Transportation Research Interdisciplinary Perspectives 22 (2023) 100964

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

Fuel-saving opportunities for automated vehicles: A driving cycle analysis

Edgar Jungblut[a,b,*], Thomas Grube[a], Jochen Linssen[a], Detlef Stolten[a,b]

[a] Forschungszentrum Jülich GmbH, Institute of Energy and Climate Research – Techno-economic Systems Analysis (IEK-3), Jülich 52425, Germany
[b] RWTH Aachen University, Chair for Fuel Cells, Faculty of Mechanical Engineering, Aachen 52062, Germany

ARTICLE INFO

Keywords:
Automated driving
Vehicle fuel demand
Driving cycle
Automation system
Energy demand
Eco-driving

ABSTRACT

We calculate the energy demand of automated vehicles for different driving cycles. We alter standard driving cycles to depict the driving behavior of automated vehicles. We further assume additional energy demand for automation systems and investigate trade-offs between reductions in mechanical energy demand and increases in auxiliary energy demand. In the case of trucks, we find that smoother driving and the additional energy demand offset one another for highway driving. However, a notable reduction in energy demand can be achieved by lowering the maximum driving speed. For cars, we find that the additional energy demand slightly outweighs the effects of smoother driving on highways. When considering city driving, the additional energy demand increases the energy demand of a mid-size car in the standard driving cycle by one third. Reducing driving speeds and stops is not able to offset this increase in energy demand.

1. Introduction

The transportation sector was responsible for about 22 % of greenhouse gas (GHG) emissions in Europe in the year 2020 (EEA, 2022). Furthermore, it is difficult to make GHG neutral with an increase of nearly 3 % in GHG emissions in 2020 compared to 1990, whereas total emissions from all sectors decreased by about 34 % in the EU (EEA, 2022). With different forecasts anticipating an increase in transport demand over the next few decades, the contribution of transportation to overall GHG emissions will further grow. In one study, a 22 % increase in transport demand from 2019 to 2049 in the US is expected, with the largest portions deriving from freight transport (combination truck mileage, growing by 57 %, and single-unit truck mileage, growing by 101 %) (FHWA, 2022). In another study, a 9.9 % increase in motorized individual traffic for passenger transport from 2010 to 2030 and an 18.9 % increase in road freight transport is expected for Germany (Schubert et al., 2014). Traffic forecasts for the UK, meanwhile, anticipate an increase of 17 % to 51 % from 2015 to 2050 (UK DfT, 2018). These increases will lead to an even stronger imperative for decarbonization. This might be achieved using alternative drivetrains like battery– or fuel cell–electric solutions. Another important aspect to consider is future technologies such as automated driving. Automated driving might, on the one hand, change (increase) overall transport demand and, on the other, lead to different driving styles. Driver assistance systems like adaptive cruise control (ACC) nowadays already keep vehicle speeds smooth and reduce acceleration and deceleration. Connectivity between vehicles and with infrastructure might also further increase the foresightedness of the vehicles and therefore make traffic flows even smoother. The effects of these measures must be investigated in order to see which might provide the best opportunities for fuel saving. However, deploying the technology is costly and must therefore be optimized (Moubayed et al., 2020). It remains to be seen whether the benefits of the technology justify its costs. As neither automated vehicles nor vehicle-to-infrastructure communication are widely available yet, current studies must rely on simulations to estimate the impact of these technologies.

In this paper, we will consider the role of automated driving to change the driving cycles of vehicles. The changes we identify range from foresighted, smoother driving and reduced driving speeds for trucks on highways, to city driving without stops at traffic lights and reduced speeds for cars. We will investigate the changes in fuel demand of automated vehicles under the adjustments we make to the driving cycles. In our analysis, we will also consider mechanical energy demand, as well as the auxiliary energy demand of vehicles. For auxiliary energy demand, we especially focus on the additional energy demand needed to operate the automation system.

