Issue 22(3), 2022, pp. 1-26
https://doi.org/10.18757/ejtir.2022.22.3.5842

TU Delft OPEN

EJTIR

ISSN: 1567-7141
http://ejtir.tudelft.nl/

The impact of self-driving cars on the national transport system: an assessment for Belgium

Laurent Franckx[1]
Federal Planning Bureau, Brussels, Belgium

We study how full automation of the car fleet affects traffic volumes, congestion, and fuel consumption at the country level in Belgium. The central scenario in this paper looks at the combined effect of a lower opportunity cost of travel time, an increase in the acquisition price of cars by 20%, a decrease in insurance costs by 50% and a decrease in fuel consumption per km by 10%. The improvement in fuel efficiency always dominates the increase in acquisition costs, and average monetary costs decrease. Overall car travel increases by 21 up to 26%. Despite the improvement in fuel efficiency, total fuel consumption for diesel and gasoline increases by 5 up to 10%. The impact on the speed of road modes is highly location specific. A sensitivity analysis revealed that there is a threshold improvement in fuel efficiency where the "rebound effect" is nullified. To counteract the effects of full automation on total demand for car travel, a road charge close to 20 EUR cent per km would be needed.

Publishing history

Submitted: 14 June 2021
Accepted: 30 September 2022
Published: 10 October 2022

Cite as

Franckx (2022). The impact of self-driving cars on the national transport system: an assessment for Belgium. European Journal of Transport and Infrastructure Research, 22(3), 1-26.

Keywords: *automated mobility, congestion, self-driving cars.*

1. Introduction

Less than two decades ago, driving road vehicles was considered out of bounds for computers. But then, around 2010, combined breakthroughs in sensor technologies and artificial intelligence changed the rules of the game. While an ever-increasing number of new car models included partial automation, hand in hand with increased connectivity, some firms also started extensive field trials with self-driving cars.

[1] Belliardstraat 14-18, 1040 Brussels, Belgium, lf@plan.be

Even if not all the hype has (yet) kept its promises, transport specialists still think that the potential implications of automation are huge. For instance, Fulton (2017, 2018) uses the concept of the "three revolutions in urban transportation" to refer to the combined emergence of vehicle electrification, automation, and shared (on-demand) mobility. The interaction between these three would cut global energy use from urban transportation by more than 70% and reduce CO_2 emissions of urban transportation by more than 80% by 2050. However, the International Transport Forum (2015) has warned that, without a massive uptake of ridesharing, the use of autonomous taxis could well lead to important increases in traffic. Given those far-reaching potential implications, societies need to reflect on the likely consequences of full automation, and on the appropriate policy frameworks.

In this paper, we take a first step towards an analysis at the country level for Belgium. To do so, we use the PLANET model. PLANET has been developed by the Belgian Federal PLANning Bureau (FPB) in collaboration with the Belgian Federal Public Service Mobility and Transport. Since 2008, the model has been used to inform Belgian policy makers and other stakeholders.

Unless stated otherwise, all the results in this paper are defined as changes compared to the values for 2030 used in the most recent long-term projections of transport demand in Belgium (Bureau fédéral du Plan 2019). This "reference scenario" takes into account all European, Belgian and regional policies that were decided at the time of the publication.

We will not look at the transition dynamics but focus on the impacts of an entirely automated (Level 5) and connected fleet – note that these transition dynamics, with AV sharing the road with human-driven cars, may be quite different from the final outcomes (Narayanan et al. 2020).

As explained in detail further in the paper, the only source for induced demand considered in the current analysis are changes in the time costs and the monetary costs of car transport. The relocation of firms or households falls outside the scope of our modelling work. Induced demand by people who are currently not able or allowed to drive will be considered in future work.

We will only consider private cars. This does not mean that we deny some of the elements in favour of the hypothesis that AV will be shared. For instance, sharing automated cars will allow to spread the fixed costs over a much higher annual mileage, and full automation will overcome one of the key limitations of current carsharing models (the spatial and temporal dimension of matching supply and demand). However, shared automated vehicles (automated taxis) and shared rides face specific issues (such as the re-positioning of empty vehicles waiting for new clients and changes in the size of the fleet that is needed to serve given mobility needs) that are especially challenging in countries with an important share of long commutes, such as Belgium. Addressing these issues exceeds the scope of the current analysis.

Automation is also likely to fundamentally modify the operation of public transport modes– for instance, it is likely to lead to the optimisation of vehicle size according to the route and the time of the day. In general, one can expect the boundary between shared modes and public transport to become increasingly blurred. A similar point applies to freight transport: how automation will affect the overall personnel costs of freight operators cannot be separated from other aspects of the logistical chain that will be affected by automation, such as the operation of warehouses. Therefore, we keep those issues as a topic for further research and keep the public transport and freight modules as used in the reference scenario.

The analysis in this paper focuses on the impact on overall traffic levels, road speed, modal split, and energy consumption. Safety aspects and accessibility fall outside the scope of the paper.

To the best of our knowledge, this is the first paper that addresses the impact of automated cars on the national transport system, using a model with endogenous modal and time choice, and that considers differentiated impacts according to the travel motive.

The paper is structured as follows.

We first review the relevant literature. We discuss the different assumptions that are used in the literature, for key values such as the impact of full automation on speed-flow relations, on the value of time spent traveling, and on the financial costs of private cars. We then address the key impacts on the transport system that are reported.

Next, we introduce the model that has been used for the analysis in this paper, highlighting the features that are essential for understanding the key drivers behind our results.

Based on the key findings of the literature, we define the scenarios that are used in this paper. More specifically, we assume that the automation of the car stock may lead to changes in: (a) the speed-flow relations on the road network (b) the monetary costs of owning and operating a car (c) the value of travel time.

Next, we present the results of the simulations with the PLANET model. We consider the impact on passenger kilometres (*pkm*) for each mode, on the kilometres travelled by car (*vkm*), on the average road speeds, on the average travel time, on total fuel consumption and on the generalized costs.

The key result of the paper is that full automation without trip sharing leads to an important increase in car traffic (by around 21 up to 26%) and could also lead to a significant increase in fuel consumption, mainly as the result of the decrease in the value of travel time.

Given that the key parameters of the model are subject to substantial uncertainty, we perform a sensitivity analysis on the impact of full automation on fuel consumption and on the acquisition costs.

The negative impacts of car automation on congestion and fuel consumption raise the question of the policy measures that could counteract them. We therefore give an indication of the magnitude of a distance-based road charge that would be needed for this purpose.

Finally, we summarize the results and identify the needs for further research - mostly the inclusion of several sources of induced demand that are currently omitted from the analysis.

2. Overview of the literature

Recent extensive literature reviews of self-driving cars and their impacts include Cohen and Cavoli (2019), Milakis et al. (2017b), Milakis et al. (eds, 2020), Soteropoulos et al. 2019, Taiebat et al., 2018, and Wadud et al. (2016). We refer the interested reader to those papers for the aspects we do not cover here, such as the purely technological aspects, privacy and traffic safety issues, the impact on urban planning and road design, the impact on employment in the transport sector or the market structure of AV provision (as in van den Berg and Verhoef 2016). In this review, we limit ourselves to the aspects that are directly relevant to the current paper: the impact of full automation on speed-flow relations, on the value of time spent traveling, and on the financial costs of private cars.

First, self-driving cars are expected to improve traffic throughput, for instance thanks to the shorter reaction time of AVs[2], shorter headways between vehicles, a reduction in the number of accidents, a better distribution of the traffic over the network and a better synchronization with traffic lights (Cohen and Cavoli 2019, Milakis et al. 2017b, Narayanan et al. 2020). Most studies seem to agree that CAVs could lead to improvements in road capacity ranging from 200 to 300% - even though all results are in the same order of magnitude, this is still a wide range.

[2] Throughout the paper, we refer to automated vehicles as AVs and to connected and automated vehicles as CAVs.

Second, with full automation, the driver will no longer be required to pay attention to the road and will thus be able to devote his travel time to work or to leisure activities. This will affect the value of time (VOT) for traveling by car.

On top of this direct effect, the ability to hold (for instance) work meetings in the car will make it easier to comply with *coupling constraints* for those activities where a physical presence at a given location remains essential (think for instance of getting children at school or day-care, as in Schwanen 2008). Given that this type of benefit is highly situation-specific, traditional measurements of the VOT are likely to underestimate this type of benefit.

Estimated values for the VOT spent traveling for commuting purposes in CAVs range from around 60% to 100% of the current value of the VOT for *driving* a car (see De Ameida Correia et al. 2019, Kolarova et al. 2019, Milakis et al. 2017a). For other travel motives, the impact of automation on VOT is estimated to be very small, and some authors even argue that the VOT may increase with full automation.

Third, automation will affect private financial costs and benefits. When estimating the financial costs of full automation, it is not always clear what features should be considered as being additional to existing technologies. Indeed, several of the features needed for automation and connectivity (certainly GPS systems) have been present in new cars for a while. In the premium market, cars are already equipped with features such as adaptive cruise control.

Moreover, the costs of those technologies have decreased rapidly in the last few years. Between 2013 and 2017, the costs of LIDAR[3] technologies have decreased by 90%. Costs are expected to fall further in the coming years (Nieuwenhuijsen et al. 2017). Not surprisingly, there is a wide range of projections for the cost of future additional equipment: from 3,000 to 10,000 EUR (Compostella et al. 2020, Wadud 2017), with some sensitivity analysis considering a cost of 30,000 EUR.

There are also several channels through which vehicle automation and connectivity could lead to decreases in the *fuel consumption* per km (Lee and Kockelman 2019, Milakis et al. 2017b, Taiebat et al 2018, Wadud et al. 2016), such as more efficient driving thanks to congestion mitigation and automated eco-driving. However, the additional equipment needed for autonomy and connectivity also requires higher auxiliary power from vehicles and could alter vehicle aerodynamics, which could contribute to a higher fuel consumption. In the recent literature, the net effect of vehicle automation on fuel consumption per km is estimated to be a reduction by 5 to 40%.

The effects on maintenance costs are too speculative to have a meaningful discussion about them - see Wadud (2017) and Bösch et al. (2018).

Fourth, concerning the potential *impacts* of CAVs, a reduction in the generalized costs of driving by car will lead to more or longer trips, for instance as the result of an increase in discretionary trips and less trip chaining (Rodier 2018). Indirectly, this could also lead to relocation of households and firms (Milakis et al. 2017b), resulting in urban sprawl and/or the creation of new urban centres.

