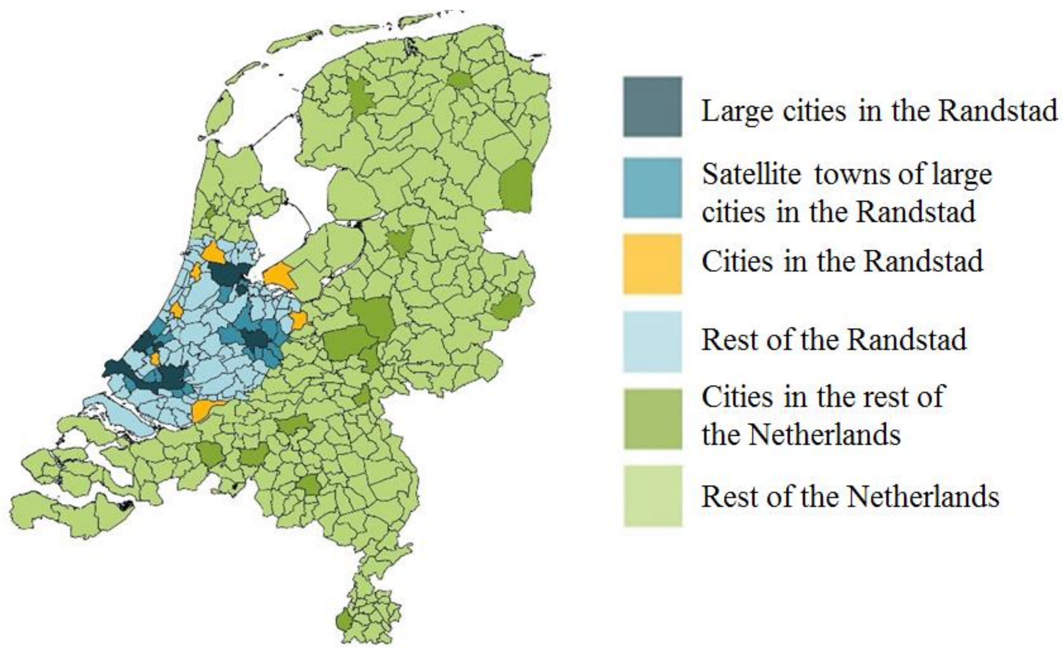

FIGURE 3 Map of the Netherlands with 6 area types.

The focus of this paper is on 4 characteristic relations:

1. Within the 4 large cities in the Randstad (In large cities). The Randstad is a megalopolis in the central-western Netherlands consisting primarily of the four largest Dutch cities (Amsterdam, Rotterdam, The Hague and Utrecht) and their surrounding areas. The results of this relation are easy to interpret as the results cover only 4 cities.
2. Between a city in the Randstad and the rest of the Randstad (Regional). This relation focuses on regional roads.
3. From the rest of the Netherlands to rest of the Netherlands (Rural). This relation is chosen because of its magnitude. At least 40% of all trips are made on this relation.
4. Between the 4 large cities (Between large cities). This relation is very insightful as it consists of a limited amount of motorways, but still has quite some volume. This is also a relation where impacts of automated vehicles are expected.

3.1 Penetration Rate Automated Vehicles

The most important input for the model with respect to AV is the penetration rate of different levels of AVs. As explained before the penetration rate of different levels of AVs is highly uncertain. Figure 4 shows the assumed mix of level 0, 1/2, 3 AV for the years 2013 to 2050 for both scenarios. These penetration rates are taken from Nieuwenhuijsen [17]. As far as known to the authors this is the only study in which a quantitative model is used to calculate the diffusion of automated vehicles for different SAE-levels. His model is underpinned with expert opinions and literature.

The results of Nieuwenhuijsen [17] are shifted 10 years in time to compensate for the fact that his model presents a too optimistic view for 2015, namely 30% level 2 vehicles, where this appeared to be less than 1%. There is enough evidence to trust the curves, but not to trust the starting point. Secondly, the model of Nieuwenhuijsen estimates the percentage of automated vehicles owned in the Netherlands and not the percentage of trips made with automated vehicles. Litman [4] describes that in the first 10 years of the lifespan of a vehicle more than double the amount of kilometers is driven compared to the years thereafter. This effect can lead to a steeper introduction curve. However, this effect is not taken into account in our model as this would lead to much more complexity because vehicles should be divided in age classes. The forecasts of Nieuwenhuijsen are for passenger cars. We use the same introduction graphs for trucks, as there is currently no other literature available.