The paper is structured as follows: In chapter 2, we outline some of the studies that have been conducted on the influence of vehicle

* Corresponding author at: Forschungszentrum Jülich GmbH, Institute of Energy and Climate Research – Techno-economic Systems Analysis (IEK-3), Jülich 52425, Germany.
E-mail address: e.jungblut@fz-juelich.de (E. Jungblut).

https://doi.org/10.1016/j.trip.2023.100964
Received 12 July 2023; Received in revised form 21 September 2023; Accepted 1 November 2023
Available online 9 November 2023
2590-1982/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

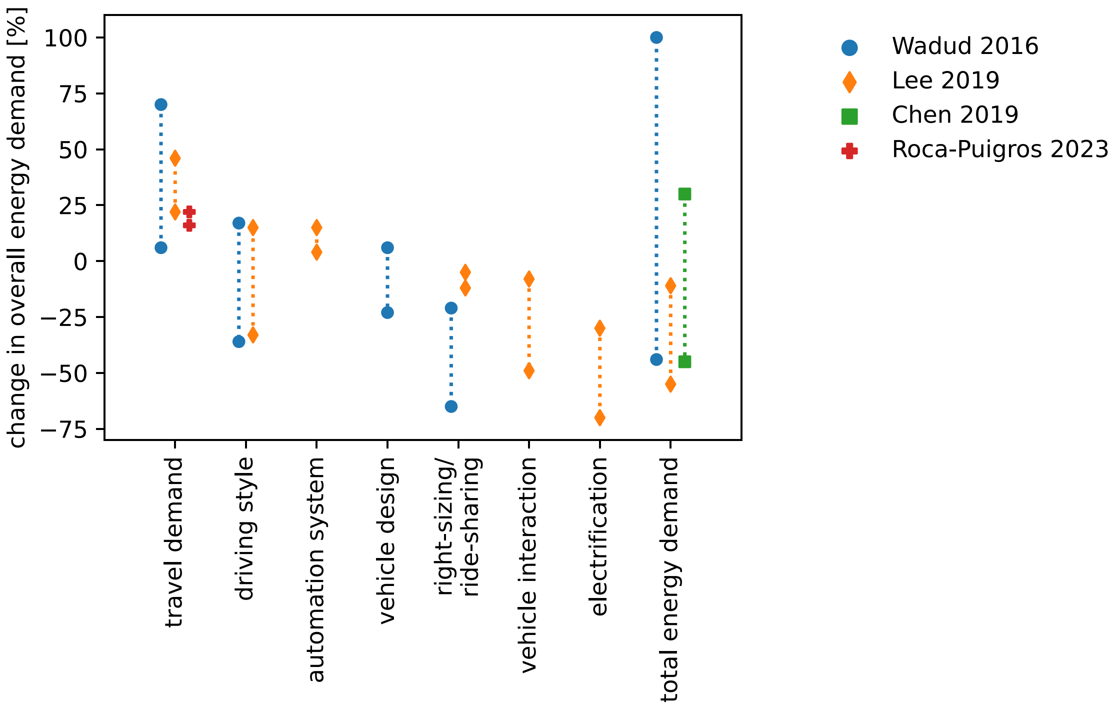

Fig. 1. Possible effect of automated driving on vehicle energy demand; see: Chen 2019 (Chen et al., 2019), Lee 2019 (Lee and Kockelman, 2019), Roca-Puigros 2023 (Roca-Puigròs et al., 2023), Wadud 2016 (Wadud et al., 2016).

automation on vehicle fuel demand. Afterwards, we lay out our methodology in chapter 3. We apply this to analyzing highway and city driving in chapter 4, and discuss the implications of our results in chapter 5. Finally, we summarize our findings in chapter 6.

2. Literature review: The many influences of automated and connected driving on the energy demand of the transport sector

Automated vehicles perceive their environment using a wide range of sensors. Based on the data collected by these, algorithms are used to plan long- and short-term vehicle driving routes and to control vehicle movement (Campbell et al., 2010; Pendleton et al., 2017). Details on the sensors used, their limitations, and current challenges are described in Feng et al. (2021) and Yeong et al. (2021).

The design of suitable algorithms currently poses major challenges to automated driving. In addition to the obtaining of timely and reliable results, the energy demand of the automation system is a major constraint that we will further investigate herein.

In addition to the higher energy demand deriving from the automation system, the potential to reduce the specific energy demand per vehicle kilometer driven lies in the changes in driving style that automated vehicles may feature compared to conventional ones. Based on a more precise perception of vehicle velocities and distances, automated vehicles may be more farsighted, which would lead to a smoother driving style with fewer acceleration and deceleration phases. Communication between vehicles and with infrastructure may further increase perception of the traffic situation and therefore the vehicle's planning horizon (Dong et al., 2020; Pendleton et al., 2017). However, the optimal layout of such an infrastructure communication system with regard to coverage and cost is still a topic under investigation (Moubayed et al., 2020).

A multitude of studies have been conducted to estimate the possible effect of automated driving on energy demand and greenhouse gas emissions in passenger and freight transport. In order to obtain an overview of the potential impacts, we start with the results of three review papers by Lee and Kockelman (2019), Massar et al. (2021), and Wadud et al. (2016) and related studies.