Self-driving cars can also lead to induced demand by segments of the population that are not able to drive, such as children and mobility impaired people (Harper et al. 2016, Milakis et al. 2017b, Soteropoulos et al. 2019). Estimates of the impact of those groups on vehicle kilometres mostly lie between 2 and 10%, with an upper bound of 40% (Milakis et al. 2017b, Rodier 2018).

One issue that has drawn a lot of attention over the last few years is the relation between automation and car sharing. As pointed out by Wadud et al. (2016), vehicle automation may make car-sharing more attractive "by allowing vehicles to deliver themselves to the user on-demand, reducing the need for geographic concentration of vehicles". Sharing of automated vehicles would

[3] LIDAR (Light Detection and Ranging) sensors use infrared light to create three-dimensional maps of a car's environment. Note that while Tesla reckons that improved cameras in combination with radars will render LIDAR obsolete, most car manufacturers see LIDAR and cameras as complements (Domke and Potts, 2020).

also allow to spread the fixed costs over a higher customer base, making CAVs more attractive. Hence, automation and car sharing are two forces of mobility innovation that mutually reinforce each other.

"Right-sizing" of vehicles to the requirements of individual trips would also be possible in a system of automated car-sharing (see Morrow et al. 2014). Given current occupancy rates, the theoretical potential of right-sizing on congestion and fuel consumption is important.

However, automated car-sharing has also potential drawbacks. For instance, simulations of the situation in Lisbon by the International Transport Forum (2015) have shown that, with a 100% shared automated vehicle fleet, the relocation travel needed to serve new clients could lead to an important increase in car kilometres travelled.

Moreover, even without formal car sharing, full automation could lead to more relocation travel, for instance because automation creates the possibility to reposition to serve multiple family trips simultaneously (De Ameida Correia and van Arem 2017). Also, in areas with little (or only expensive) parking facilities, owners could send their car to a free parking space within a given perimeter or to drive around until called. Given that we do not model car-sharing in this paper, we will not elaborate on this specific subject, but it remains an important topic for further research.

Fifth, the reduced generalized cost of AV is also expected to lead to a modal shift away from conventional cars and bus (Malokin et al. 2019, Truong et al. 2017, Zhao and Kockelman 2018). However, this needs not be the case: AV can also act as complements to public transport (Kolarova et al. 2019, Taiebat et al. 2018). Besides the "conventional" modal shift from regular public transport to private modes, the automation of public transport could also lead to the growth of semi-collective transport, which smaller buses operating on flexible schedules (Milakis et al. 2017b). Some long-distance travellers could also shift to ground transport, causing a decrease in air travel. CAVs could serve as mobile overnight sleeping compartments, decreasing demand for hotels for long-distance trips (La Mondia et al. 2016).

Sixth, additional travel induced by lower generalized costs could lead to a net increase in congestion and fuel consumption (the "rebound effect"). The magnitude of this effect depends on factors such as whether rides are shared - in the most extreme case, fuel consumption could increase by 200 % (Stephens et al. 2016).

3. Description of the PLANET model

In short, PLANET is a multimodal transport model, that covers both passenger and freight transport[4]. It considers the following modes for passenger transport: "car alone", "car with a passenger", bus, metro, moto, "slow" (walking and cycling), train and tram. Air travel and semi-collective transport fall outside its scope. Driving with a passenger includes all instances where more than one person travels by car and is not restricted to organized forms of carpooling - it also includes parents driving their children to school or to a hobby activity.

PLANET distinguishes a peak period (which corresponds, on weekdays, to the time slots from 7:00 to 9:00 and from 16:00 to 19:00) and an off-peak period, which encompasses the rest of the time, including the whole weekend. PLANET covers the entire territory of Belgium.

The PLANET model is inspired by the approach used for four step transport models. It produces passenger kilometres per origin-destination pair, travel motive, travel mode and period of the day in the following steps:

[4] A detailed description of PLANET (including of the data sources) can be found in Daubresse and Laine (2020).

- In the trip generation and distribution module[5], we determine the number of passenger trips for each origin-destination pair and travel motive, all modes and periods of the day combined.
- In the modal and time choice module, we allocate the output from the trip generation and distribution module to the individual travel modes and periods of the day.

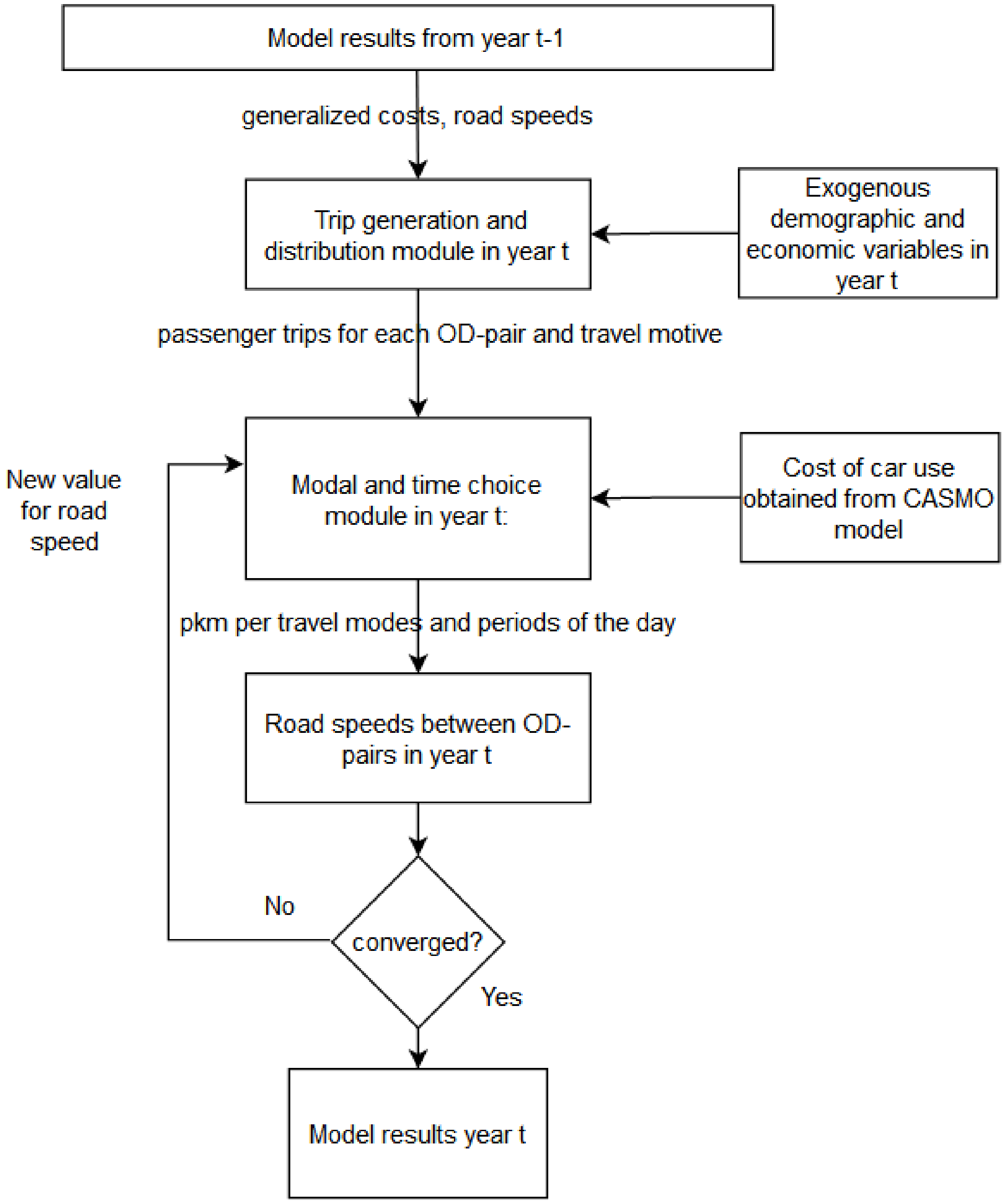

Figure 1. The general structure of the PLANET model

Given the high level of geographic aggregation of the origin-destination (OD) zones (NUTS3 zones), PLANET does not contain an explicit traffic assignment module, but the network models

[5] In PLANET, trip generation and distribution are thus combined in one step.

used by the Flemish and Brussels regional administrations have been used to approximate the speed-flow relationships.

A key driver in each step is the generalised cost (*GC*) of transport. For a given origin-destination pair (*O,D*), travel mode, travel motive and time of the day (*ToD*), the generalised cost per km is given by:

$$\frac{GC(.)}{pkm(.)} = \frac{MonCost(.)}{pkm(.)} + VOT(.) * \frac{Tr\,T(.)}{pkm(.)} \tag{1}$$

Where *MonCost(O,D,mode, TOD)* is the monetary cost (which can depend on the time of the day if prices vary between peak and off-peak), *pkm(O,D)* is the average distance expressed in passenger kilometres between zone O and zone D, *VOT(mode, motive)* is the value of time (expressed in EUR per unit of time) and *TrT(O,D,mode,ToD)* is the average travel time between zone O and zone D. Given that total travel time depends on congestion levels, and that congestion itself depends on traffic volumes, the GC is endogenous for all road modes.

Let us look in some more detail at each step.

3.1 *Trip generation and distribution*

For passenger transport, the trip generation and distribution modules distinguish the following travel motives[6]:

- commuting to work
- commuting to school or establishments of higher education
- business trips: work-related trips, outside commuting and the transportation of goods
- ‘other’ motives: private trips such as shopping, leisure, drop off/pick someone up, family visits, walking around.

The detail of the data available for the estimation of transport activity in the base year of the model (2015) is highly variable. As a result, the details of the procedure vary from travel motive to travel motive. The key common elements are:

- We identify exogenous economic and demographic variables (number of inhabitants per age category, employment, number of students, etc) in each zone to forecast the production and attraction of trips for each zone in each projection year *t*.
- The number of trips per year between an origin-destination pair (O,D) for a given travel motive is given by: *Trips(O,D,Motive)* = TR_t*(O,D,motive)* * *N(O,D,motive)* where TR_t*(O,D,motive)* is the trip rate between (*O,D*) and *N(O,D,motive*) is the number of people travelling between (*O,D*) for this travel motive. We assume that each outward journey is followed by a return trip and thus that, on average, the number of people travelling from *O* to *D* per year equals the number of people travelling from *D* to *O*.
- For each origin-destination pair (*O,D*) and travel motive, an initial estimate for the trip rate in year t, $TR_t^{init}(O, D, motive)$ is obtained from an econometric model, using the following exogenous variables: region of residence, age, sex, socio-economic status, household size, an index of urbanisation, education level and available income. This initial estimate for the trip rate is updated to take into account the evolution of the average generalised cost of transport in the previous year[7], GC_{t-1} compared to the average generalised cost of transport

[6] Given that the paper focuses on passenger transport, we omit a detailed description of the freight modules for the sake of conciseness. However, the general approach for freight is very similar to the approach for passenger transport.