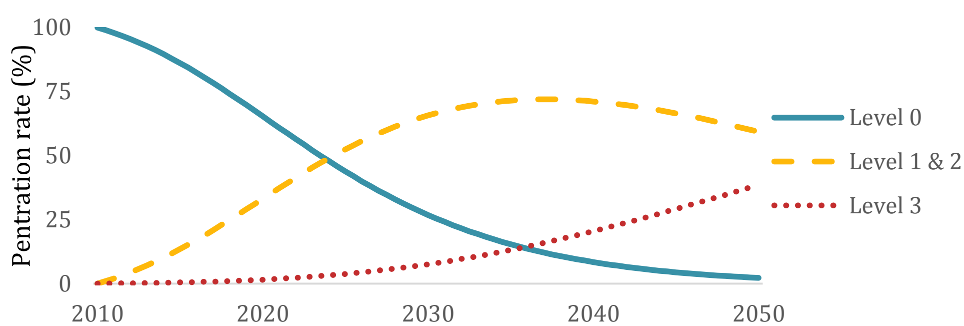

FIGURE 4 Percentage of automated vehicles over time in the Netherlands from 2010 till 2050, derived from Nieuwenhuijsen (2015).

3.2 Assumptions on Capacity, Value of Time and Monetary Costs of Automated Vehicles

Table 1 shows the other model inputs for the autonomous and cooperative scenario. For different variables an upper and lower bound is derived from literature. Not only the base case, but also these upper and lower bounds are simulated. To do so, 2000 simulation runs are carried out with a uniform distribution between the bounds.

TABLE 1 Model Input for the Autonomous and Cooperative Scenario for the Value of Time, Capacity and Fuel economy effects

Level	**Relation type**	**Penetration rate**	**Autonomous**		**Cooperative**	
			Base	**Bandwidth**	**Base**	**Bandwidth**
Value of time						
0	All	[0%-100%]	100%	-	100%	-
1 and 2	All	[0%-100%]	100%	-	100%	-
3	In large cities	[0%-100%]	100%	-	100%	-
3	Rural/regional	[0%-100%]	90%	80%-100%	90%	80%-100%
3	Between large cities	[0%-100%]	80%	70%-90%	80%	70%-90%
PCU (Capacity)						
0	All	[0%-100%]	1	-	1	-
1 and 2	In large cities	[0%-100%]	1	1.1 - 0.9	1	1.1 - 0.9
1 and 2	Rural	[0%-100%]	1	1.05 - 0.95	1	1.05 - 0.95
1 and 2	Regional	[0%-100%]	1	1.05 - 0.95	1	1.05 - 0.95
1 and 2	Between large cities	[0%-40%]	1	1.05 - 0.95	1	-
1 and 2	Between large cities	[40%-100%]	1	1.05 - 0.95	0.95	1.1 - 0.9
3	In large cities	[0%-100%]	0.95	1.1 - 0.9	0.95	1.0 - 0.9
3	Rural/regional	[0%-40%]	1	1.05 - 0.95	1	-
3	Rural/regional	[40%-100%]	1	1.05 - 0.95	0.95	1.0 - 0.9
3	Between cities	[0%-40%]	1	1.05 - 0.95	1	-
3	Between cities	[40%-100%]	1	1.05 - 0.95	0.9	1.0 - 0.7
Fuel Economy						
0	All	[0%-100%]	1	-	1	-
1 and 2	All	[0%-40%]	0.95	-	0.95	-
1 and 2	All	[40%-100%]	0.95	-	0.85	-
3	In large cities	[0%-100%]	0.95	-	0.95	-
3	Rural/regional	[0%-40%]	0.95	-	0.95	-
3	Rural/regional	[40%-100%]	0.95	-	0.85	-
3	Between large cities	[0%-40%]	0.95	-	0.95	-
3	Between large cities	[40%-100%]	0.95	-	0.85	-

- = no bandwidth (i.e. not included in sensitivity analyses)

Table 2 summarizes the changes in the 'real world environment'. In the Ceteris Paribus environment these factors are not taken into account.