Lee and Kockelman (2019) analyzed the impact of automated vehicles on the energy demand for passenger transport in terms of the additional travel induced by automated vehicles, changes in driving style, vehicle interactions, and powertrain choice. They found travel to increase by 22 % to 46 %, changes in driving style to change energy demand from –33 % to + 15 %, vehicle interaction to reduce energy demand by 8 % to 49 %, and switching from a combustion engine to an electric drivetrain to reduce energy demand by 30 % to 70 % (Lee and Kockelman, 2019). Furthermore, they found energy demand for the automation system to increase overall energy demand by 4 % to 15 %, whereas the right-sizing of vehicles and ride-sharing were found to decrease overall energy demand by 5 % to 12 % (Lee and Kockelman, 2019).

Wadud et al. (2016) differentiated the effects on energy demand into energy intensity and travel demand factors. Energy intensity factors include eco-driving, congestion-mitigation, platooning, higher driving speeds, lower acceleration, crash-avoidance, right-sizing, and vehicle features for comfort. Travel demand factors include reduced travel costs, new user groups, and changes in transport services. The authors expected the energy intensity factors to already have an impact at low levels of automation and to lead to a decrease in energy demand, whereas the travel demand factors only start having an impact at higher levels of automation, leading to an increase in energy demand.

Chen et al. (2019) used the changes in fuel demand specified by Wadud et al. (2016) and coupled them with market introduction scenarios for both partially and fully automated vehicles in highway and city driving settings. In the most pessimistic scenario, with a strong increase in travel demand and low fuel savings by automated vehicles, they found overall energy demand to increase by 30 % compared to the base scenario, whereas for the most optimistic scenario, they found overall energy demand to decrease by 45 % (Chen et al., 2019).

Roca-Puigròs et al. (2023) conducted a further study focused on a market introduction and car fleet development for automated vehicles, investigating the impact of vehicle electrification, automation, and shared mobility. They assumed that automated vehicles will lead to an increase in passenger kilometers traveled by 16.4 % to 21.8 % as a result of new user groups. In turn, they found the utilization of ride-sharing to

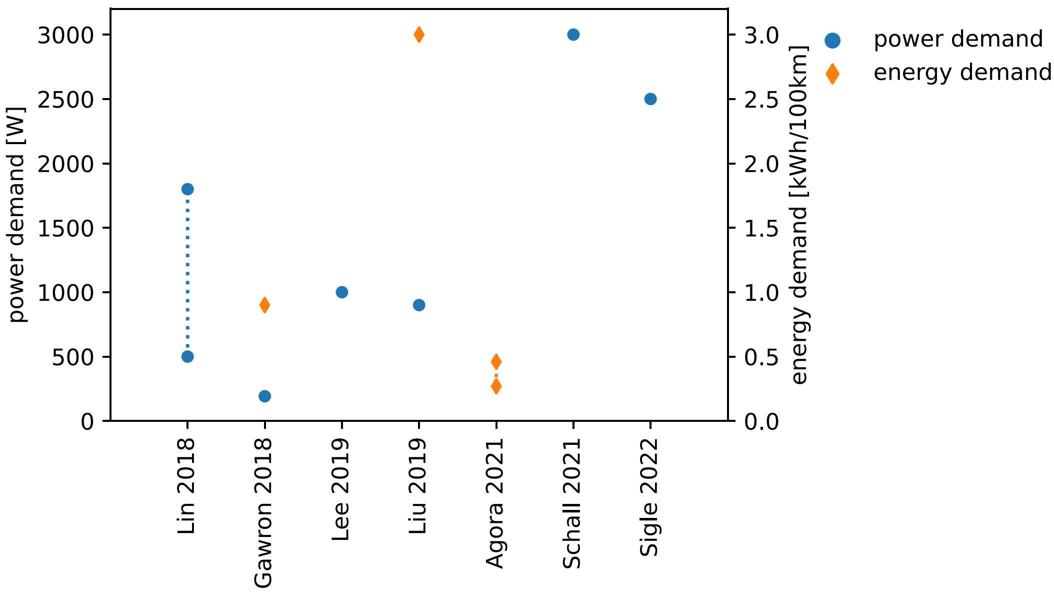

Fig. 2. Estimated power and energy demand of the automation system; see: Agora 2021 (Agora, 2021), Gawron 2018 (Gawron et al., 2018), Lee 2019 (Lee and Kockelman, 2019), Lin 2018 (Lin et al., 2018), Liu 2019 (Liu et al., 2019), Schall 2021 (Schall et al., 2021), Sigle 2022 (Sigle and Hahn, 2022).

counter the increase in passenger kilometers and lead to an overall reduction in energy demand. However, the largest impact on energy demand and greenhouse gas emissions was caused by the electrification of the vehicle fleet.