[7] The average generalised cost of transport is calculated as the average across all modes. It is the output of the modal and time choice module of the previous year – see further. It is also possible to create an iterative procedure in year

in the reference year, GC_0 (where $\in_{gc}$ is the (exogenous) overall elasticity[8] of trip rates to the generalised costs of transport):

$$TR_t(.) = TR_t^{init}(.).\left(1 + \in_{gc}(motive).\frac{GC_{t-1}(.) - GC_0(.)}{GC_0(.)}\right) \quad (2)$$

In each projection year, the number of persons originating trips in zone *O* and the number of persons with destination in zone *D* are imposed exogenously (based on extrapolations of historical observations). These totals act as constraints in the calculation of *N(O,D,motive)*. The calculation method used depends on the availability of data, which varies a lot from travel motive to travel motive. We have used two approaches:

- In doubly constrained gravity models[9], the number of people that commute from zone *O* to zone *D* is a decreasing function (the "gravity" function) of the generalised cost of transport between zone O and zone D: $N(O,D,motive) = f(A(O),B(D),gc_t(O,D))$ where *A(O)* and *B(D)* are the elements that affect departures and arrivals in zone *O* and *D* respectively, and $gc_t(O,D)$ represents the average generalised cost of transport between zone *O* and *D*. The gravity function is estimated using observations in the base year.
- In Iteratively Proportional Fitting Procedure (or RAS) procedures, the number of persons in each cell of the origin-destination matrix is determined so as to obtain the values that are the "closest" to the origin-destination matrix in the base year, but adjusted to respect the new row and column totals for the projection years[10]. We have used RAS procedures for the travel motive "school", where the level of detail of the available data did not allow an estimation of a gravity function.

Note that the only source of induced travel demand that is endogenous in the model follows from the dependency of the trip rate on the generalised cost of transport. Modelling the impact of household or firm relocation requires changing the exogenous scenarios for the economic and demographic variables per NUTS3 zone.

As output of the trip generation and distribution module we obtain the number of passenger trips for each *OD*-pair and travel motive. For each travel motive, the passenger kilometres (*pkm(O,D,motive)*) between origin-destination pair *O,D* for each period of the day are then given by:

$$pkm(.) = Trips(.)\,.Dist(.) \quad (3)$$

where *Trips(O,D,motive)* is the number of trips between O and D and *Dist(O,D)* is the average distance between *O* and *D*. In the Modal and Time Choice module, these *pkm* will be allocated to individual modes and periods of the day.

3.2 Modal and time choice

We will first summarize the Nested Constant Elasticity of Substitution (NCES) approach to representing consumer preferences for different modes, and then explain how we use it to determine the shares of the different travel modes, *given* the output of the trip generation and distribution module.

Informally, we will follow the nest structure function for passenger transport represented in Figure 2, which can be interpreted as follows. Let us first consider the bottom branches of the tree: these are "composite" modes (for instance, *car*) that end in "leaves" that represent a "real" mode - for instance "solo" (= driving a car without passengers). Each composite mode in the tree is composed

t between the trip generation module and the modal and time choice module. Such a full endogenization of the trip rate and the generalised cost of transport slows down the model a lot without changing the results substantially compared to the approach taken here.

8 The values of the elasticities reflect expert opinions based on the relevant literature.

9 See Ortuzar and Willumsen (2011) for more details

10 See Norman (1999) for a rigorous mathematical definition.

of several (composite or real) modes, and if we climb up the tree, we reach the root of the tree, which gives us total *pkm* for a given OD-pair and travel motive. The NCES approach sequentially allocates the *pkm* for each composite mode (starting from the root of the tree) to the composing modes, until we reach the leaves of the tree.

For the mathematical derivation, we consider a representative consumer whose utility is determined by the number of passenger kilometre undertaken per mode[11] and assume that the utility function follows a Nested Constant Elasticity of Substitution (NCES) function. As discussed by Proost and Van Dender (1999), the NCES function has as key advantage that it is easy to calibrate and requires a minimum of behavioural information, certainly compared to nested logit discrete choice models. Moreover, Verboven (1996) has shown the equivalence between the demand functions derived from NCES utility functions and those obtained from nested logit discrete choice models. We refer to Keller (1976) for a formal derivation of the results that we discuss here at an intuitive level.

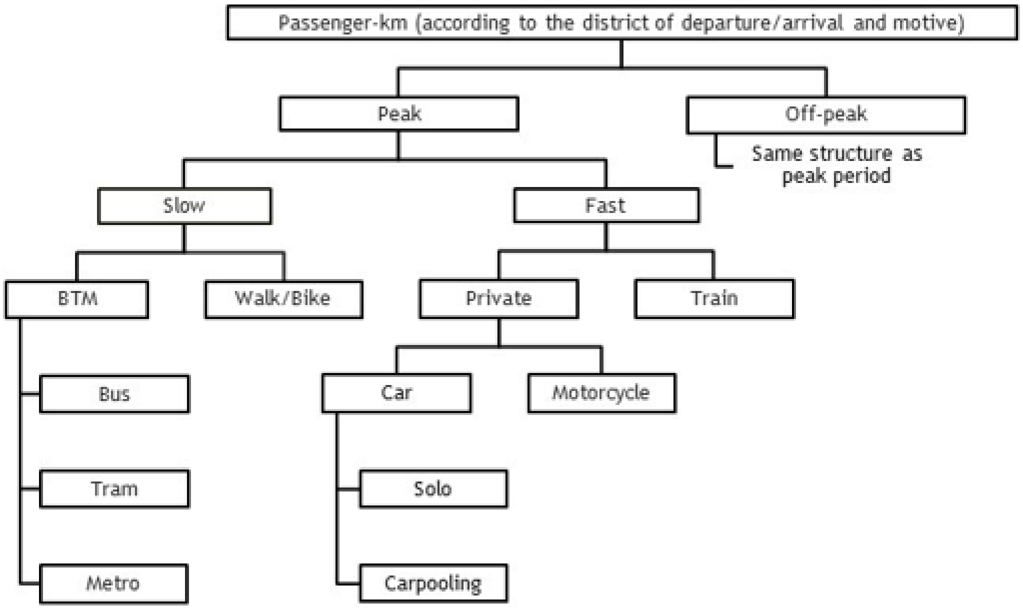

Figure 2. The CES tree for passenger transport

The utility of a "composite mode" J_I at the bottom of the tree depends on the *pkm* of the composing "leave" modes according to a constant elasticity of substitution function:

$$U(J_I) = \left(\sum_i^I \alpha_i^{\frac{1}{\sigma}} \cdot pkm_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

Where $U(J_I)$ is the utility of the composite mode; pkm_i is the *pkm* of each composing mode *i*; σ is the (constant) elasticity of substitution between the composing modes, and α_i are parameters such that $\sum_i^I \alpha_i = 1$ [12].

Now suppose that the representative consumer maximizes his utility under the budget constraint $Y = \sum_i^I pkm_i . gc_i$, where gc_i is the generalised cost per *pkm* of mode *i*, and Y is the budget

[11] Alternatively, we could assume that utility depends on the number of trips. Given that *Dist(O,D)* is a constant for any given (*O, D*) pair, the two approaches are equivalent.

[12] The elasticities of substitution used in PLANET combine values found in literature surveys (such as Litman 2019) with expert judgement The α parameters, however, have been chosen to reproduce the observed modal shares in the base year exactly. They thus depend on the value of the gc_i.

constraint. It can then be shown (see Keller 1976) that, for each mode i of which J_I is composed, the utility maximizing number of *pkm* is:

$$pkm_i = pkm_J . \frac{\alpha_i \ . \ gc_i{}^{-\sigma}}{\sum_i^I \alpha_i \ \ .gc_i{}^{-\sigma}}. \tag{5}$$

where pkm_J is the total *pkm* for a given zone-pair and travel motive by the composite mode ($pkm_J = \sum_i^I pkm_i$). In other words, if we know the total *pkm* travelled by the composite mode and the generalized costs of the composing modes, Equation (5) allocates these *pkm* to the composite modes.

When we further climb up the CES tree, the utility of each composite mode is a CES function of the (real or composite) modes of which it is composed. Equations (4) and (5) generalize to all levels until we reach the top node, where the choice is between travelling during the peak or the off-peak period.

To allocate the total $pkm(O, D, motive)$ per day obtained from the trip generation and distribution module, we use equation **Error! Reference source not found.** to obtain *pkm* for all "real" modes by following the tree from the root to the leaves. The *pkm* at the root of the tree is first allocated to "peak" and "off-peak". Then, for each time period, the *pkm* are allocated to "fast" and "slow" modes; the *pkm* for the "fast" modes are allocated to "train" and "private" modes, etc, until all *pkm* are allocated to "real" modes.

The tree structure is used to represent that some modes are more "alike" than others. Indeed, if all modes were perfect substitutes to each other and if the population were perfectly homogeneous, everybody would use the transport mode with the lowest generalised cost. In reality, all modes have some features that affect their utility but that are not captured by their generalised cost: think of their comfort and reliability, for instance. Moreover, the population is heterogeneous, and the "average" generalised costs of transport may vary from person per person.

The elasticity of substitution between two modes represents how sensitive the modal share of the transport mode is to all elements that affect the utility of a transport mode but are not captured in the generalized cost, or that vary across the population. Formally, the elasticity of substitution between modes x and y is the percentage change in the ratio of the *pkm* driven with those modes to a percentage change in their generalised costs:

$$\sigma = \frac{\frac{\Delta pkm_x / pkm_x}{\Delta pkm_y / pkm_y}}{\frac{\Delta GC_x / GC_x}{\Delta GC_y / GC_y}} \tag{6}$$

where σ is the elasticity of substitution, pkm are the passenger kilometres and GC are the generalised costs.

Now that we have introduced the NCES representation, we can move to the actual procedure that is used to determine the modal shares. The key point here is to remember that the generalised cost is the sum of the monetary costs and the time costs. For the road modes, the travel time depends on the traffic flows – but traffic flows themselves depend on the modal share of road modes!