TABLE 2 Model Input for the Real World Scenario

Input	Change per year	Source
Population growth	Between 0.1% and 0.4%	PBL [19]
More car ownership	0.2 %-point extra cars available	LMS assumption [24]
Higher PT costs /km	0.5% extra €/km	
Decrease car costs / km	0.7% less €/km	
More trucks	1.4% extra trucks	
Faster trains	0.3 minutes (between 2017 and 2030)	Program High Frequency Rail [25]
Extra road capacity	Between 0.8% and 1.3% extra	Assumed based upon highway expansion between 2014-2017 [26]

3.3 Results Ceteris Paribus Environment

Figure 5 shows the expected impact of AV for the autonomous (A) and cooperative (C) scenario in the Ceteris Paribus. The blue line indicates the expected changes over time (base case). The uncertainty bandwidths are indicated in grey. Note that the Y-axis has different scales. As in large cities (relation 1) no cooperative functions are simulated the autonomous and cooperative scenario are the same.

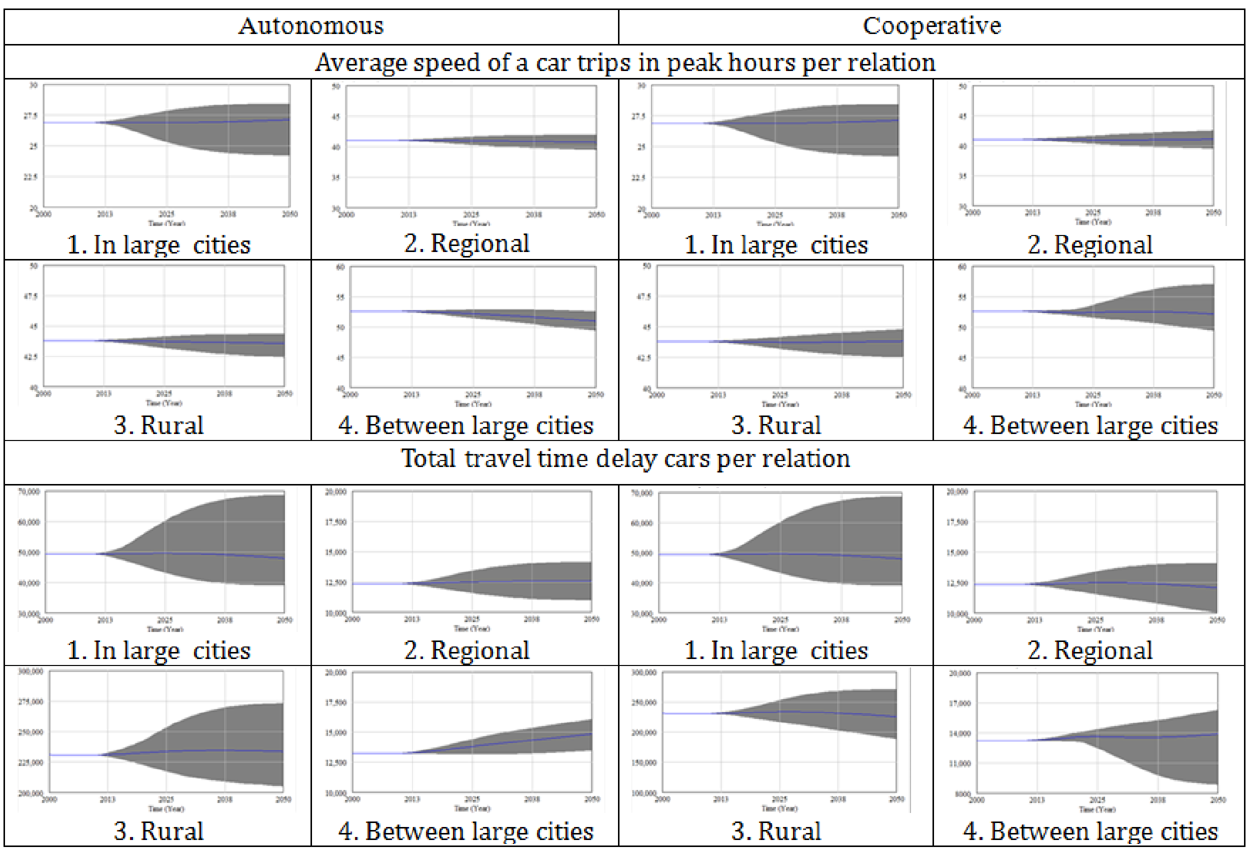

FIGURE 4 Simulations of the 4 relations in the Ceteris Paribus for the cooperative and autonomous scenario.