In four-step transportation models that include an explicit road network, the relationship between speed and transport flows on the road is given by speed-flow functions. Each vehicle type is represented by a Passenger Car Equivalent (*PCE*) to express its impact on road speed[13].

PLANET does not have its own network model. Instead, PLANET uses the output from the network models developed by the Flemish and the Brussels regional administrations to estimate

---

[13] For instance, a motorcycle is assumed to be equivalent to 0.75 passenger cars in terms of impact on congestion. For buses and trams that do not drive on dedicated lanes, the equivalence factor is 2.5.

piecewise linear congestion functions for five geographical zones[14] and two road types[15]. Those linear approximations are summarized in the speed flow elasticity, the percentage change in on-road speed for a given percentage change in traffic flow:

$$\eta_{SF} = \frac{\frac{\Delta V}{V}}{\frac{\Delta F}{F}} \quad (7)$$

where V and F represent the speed and the road flow (expressed in PCE), respectively.

Table 1 gives the elasticities used in PLANET, differentiated per period, region and per road type. We also report the mean speed in the reference scenario.

Table 1. Speed flow elasticities used in PLANET

Period	Geographical zone	Road type	Speed-flow elasticity	Mean speed in the reference scenario (km/hr)
Peak	Antwerp	tollroad	-1.7	57
Peak	Ghent	tollroad	-0.8	94
Peak	GEN zone	tollroad	-2.8	57
Peak	Brussels	tollroad	-0.8	12
Peak	Rest of Belgium	tollroad	-0.3	94
Off-peak	Antwerp	tollroad	-0.9	86
Off-peak	Ghent	tollroad	-0.3	105
Off-peak	GEN zone	tollroad	-0.5	95
Off-peak	Brussels	tollroad	-0.7	22
Off-peak	Rest of Belgium	tollroad	-0.1	99
Peak	Antwerp	other	-0.7	36
Peak	Ghent	other	-0.3	50
Peak	GEN zone	other	-0.5	47
Peak	Rest of Belgium	other	-0.1	64
Off-peak	Antwerp	other	-0.4	50
Off-peak	Ghent	other	-0.2	59
Off-peak	GEN zone	other	-0.1	60
Off-peak	Rest of Belgium	other	-0.1	66

Given that the modal and time choice depend on the GC, but that the GC depends on road congestion levels (and thus also on the mode choice), an iterative procedure is needed to reach an equilibrium:

- Use the equilibrium road speed from the previous year as initial value tS_k, $k=0$,
- Compute the generalised costs GC_k per km for each road travel mode based on tS_k;
- Apply equation **Error! Reference source not found.** to the total *pkm* between *O* and *D* obtained from the modal and time choice to derive the demand for each road travel mode D_k based on GC_k;
- Compute a resulting speed rS_k determined by the road congestion corresponding to demand D_k using speed-flow relationships;
- If $|tSk - rSk| > \varepsilon$ (where ε is an exogenous threshold), a new iteration is started with $tS_{k+1} = \frac{1}{2}.(tS_k + rS_k)$; set $k=k+1$.

[14] Antwerp, Ghent, Brussels, the area surrounding the capital region (the zone delimiting the Regional Express Network, or GEN-zone) and the “Rest of Belgium”.
[15] Roads subject to the distance-based road charge for heavy good vehicles (“tollroad”) and “other” roads.

3.3 Car stock model

The car stock is explicitly modelled in a separate module, called CASMO (Car Stock Model) - see Franckx (2019) for an extensive discussion.

The approach to the car stock model can be summarized as follows.

First, the total desired car stock per capita follows a Gompertz curve: $V_t = V^*. e^{\gamma e^{\beta.y_t}}$, where V_t is the desired car stock per capita in year t, V^* is the saturation level of vehicle ownership expressed as car per capita, and y_t is GDP per capita in year t.

Second, we estimate the probability that a car of a given car class[16] is scrapped in the current year as a function of its age. The outcomes are aggregated to determine the total number of cars that are retired from the car stock, and thus also the remaining car stock at the end of each year. The desired car stock is then confronted with the remaining car stock to determine total car purchases in a given year.

Third, a discrete choice model[17] is used to split these new purchases according to the different car classes, which results in a new inventory.

The interaction between CASMO and the other modules of PLANET goes both ways. On the one hand, the modal choices in the transport demand model are affected by the average costs of car use, which depend on the composition of the car stock. On the other hand, the activity levels predicted by the transport demand models influence the ratio between fixed and variable costs, and thus also the demand for specific car types.

4. Definition of the scenarios

4.1 Changes in effective road capacity

The first channel through which self-driving cars can affect the generalized cost of transport is the effective road capacity. If CAVs lead to an increase in road capacity, road speed will be higher for any given transport volume. We therefore model changes in the effective road capacity as changes in the speed-flow elasticities.

We consider two extreme values for the elasticities $\epsilon_{SF}^* = \alpha \,. \epsilon_{SF}$, with α = 10 or 90%. With $\alpha < 1$, the absolute value of the elasticity becomes smaller, which means that the reduction in the average speed for a given increase in traffic flows becomes smaller. In other words, the lower α, the more effective road capacity increases.

4.2 Changes in the generalised costs of transport

We will analyse the combined impact of the following consequences of full automation:

- We consider two possible *VOT* for travelling with a fully automated car: 0.06 and 0.1 EUR per minute (Table 2 summarizes the *VOT* used in the reference scenario). To keep things simple, in the alternative scenarios, the *VOT* is not differentiated according to the travel motive.
- Regarding the monetary costs, we use the scenario reported in Bösch et al. (2018): an increase in the acquisition price of cars by 20%, a decrease in insurance costs by 50% and a decrease in fuel consumption per km by 10% (or in electricity consumption for electric cars or PHEVs).

[16] These car classes are differentiated according to the COPERT classification for emission modelling (see https://www.emisia.com/utilities/copert/), which takes into account the fuel type and the engine displacement.
[17] The discrete choice model uses a SP model estimated for The Netherlands (Hoen and Koetse 2014), that was calibrated to the Belgian context.

Table 2. Value of time (EUR per minute) in the reference scenario

Mode	Business trips	Other motives	Commuting to school	Commuting for studies	Commuting for work
Car with passenger	0.42	0.12	0.12	0.12	0.15
Car alone	0.52	0.15	0.15	0.15	0.18

5. Results

5.1 Changes in effective road capacity

It turns out that the *national* impact of changes in the speed-flow elasticity α is extremely small: passenger kilometres (*pkm*) per mode change at the very most by around 1%. The impact on modal shares and on vehicle kilometres are similar. We have also obtained that the improvement in the effective road capacity leads to a decrease in average travel time by car by at most 3%.

However, PLANET allows us to go beyond the average impacts at the national level. Table 3 shows the impact on the average road speed per zone, road type and period of the day. For the sake of readability, we have only kept the *Period-Geographical zone-Road* combinations with the most important changes compared to the speed in the reference scenario.

Given that the increase in effective road capacity does not lead to important increases in car traffic, the improvement in road capacity dominates the effect of induced traffic, and the net effect of CAVs is a (small) increase in road speed, with a maximum of around 10% on the toll roads around Antwerp in peak hours. The effect tends to be larger during the peak hour and in heavily congested zones (Antwerp, Brussels, GEN zone), even if this tendency is not unequivocal. So, despite the very small impact at the aggregate level, we observe some non-negligible (if far from spectacular) changes in some geographic zones.

Table 3. Changes in congestion elasticity: impact on road speed

Period	Geographical zone	Type of road	Speed in reference scenario (km/h)	Percentage changes in speed for α = 90 %	Percentage changes in speed for α = 10 %
Off-peak	Antwerp	other	50	0.7	5.7
Off-peak	Brussels	tollroad	22	0.6	5.4
Peak	Antwerp	other	36	0.7	5.4
Peak	Antwerp	tollroad	57	1.0	10.0
Peak	GEN zone	tollroad	57	0.6	8.6

All in all, we see that, even if self-driving cars lead to a very important improvement in effective road capacity, this effect on its own is unlikely to fundamentally alter the transport system. This can be better understood by looking at the geographic and temporal distribution of car traffic in Belgium in Figure 3. Both in the "peak" and in the "off peak" period, around 63.5 % of car vehicle km (*vkm*) are driven in the "Rest of Belgium". In other words, almost two thirds of traffic in Belgium is not subject to high levels of congestion in the first place. As pointed out by Alonso Raposo et al. (2017), parts of the network that do not operate close to capacity will not benefit from a better throughput. Improving traffic flows in these areas is unlikely to change the demand for private cars.

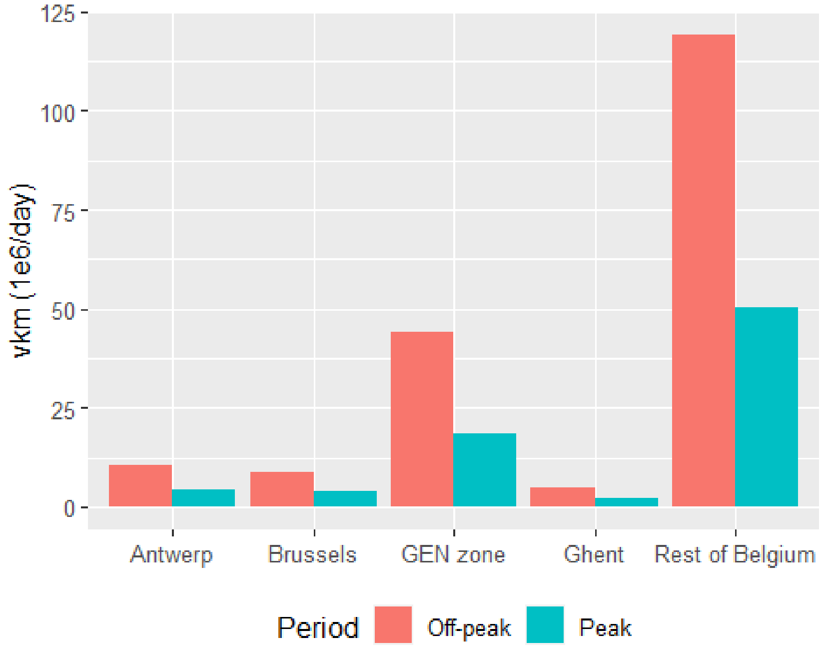

Figure 3. Vehicle kilometres in the reference scenario (per GEO zone)

Therefore, in what follows, we will no longer consider this impact and focus on changes in the generalized costs.

5.2 Central scenario: changes in the generalised costs of transport

We report here the impact of changes in the monetary costs in combination with the changes in the *VOT*. As a reference point, we also report the changes for the *VOT* used in the reference scenario (*RefVOT* – see Table 2).

The first variable we consider is the percentage change in generalised costs compared to the reference scenario. The impact on the generalized cost varies a lot, depending on travel motive, period of the day and mode. Table 4 represents the impact for 3 *Period-Mode- Motive* combinations for the sake of illustration.

The results in the column with *"% Δ(cost) for RefVOT"* show that the overall change in the generalized costs for *RefVOT* is very small when full automation only affects the monetary costs. However, for *VOT = 0.06 EUR/min* and *VOT = 0.1 EUR/min*, the changes are substantial. The impact is the largest for the travel motive "business trips", and the smallest for "commuting for studies". For *VOT = 0.1 EUR/min*, there is a factor five difference between the smallest and the largest impact.

Table 4. Impact of changed VOT and monetary costs on the generalised cost

Per	Mode	Motive	Generalized costs in the reference scenario (EUR/km)	% Δ(cost) for RefVOT	% Δ(cost) for VOT = 0.1 EUR/min	% Δ(cost) for VOT = 0.06 EUR/min
op	Car with passenger	Business trips	0.66	-0.79	-62.26	-70.32
p	Car with passenger	Commuting for studies	0.34	-1.95	-11.60	-30.93
p	Car with passenger	Commuting for studies	0.40	-1.18	-22.52	-41.55

The table represents the impact of the changes in the monetary costs (see Section 4.2) in combination with different values of the VOT. RefVOT is the VOT used in the reference scenario.

In all cases, the generalised costs decrease. Indeed, all other things being equal, the decrease in the *VOT* and in fuel consumption per km induce an increase in *pkm*. As a result, the decrease in variable costs dominates the increase in fixed costs (which are now spread over a higher annual mileage). In the sensitivity analysis (Section 5.4), we shall verify whether this also holds for higher increases in the fixed costs.

We will now consider the following indicators for the impact on the transport system: (a) the change in the passenger km (pkm) per mode (b) the change in vehicle km per car (c) the impact on fuel consumption (d) the change in *pkm* per travel motive (e) the impact on road speed per region and road type (f) the impact on total travel time.

Figure 4 represents the absolute change in *pkm* compared to the reference scenario. We observe an unambiguous shift in transport demand away from all modes in favour of travelling by car. As expected, this change is larger, the larger the decrease in the VOT.

This reflects not only a modal shift, as the increase in the *pkm* travelled by car exceeds the decrease in travel by other modes. In other words, there is a significant net increase in overall passenger transport demand:

For *RefVOT*, the changes are very small, though: it is the *combination* of changes in the VOT and the financial costs that induces important modal changes.

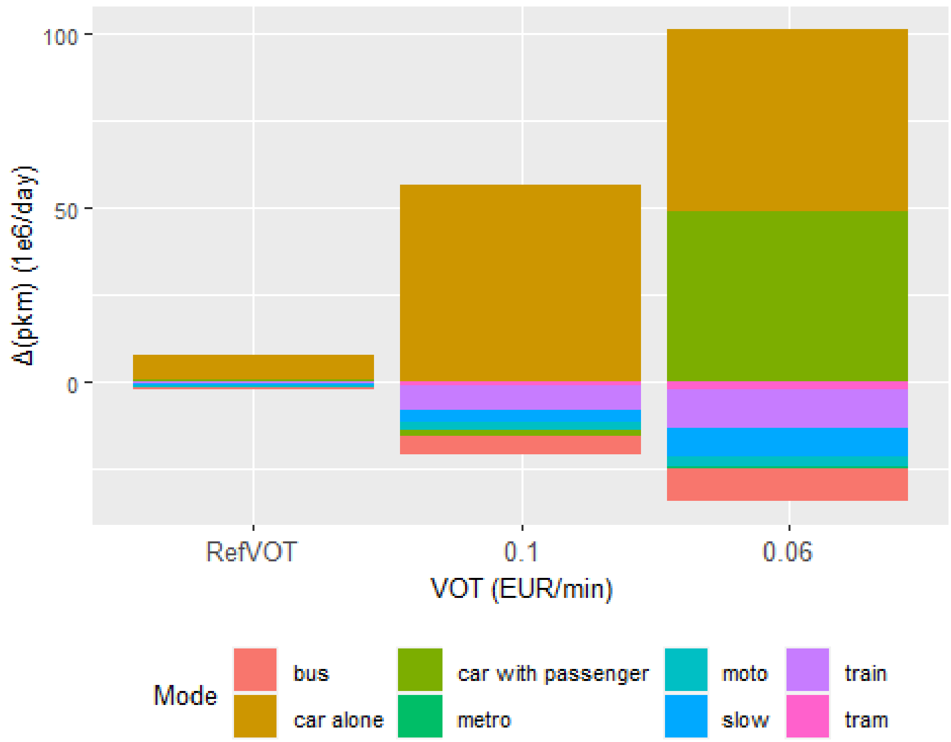

Figure 4. Absolute changes in pkm per mode compared to the reference scenario

For *VOT = 0.06 EUR/min*, there is a small decrease in travelling by car with passenger, which is however completely overwhelmed by the increase in travelling by car on one's own.

The decrease in travelling with passenger can be explained as follows. In the reference scenario, the *VOT* for driving with passengers is lower than for driving alone (Table 1), reflecting that the interaction between passenger(s) and driver is seen as valuable. In Level 5 self-driving cars, the distinction between driver and passenger disappears. Hence, we observe two types of substitution effects. First, due to the decrease of the *VOT*, there is a substitution towards driving by car, away from the active modes and public transport. Second, there is a substitution effect away from driving with passengers to driving alone, given that the decrease in the *VOT* is much larger when driving alone. Figure 4 illustrates that the second effect dominates for small changes in the *VOT*, but not for larger changes.

The overall impact on the transport system (congestion, emissions) is however not determined by the changes in the *pkm*, but by the *vkm*. Figure 5 summarizes the overall impact for cars (covering both cars with and without passengers). Again, the impact for *RefVOT* is small, but for *VOT= 10* and *0.06 EUR/min*, the increase in overall car *vkm* lies between 20 and 25%.

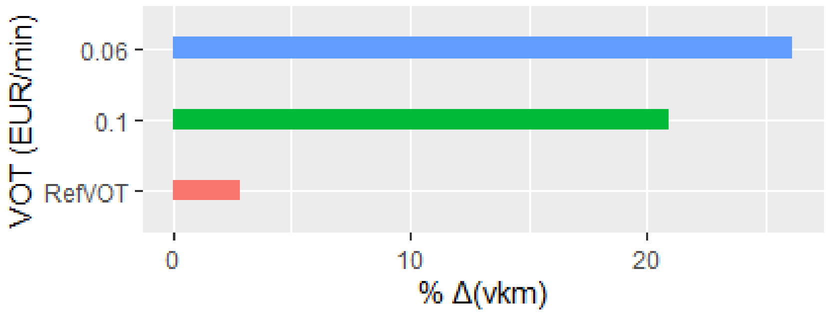

Figure 5. Percentage changes in car km compared to the reference scenario

Now remember that one of the drivers for this result is a decrease in fuel consumption per km by 10%. Figure 6 summarizes the overall change in gasoline and diesel consumption (including from hybrid cars). With *RefVOT*, the improvement in fuel efficiency dominates the increase in *vkm* and overall fuel consumption decreases. However, this is not true for *VOT ≤ 0.1 EUR/min*: there is a net rebound effect and the increase in *vkm* dominates the increase in fuel efficiency.

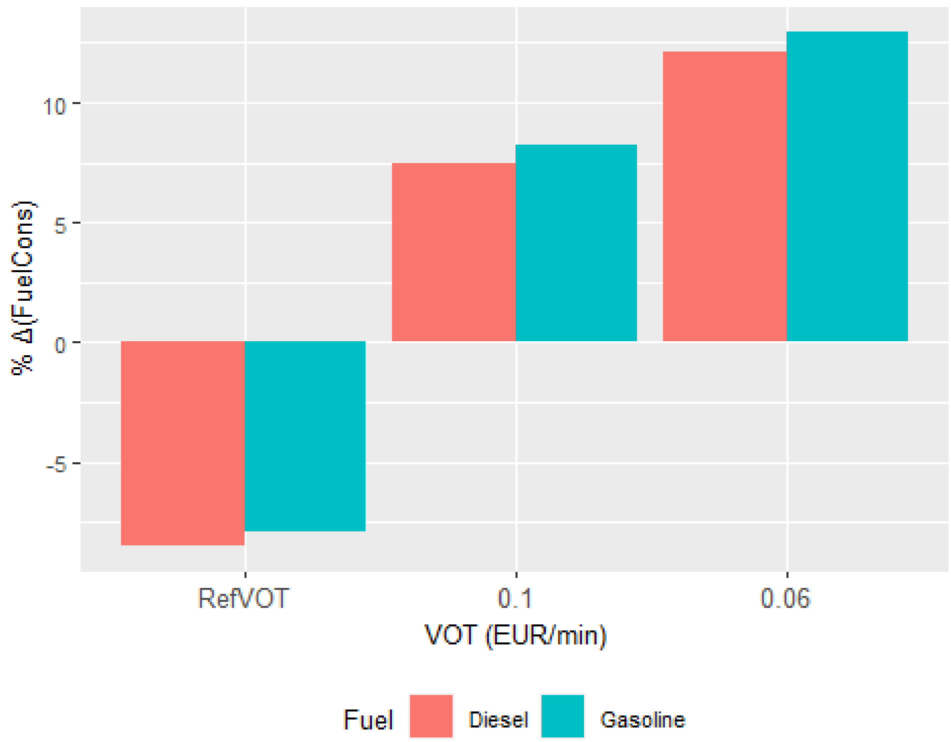

Figure 6. Percentage changes in total fuel consumption compared to the reference scenario

The impacts on the passenger km per travel motive is summarized in Figure 7 for *VOT = 0.06 EUR/min* (the effects for the other VOT are similar). For the travel motives "commuting to school" and "commuting for studies", the small increase in travel by car is completely compensated by a decrease in the *pkm* or the other modes: this is purely a modal shift, without any induced travel. There is a small net increase in travel for the motives "commuting for work" and "business trips", but most of the induced travel is for "other" motives, where the increase in car travel is much larger than the decrease in travel by other modes.