In general, it can be expected that the number of trips by car increases due to the reduction in value of time. As a result, the level of congestion increases, which has a small damping effect on the increase of car traffic. In most scenarios, a lower PCUA value (i.e. increase of capacity) is assumed which reduces the level of congestion which again attracts car traffic (changes in modes and departure time). The opposite effect happens when a PCUA value higher than 1 is chosen. This explains why the impact of AV on the number of car trips, the average speed for cars and the level of congestion can both be positive and negative.

In large cities (relation 1), the number of car trips increases with 1% up to 2050 in both scenarios. The average car speed increases as well with 1% and the total delay decreases with 3% in the base case. However, the uncertainty bandwidth is quite large in large cities. There is a large probability that the average speeds decrease instead of increase. Similarly, the total delay may be 40% higher or 20% lower compared to the base case.

On regional relations (relation 2), the number of car trips is expected to increase with respectively 1% and 2% up to 2050 in the autonomous and cooperative scenario. In the autonomous scenario, the level of congestions (total delay) is expected to increase with 2% with a reduction of 1% in average car speed as a result. In the cooperative scenario the level of congestion is expected to decrease with 2%, which results in a very small increase of average car speeds (stays nearly the same). In this case the uncertainty bandwidths are smaller and more or less equally positively and negatively spread. This is a consequence of the assumptions made.

On rural relations (relation 3), the number of car trips is also expected to increase with respectively 1% and 2% up to 2050 in the autonomous and cooperative scenario. In the autonomous scenario, the level of congestions (total delay) is expected to increase with 1% whereas in the cooperative scenario the total delay is expected to decrease with 3%. The average speed stays more or less the same in both scenarios. This is explained by the fact that the level of congestion on rural roads is quite low. Therefore, small changes don’t have an impact on the average speed. In this case the uncertainty bandwidths indicate that the probability on lower speeds compared to the base case is larger than the probability of higher speeds.

Finally, between large cities (relation 4) respectively 6% and 9% extra car trips are expected in the autonomous and cooperative scenario. The level of congestion is expected to increase with 12% and 4% respectively. In the autonomous case this can be explained by an increased amount of cars on the road, in combination with few capacity benefits. In the cooperative case, the capacity increases, but due the large increase in number of trips, there is more congestion expected. The average speeds are expected to reduce with 3% and 1%. In the autonomous scenario the uncertainty bandwidths are small and more or less equally positive and negative biased. In the cooperative scenario there is a large probability that the effect will be more positive.

3.4 Results Real World Environment

Figure 6 shows the results of the simulations between large cities (relation 4). Only the base case simulations are shown (no uncertainty bandwidths).