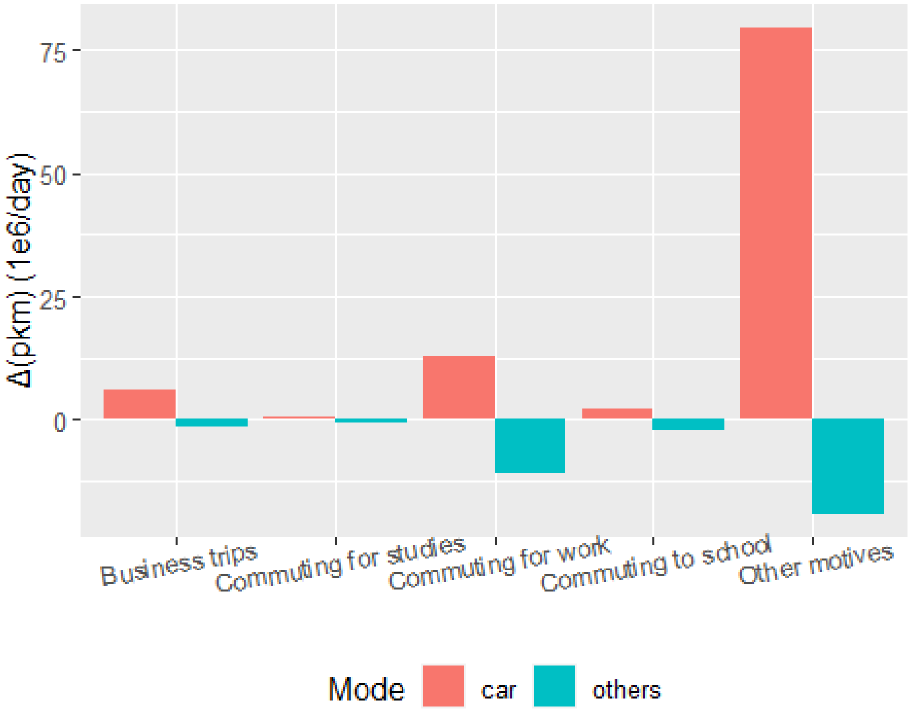

Figure 7. Absolute changes in pkm per travel motive compared to the reference scenario (for VOT = 0.06 EUR/min)

Given that national averages can hide important differences at the local level, Table 3 shows the impact on the average road speed per zone, road type and period of the day. For the sake of readability, we have only kept the *Period-Geographical zone-Road* combinations with the most important changes compared to *RefSpeed*, the speed in the reference scenario. In the Brussels Region, the decrease in the speed of road modes is important, both in peak and off peak, even though the baseline speed in this region is already very low (22 km per hour during off peak hours and 12 km per hour in peak hours). During peak hours, the decrease in speed is also important in the GEN zone, albeit from a higher baseline speed. In Antwerp, there is an important decrease in speed, both during peak hours and during of peak hours, but also starting from a higher baseline than in the Brussels region.

While Table 5reports the impact on the road speed in specific geographical zones and on specific road types, summarizes the impact on the overall travel time per mode and time the day, where the national average Table 6 has been obtained as the weighted average of travel times between all *OD*-pairs, with the passenger kilometres as weighting factor.

Table 5. Impact of changed VOT and monetary cost on road speed

Per	Geo	Road	RefSpeed (km/hour)	% Δ(speed) for RefVOT	% Δ(speed) for VOT = 0.1 EUR/min	% Δ(speed) for VOT = 0.06 EUR/min
Off-peak	Antwerp	other	50	-1	-12	-18
Off-peak	Antwerp	tollroad	86	-2	-9	-10
Off-peak	Brussels	tollroad	22	-1	-20	-33
Off-peak	GEN zone	tollroad	95	-1	-8	-9
Peak	Antwerp	other	36	-1	-16	-25
Peak	Antwerp	tollroad	57	-2	-14	-16
Peak	Brussels	tollroad	12	-1	-22	-36
Peak	GEN zone	other	47	-1	-10	-15
Peak	GEN zone	tollroad	57	-3	-28	-39

The table represents the impact of the changes in the monetary costs (see Section 5.2) in combination with different values of the VOT. RefVOT is the VOT used in the reference scenario

Again, we only report the largest changes compared to the reference scenario. As expected, the decrease in the *VOT* has a strong impact on the travel time by car. For a *VOT* of 0.06 EUR/min, the time travelled by "car alone" could increase by close to 25% in peak hours. But the increase in road congestion also affects public transport modes that are exposed to road congestion. All in all, one can conclude that the decrease in the cost of time (or, alternatively, of the *perceived* time) implies that the budget for *physical* travel time has gone up.

Table 6. % Changes in travel time for changes in VOT

Mode	Per	RefTravelTime (minutes)	% Δ(travel time) for RefVOT	% Δ(travel time) for VOT = 0.1 EUR/min	% Δ(travel time) for VOT = 0.06 EUR/min
bus	op	35.20	0.34	4.42	7.01
bus	p	47.14	0.54	8.38	13.78
car with passenger	p	28.56	0.05	4.52	12.82
car alone	p	42.38	0.80	11.80	23.51
tram	p	28.49	0.00	4.10	8.00

The table represents the impact of the changes in the monetary costs (see Section 5.2) in combination with different values of the VOT. RefVOT is the VOT used in the reference scenario

To summarize, full automation leads to:

- an overall increase in car travel
- an increase in fuel consumption
- a further slowdown of road traffic in the most congested zones
- an increase in overall fuel consumption
- an increase in overall travel time for road modes.

The key driver for those changes is the reduction in the *VOT*, which strongly amplifies the immediate impact of the higher fuel efficiency.

5.3 *Sensitivity analysis: higher fuel efficiency*

We now explore what happens if we consider a reduction in fuel consumption per kilometre by 40% rather than 10%. Changes are calculated compared to both the scenario discussed in Section 5.2 (the "central scenario") and to the reference scenario.

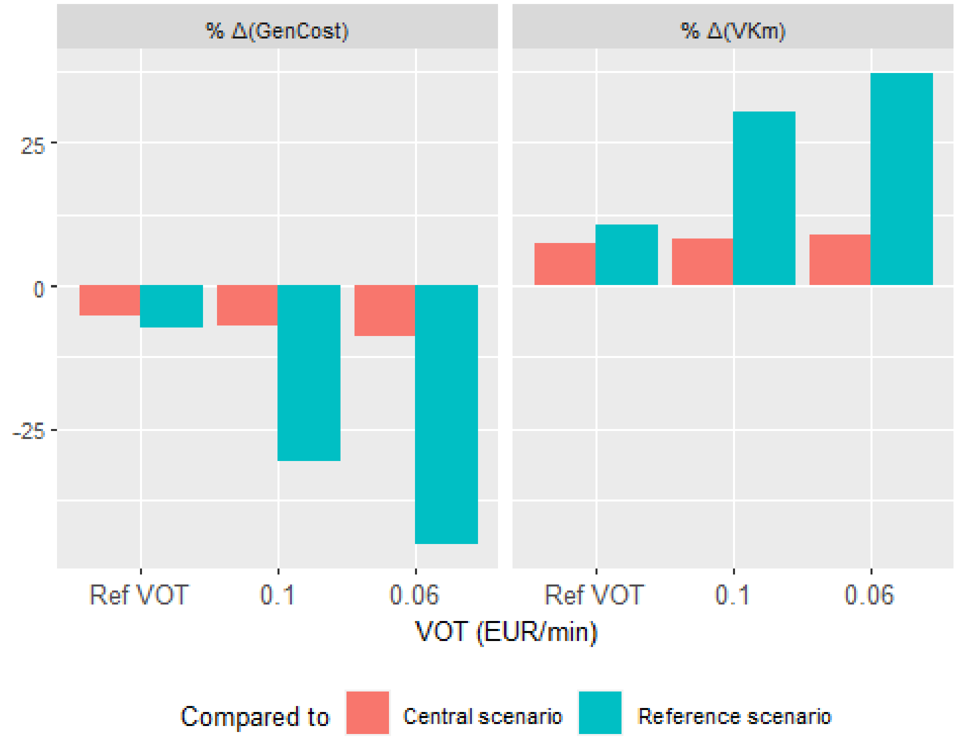

Figure 8. Sensitivity scenario for fuel consumption : impact on generalised cost and car vkm

Compared to the central scenario, the generalized costs decrease (Figure 8) as the result of a higher fuel efficiency. The impact on car *vkm* is almost a mirror image of the impact on generalised costs. The effects are stronger, the lower the *VOT*: the lower the *VOT*, the more important changes in the monetary variable costs are compared to the time costs of travel, and the higher the increase in the *vkm*. However, the differences are not very large.

The changes compared to the reference scenario are much larger and much more sensitive to differences in the *VOT*. In other words, the effect of a decrease in fuel consumption by 10% (as in the "central" scenario) is much higher than the additional effect of a decrease by a further 30% point. For *RefVOT*, the differences are even minimal: the driver behind the changes in the generalised cost is the improvement in the *VOT*, and the improvements in fuel efficiency mostly reinforce this channel.

Figure 9 illustrates that, with a reduction in fuel consumption per *vkm* by 40%, this higher fuel efficiency dominates the increase in *vkm*, and total fuel consumption (and emissions) decreases, even for *RefVOT*. There is thus some threshold improvement in fuel efficiency for which the impact of full automation on total fuel consumption is neutral.