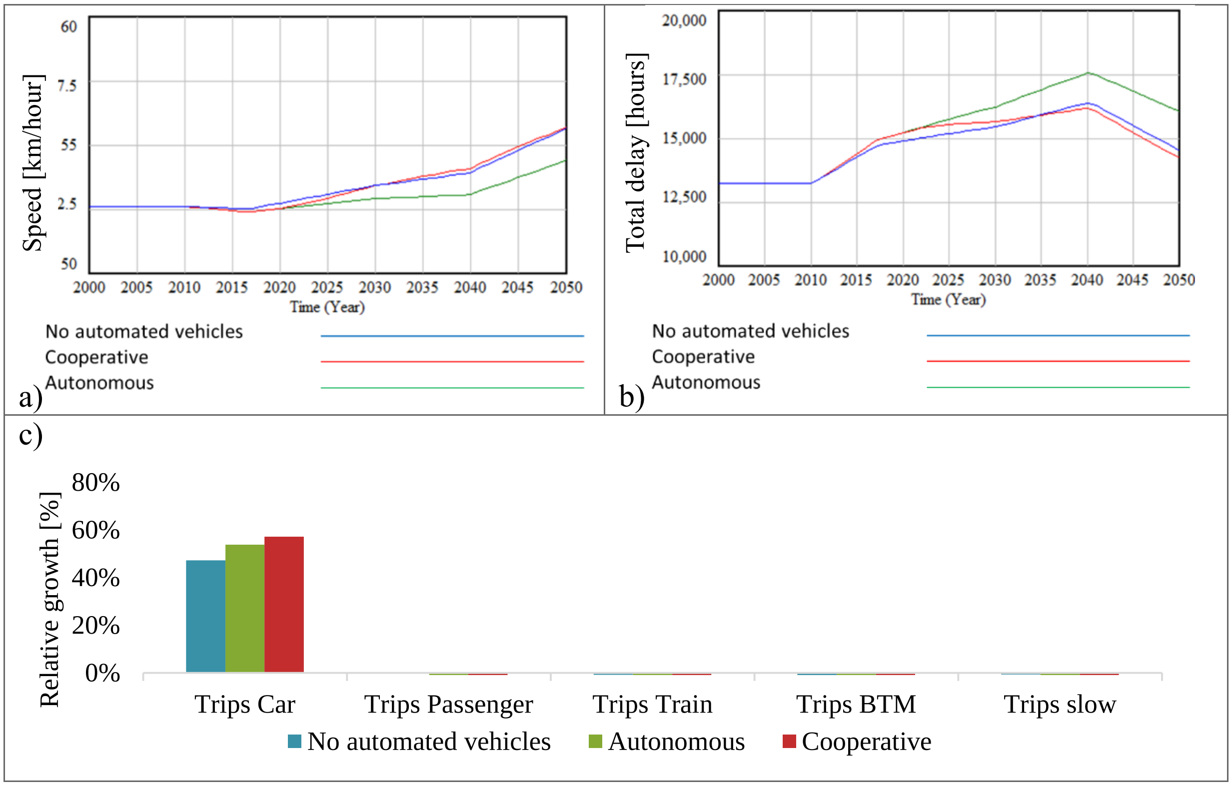

FIGURE 5 Results of simulations for the real world environment – a) average speed of a car trips in peak hours; b) total travel time delay cars (VoT corrected); c) relative growth in trips related to 2013.

The same effects which can be seen from the Ceteris Paribus environment can be seen here. In the case of autonomous vehicles the car becomes more attractive (less costs and lower value of time) which results in an increase of car trips. As autonomous vehicles have few capacity benefits the average speed is lower than without the technology. The total delay also increases. In contrast with the Ceteris Paribus environment, in the cooperative scenario the extra car trips made do not lead to a longer delay because of the capacity benefits. In 2021 the 40% threshold is reached and it can be seen that the extra cooperative benefits start. From this point the cooperative and autonomous simulations show differences.

4 CONCLUSIONS AND RECOMMENDATIONS

4.1 Expected Effects of Automated Vehicles

Simulations with the SD-model show that the introduction of automated vehicles is expected to cause an increase in car trips in both the autonomous and cooperative development path. The level of congestion is expected to increase on some relations. For the motorways this increase in congestion is the most severe although the uncertainty bandwidths indicate that there is a probability that the level of congestion on motorways might decrease instead of increase. In the cooperative scenario the increase in number of trips is larger than in the autonomous scenario. Furthermore, the average speeds are higher in the cooperative scenario and there is less congestion compared to the autonomous scenario.

If distribution effects are considered as well, it can be expected that automated vehicles cause an increase in trip lengths and therewith an increase vehicle kilometers travelled, because travel time is valued less negative and the cost per kilometer are lower. This might result in an additional increase in the level of congestion.

4.2 Policy Implications

The simulations show that automated vehicles do not inherently lead to less congestion. In all scenarios the amount of trips by car increases and in most autonomous scenarios and some in cooperative scenarios the congestion increases as well. From a societal point of view, the government should invest in the cooperative path, as this brings most societal benefits with it.

The focus of this paper was on regular congestion. It should be noted that AVs are expected to reduce incident risks and therewith irregular congestion caused by incidents. This results in travel time and travel time reliability benefits. It is recommend to analyze the implications of AV on irregular congestion in more detail.

4.3 The Method – Further Research

The tests and simulations with the SD-model show that this model can be used for explorative research. The model can help researchers and policy makers to get a grip on the effects that automated vehicles have on different trip choices. The main advantages of the method compared to traditional models are that the method is quick, adaptable, explorative and automated vehicles are modelled endogenous. Next to this there is a constant feedback loop from the assignment to the demand and the total introduction path can be simulated over time. Where traditional models show a 'picture' of automated vehicles, the SD-model provides a forecast in the form of a 'movie'.

Still, the model needs improvements to be able to answer all policy questions. At this moment not all effects of automated vehicle can be simulated with the model and the model is not detailed enough to draw conclusions upon all levels. An important improvement would be to consider distribution effects in the model; however this is not straightforward in a system dynamic approach. Furthermore, it is recommended to extend the model with travel time reliability and robustness (irregular congestion and safety). In next versions ride sharing or road pricing can also be incorporated in the model.

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