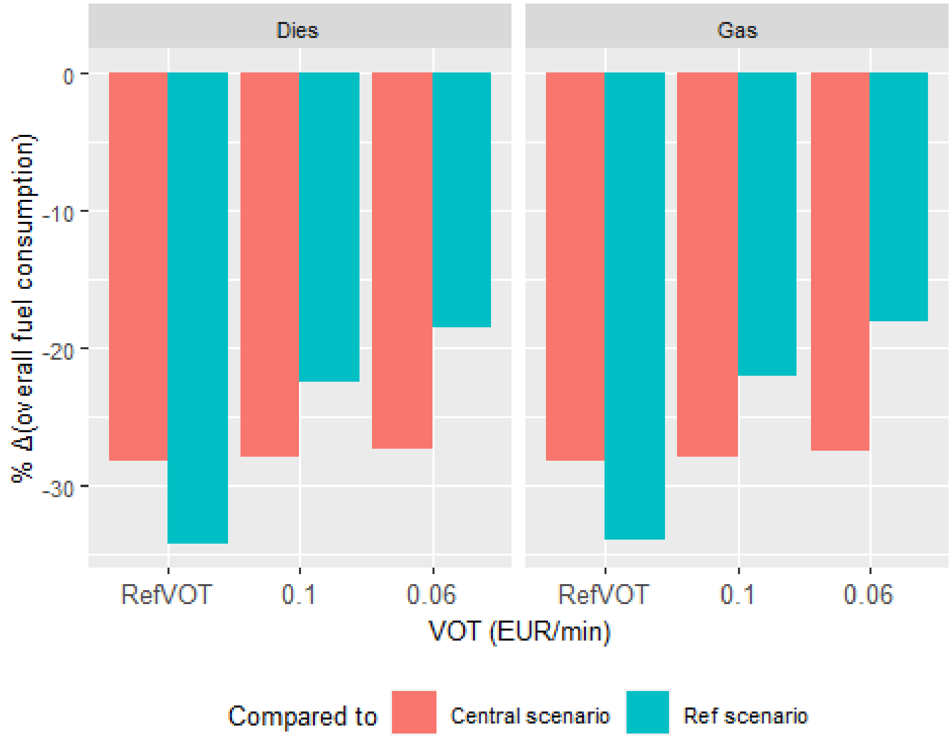

Figure 9. Sensitivity scenario for fuel consumption : impact on total fuel consumption

5.4 Sensitivity analysis: Higher acquisition costs

If the fixed costs increase in combination with a decrease in the variable costs, the net impact of monetary costs per km is not determined a priori. We therefore consider an alternative scenario with an increase in the acquisition costs by 40%, compared to what is used in the reference scenario.

Changes are again calculated compared to both the scenario discussed in Section 5.2 (the "central scenario") and to the reference scenario - remember that, in the "central scenario", we assumed a decrease in acquisition costs by 20%.

As can be seen from Figure 9, compared to the "central scenario", the generalized costs increase, and the vehicle km travelled by car decrease. Moreover, the lower the *VOT*, the more important changes in the monetary variable costs are compared to the time costs of travel.

However, for *VOT = 0.1* or *0.06 EUR/min*, the changes compared to the central scenario are much smaller in absolute value than the changes compared to the reference scenario[18]. This confirms the robustness of the central scenario.

[18] Note that for VOT = RefVOT, the net effect is an (small) increase in the generalised cost and a (minimal) decrease in vkm compared to the reference scenario.

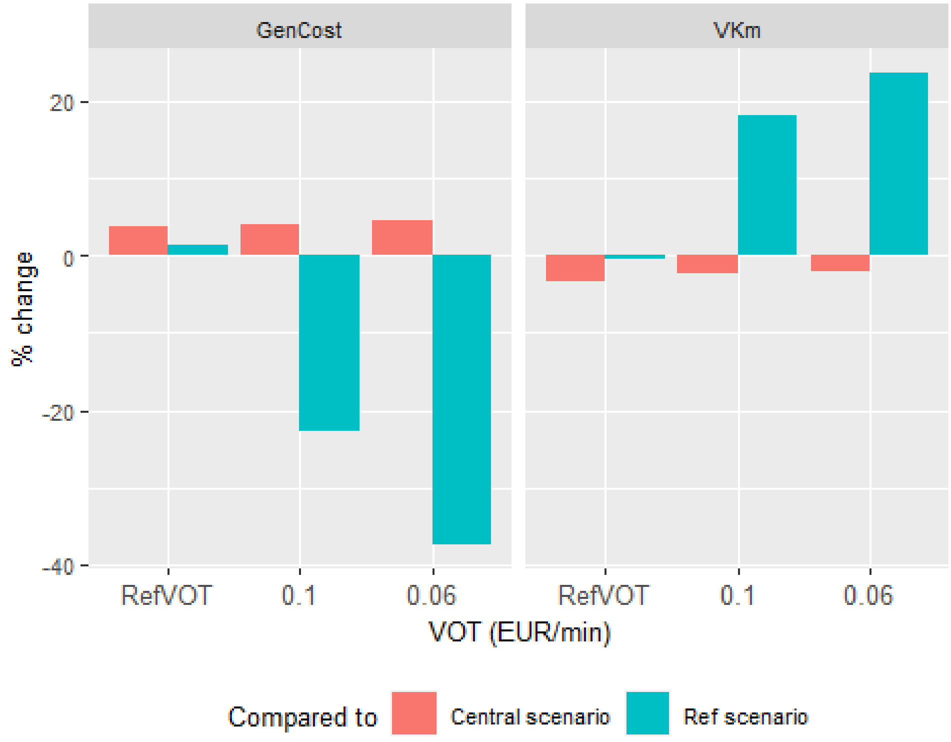

Figure 10. Sensitivity scenario for acquisition costs : impact on car vkm and generalised costs

6. Policy instruments

The previous sections have shown that full automation of the car fleet is likely to lead to a substantial increase in road traffic volumes and fuel consumption in Belgium, even if there is considerable uncertainty regarding the exact magnitude of this increase.

We therefore consider the possibility to use a price instrument to counteract these effects. We explore the effect of a uniform road tax, for all periods, zones and road types. We consider the following values: 8 and 20 EUR cent per km. Public transport modes are exempted and road freight modes are already subject to a road charge.

As expected, the introduction of a road charge always leads to an increase in generalized costs compared to the scenario of Section 5.2 (Figure 11). However, compared to the reference scenario, a road charge of 8 EUR cent per km is not sufficient to counteract the decrease in the *VOT* following automation: there is still a substantial increase in *vkm* except for *RefVOT* (Figure 12). A road charge of 20 EUR cent per km is enough to counteract the effect of full automation for all the values of the *VOT* we have considered here, though.

To give some perspective: in a recent study performed on behalf of the Flemish Government (Heyndrickx et al. 2019), several scenarios for road charges were considered, with average tariffs ranging from 3 to 8.5 EUR cent per km. In most of those scenarios, the charges were differentiated in time and space, with maximum values of around 19 EUR cent per km in highly congested areas during peak hours. The road charge that would be needed to counteract the impact of full automation would thus lie far above the average tariffs considered in the study by Heyndrickx et al.

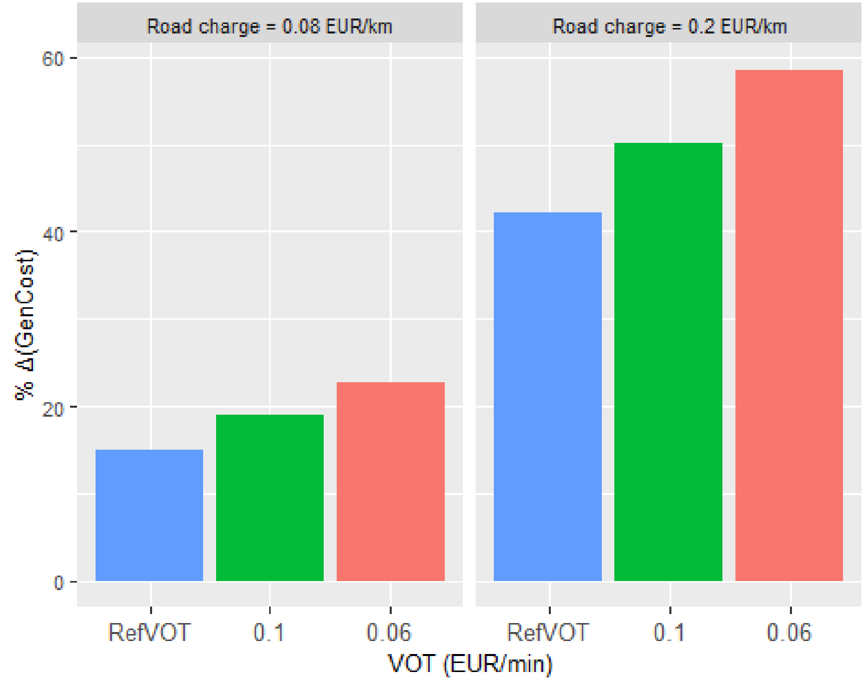

Figure 11. Road charge : changes in generalised cost compared to central scenario

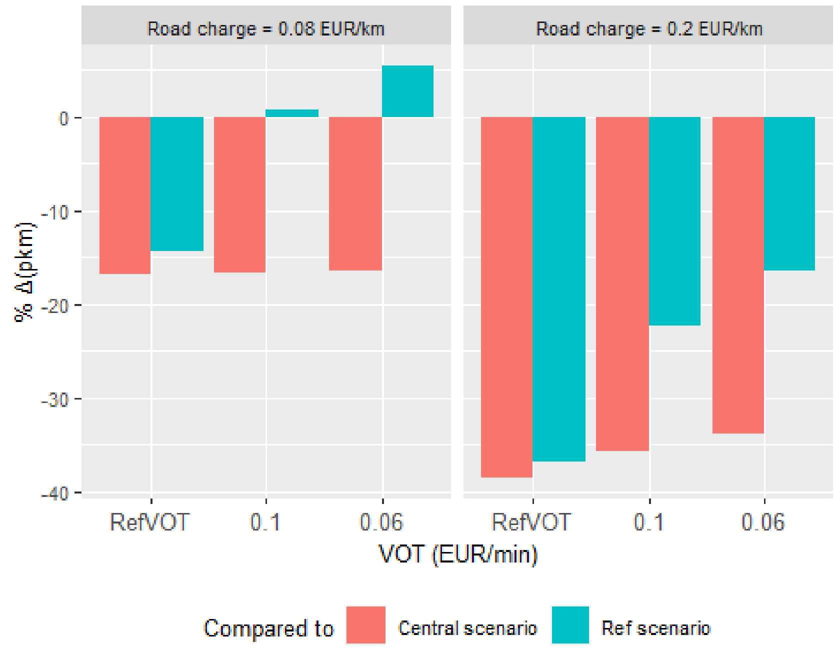

Figure 12. Road charge : changes in pkm compared to central and reference scenario

7. Conclusion

Under a wide range of assumptions, self-driving cars are likely to induce a significant increase in the car by travel (possibly up to 26%), and a shift away from public transport modes. The main driver behind this is the decrease in the value of travel time, rather than the improved fluency of road transport or changes in the monetary costs.

Most of the induced travel as the result of full automation is for "other" motives, where the increase in car travel is much larger than the decrease in travel by other modes.

The impact on the speed of road modes is highly variable. In the most congested zones (Brussels, the GEN zone, Antwerp), the decrease in the speed of road modes is important, even though the baseline speed in those regions is already very low.

The decrease in the cost of time (or, alternatively, of the *perceived* time) implies that the budget for *physical* travel time has gone up – by up to 25% on average for car travel.

The literature review has revealed that there is a wide range of estimates for the impact of CAVs on induced traffic. This is partly due to differences in modelling approaches, but also to objective differences in the areas of study. Probably the most relevant benchmark in the existing literature are the scenarios for AV development that Milakis et al. (2017a) developed, based on the feedback they received during an expert consultation in The Netherlands, a country that is comparable to Belgium in terms of size and population density. Our central results are in line with these scenarios.

To counteract those effects, a road charge of close to 20 EUR cent per km would be needed, which is high in comparison to tariffs that have recently been discussed as policy proposals.

Many elements that are not accounted for in the analysis point to the conclusion that the increase in traffic volumes could even be higher.

For instance, self-driving cars can lead to induced demand by segments of the population that are not able to drive, such as children and mobility impaired people. The lower cost of driving is also likely to lead to the relocation of households and firms, resulting in urban sprawl or the creation of new centres.

Also, the current paper has only considered privately owned cars, while automation and car sharing are two forces of mobility innovation that are likely to mutually reinforce each other. It has been argued in the literature that, unless combined with an important uptake of ridesharing, shared CAVs might lead to even more additional trips, as empty vehicles waiting for new clients will reposition themselves.

Given that a generalised adoption of ridesharing would require major behavioural changes, a charge of 20 EUR cent per km should thus be considered as the lower bound to what would be needed to counter all sources of induced traffic. This will be considered in future work.

Acknowledgements

The author would like to thank his colleagues at the Belgian Federal Planning Bureau, Christophe Heyndrickx and participants in the BIVEC-GIBET Transport Research Days 2021 for their useful comments. The paper has also hugely benefited from the comments and suggestions by the Associate Editor and two anonymous referees.

References

Alonso Raposo M., Grosso, M., Després, J., Fernandez Macîas, E., Galassi, C., Krasenbrink, A., Krause, J., Levati, L., Mourtzouchou, A., Saveyn, B., Thiel, C. and Ciuffo, B. (2018), *An analysis of possible socio-economic effects of a Cooperative, Connected and Automated Mobility (CCAM) in Europe - Effects of automated driving on the economy, employment and skills*, EUR 29226 EN, Publications Office of the European Union, Luxembourg doi:10.2760/777.

Bösch, P., Becker, F., Becker, H. and Axhausen, K. (2018), Cost-based analysis of autonomous mobility services, *Transport Policy*, 64, 76-91.

Bureau Fédéral Du Plan (2019), *Perspectives de la demande de transport en Belgique à l'horizon 2040*.

Cohen, T. and Cavoli, C. (2019), Automated vehicles: exploring possible consequences of government (non)intervention for congestion and accessibility, *Transport Reviews*, 39(1), 129-151.

Compostella, J., Fulton, L.M., De Kleine R., Chul Kim, H. and Wallington T.J., Near- (2020) and long-term (2030 - 2035) costs of automated, electrified, and shared mobility in the United States (2020), *Transport Policy*, vol 85, 54-66.

Daubresse, C. and Laine, B. (2020), *The PLANET Model: Methodological Report. PLANET 4.0*, Working Paper 1-20, Federal Planning Bureau.

De Almeida Correia, G.H., Looff, E., van Cranenburgh, S., Snelder, M. and van Arem, B (2019), On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: theoretical insights and results from a stated preference survey, *Transportation Research Part A: Policy and Practice*, 119, 359-382.

De Ameida Correia, G.H., and van Arem, B. (2017), Estimating urban mobility patterns under a scenario of automated driving: results from a model application to Delft, the Netherlands, *Conference: Transportation Research Board 96th Annual Meeting.*

Domke, C. and Potts, Q (2020), LiDARs for self-driving vehicles: a technological arms race, Automotive World, https://www.automotiveworld.com/articles/lidars-for-self-driving-vehicles-a-technological-arms-race/ , last accessed on 16 April 2022.

Franckx, L. (2019), *Future evolution of the car stock in Belgium: CASMO, the new satellite of PLANET*, Working Paper 1-19, Federal Planning Bureau, Belgium.

Harper, C.D., Hendrickson, C.T., Mangones, S. and Samaras C. (2016), Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions, *Transportation Research Part C: Emerging Technologies*, vol 72, 1-9.

Heyndrickx, C., Mayeres, I., Van Den Bergh, G. and De Ceuster, G. (2019), *OIWP4: Tarificatie, deelrapport van de studie "Uitrol van een systeem van Wegenheffing"*, study performed by the Motivity Consortium (KPMG, Transport & Mobility Leuven, Stibbe and Common Ground) on behalf of the Department Mobility and Public Works of the Flemish Regional Government.

Hoen, A. and Koetse, M. (2014), A choice experiment on alternative fuel vehicle preferences, *Transportation Research Part A: Policy and Practice,* vol. 61, 199-215.

International Transport Forum (ITF) (2015), *How shared self-driving cars could change city traffic*, Corporate Partnership Board.

International Transport Forum (ITF) (2016), *Shared Mobility: Innovation for Liveable Cities*, Corporate Partnership Board, Policy Insights.

Keller, W.J. (1976), A nested CES-type utility function and its demand and price-index functions, *European Economic Review*, vol 7, Issue 2, 175-186

Kolarova, V., Steck, F. and Bahamonde-Birke F. (2019), Assessing the effect of autonomous driving on value of travel time savings: a comparison between current and future preferences, *Transportation Research Part A: Policy and Practice*, 129, 155-169.

La Mondia, J., Fagnant, D.J., Qu, H., Barrett, J. and Kockelman, K. (2016), Shifts in Long-Distance Travel Mode Due to Automated Vehicles and Travel Survey Analysis, *Transportation Research Record*, 2566, 1-10.

Lee, J. and Kockelman, K. (2019), Energy & Emissions Implications of Self-Driving Vehicles. Presented at the *98th Annual Meeting of the TRB*, 2019.

Litman, T. (2019), *Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior*, Victoria Transport Policy Institute.

Malokin, A., Circella, G. and Mokhtarian, P.L. (2019), How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios, *Transportation Research Part A: Policy and Practice*, vol 124, 82-114.

Milakis, D., Snelder, M., Van Arem, B., Van Wee, B. and De Almeida Correia G.H. (2017a), Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050, *European Journal of Transport and Infrastructure Research*, 17 (1), 63-85.

Milakis, D., Thomopoulos, N. and Van Wee, B. (eds), *Advances in Transport Policy and Planning*, Volume 5: Policy Implications of Autonomous Vehicles, 2020.

Milakis, D., Van Arem, B. and Van Wee, B. (2017b), Policy and society related implications of automated driving: a review of literature and directions for future research, *Journal of Intelligent Transportation Systems*, DOI: 10.1080/15472450.2017.1291351

Morrow, III, W. R., Greenblatt, J.B., Sturges, A., Saxena, S., Anand, R. Gopal, A.R., Millstein, D., Shah, N. and Gilmore, E.A. (2014), Key factors influencing autonomous vehicles' energy and environmental outcome, in Meyer, G., Beiker, S. (eds.), *Road Vehicle Automation*.

Narayanan, S., Chaniotakis, E., and Antoniou, C. (2020), Chapter One - Factors affecting traffic flow efficiency implications of connected and autonomous vehicles: A review and policy recommendations, in Milakis, Thomopoulos and van Wee (eds.), *Advances in Transport Policy and Planning, Volume 5: Policy Implications of Autonomous Vehicles*

Nieuwenhuijsen, J., De Ameida Correia, G.H., Milakis, D., Van Arem, B. and Van Daalen, E. (2018), Towards a Quantitative Method to Analyze the Long-Term Innovation Diffusion of Automated vehicles Technology Using System Dynamics, *Transportation Research Part C: Emerging Technologies,* Vol. 86, pp. 300-327, 2018.

Norman, P. (1999), *Putting Iterative Proportional Fitting on the researcher's desk.* School of Geography, University of Leeds. School of Geography Working Paper 99/03.

Ortuzar, J.D. and Willumsen, L.G. (2011), *Modelling Transport*, 4th Edition, John Willey & Sons.

Proost, S. and Van Dender, K. (1999), *Final Report For Publication: TRENEN II STRAN,* Project funded by the European Commission under the transport RTD programme of the 4th framework programme. pp. 1-108, 1999

Rodier, C. J., *Travel Effects and Associated Greenhouse Gas Emissions of Automated Vehicles*, UC Davis: National Center for Sustainable Transportation. Retrieved from https://escholarship.org/uc/item/9g12v6r0, 2018.

Schwanen, T. (2008), Struggling with Time: Investigating Coupling Constraints, *Transport Reviews*, 28 (3), 337-356.

Soteropoulos, A., Berger, M. and Ciari, F. (2019), Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies, *Transport Reviews*, 39(1), 29-49.

Stephens, T.S., Gonder, J., Chen, Y., Lin, Z., Liu, C. and Gohlke, D. (2016), *Estimated bounds and important factors for fuel use and consumer costs of connected and automated vehicles*. Technical Report, National Renewable Energy Lab (NREL), Golden, CO (United States).

Taiebat, M., Brown, A.L., Safford, H.R., Qsu, S. and Xu, M. (2018), A review on energy, environmental, and sustainability implications of connected and automated vehicles, *Environmental Science and Technology*, 52 (20), 11449–1146.

Truong, L.T., De Gruyter, C., Currie, G. and Delbosc, A. (2017), Estimating the trip generation impacts of autonomous vehicles on car travel in Victoria, Australia, *Transportation*, 44, 1279-1292.

van den Berg, V.A.C. and Verhoef, E. T., Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity, *Transportation Research Part B: Methodological,* vol. 94(C), 43-60, 2016.

Verboven, F. (1996), The nested logit model and representative consumer theory, *Economics Letters*, vol 50 (1), 57-63.

Wadud, Z and Huda F. Y (2019), Fully automated vehicles: the use of traveltime and its association with intention to use, *Proceedings of the Institution of Civil Engineers - Transport*, ahead of print, 2019.

Wadud, Z (2017), Fully automated vehicles: A cost of ownership analysis to inform early adoption, *Transportation Research Part A: Policy and Practice,* 101, 163-176.

Wadud, Z., Mackenzie, D. and Leiby, P. (2016), Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles, *Transportation Research Part A: Policy and Practice*, 86, 1-18.

Zhao, Y. and Kockelman, K.M. (2018), Anticipating the regional impacts of connected and automated vehicle travel in Austin, Texas., *Journal of Urban Planning and Development,* vol 144 (4).