Massar et al. (2021) separated the factors that could increase or decrease greenhouse gas emissions for automated vehicles into positive and negative. Positive factors include eco-driving strategies, vehicle right-sizing, efficient routing, and carpooling, whereas negative ones include increased travel demand, faster travel speeds, and empty-vehicle travel. The authors conclude that the specific energy demand per vehicle kilometer driven is likely to decrease. However, the effects are outweighed by an even greater increase in overall vehicle miles traveled.

The results of the presented studies regarding the possible effect of automated driving on vehicle energy demand are summarized in Fig. 1.

In our study, we investigate the specific energy demand of automated vehicles focusing on the effects of driving styles and the energy demand of the automation system. In the following we will dive deeper into the literature regarding these topics. We will first present studies on the impact of different driving styles and fuel saving strategies and afterwards present studies on the energy demand of the automation system.

A driving strategy for freight trucks that has already been investigated quite extensively in the context of fuel-saving is ‘platooning’, whereby vehicles follow each other closely to reduce the air resistance the following vehicles are subjected to and therefore reduce their energy demand for driving. In the case of two trucks following each other in a platoon, it was found that the total fuel demand decreases by 4 % to 15 % (based on vehicle speed, loading, and following distance) compared to a case in which both vehicles are driving separately (Slowik and Sharpe, 2018; Tsugawa et al., 2016). However, platooning presents operational challenges like the need to coordinate freight trips. Furthermore, not all driving distances are suitable for platooning. It was assumed by Muratori et al. (2017) that a minimum speed of 80 km/h over a period of at least 15 min is necessary for platooning to take place and with that approach 66 % of US truck miles were found to be suitable for platooning. Combining the results from the presented studies, we arrive at a 2.6 % to 9.9 % decrease in fuel demand through platooning.

An additional benefit for freight trucks are possible changes in the operational strategies through the omission of the driver. Bray and Cebon (2022) found reducing the truck driving speed from 90 km/h to 70 km/h to be economically-viable for automated trucks, but not to be so for human-driven ones due to the additional costs in driver wages (Bray and Cebon, 2022). Furthermore, the authors found the speed reduction to reduce the vehicle’s mechanical energy demand by 26 % for a 29.5 t semi-truck in a simplified start–stop driving cycle (Bray and Cebon, 2022). Moving freight trips to other times such as during the night in order to bypass heavy traffic could be another option for saving fuel, with an estimate of about 2 % of fuel being expended in traffic jams in the US in 2016, rising to as much as 4 % in 2050 (Wadud et al., 2016).

In a simulation study, Kamal et al. (2016) found that for the merging behavior of vehicles on the highway, the introduction of cooperative adaptive cruise control (ACC), and a specifically-designed efficient driving system (EDS) for automated vehicles led to an overall increase in the fuel economy of vehicles by 2.7 % (ACC) to 8.8 % (EDS) and 6.0 % (ACC) to 14.3 % (EDS) compared to the scenario without those driving strategies, with an automated vehicle share of 10 % and 50 % respectively. In addition to that, not only the performance of the automated vehicles was better than in the base-case scenario, but also the performance of the remaining vehicles increased. Automated vehicles were thus able to improve traffic flows.

In another study, Liu et al. (2017) assumed the driving cycles of automated vehicles to have lower acceleration values and so to be smoother than those of human-driven ones. They smoothened the standard driving cycles using smoothing splines and analyzed the effect of these so-called “eco-autonomous driving cycles” on road emissions using the US Environmental Agency’s Motor Vehicle Emission Simulator (MOVES). The results showed that especially for driving cycles with many acceleration and breaking phases, emissions could be significantly reduced with the introduction of the smoother driving cycles of automated vehicles.

The studies presented thus far mostly neglect the additional energy demand for the automation system when assessing the energy implications of changes in driving behavior and utilization of the vehicles. In our study, we investigate the trade-off between driving strategies and the additional energy demand of the automation system. Therefore, we will now present some studies that focus strongly on the energy demand of the automation system.

Lin et al. (2018) estimated the power demand of the computational system on the basis of the installed hardware components. Including cooling demand and storage, they estimated the power demand to range from about 500 W for a system with one central processing unit (CPU) and one field-programmable gate array (FPGA), to 1800 W for a system with one CPU and three graphics-processing units (GPUs). The

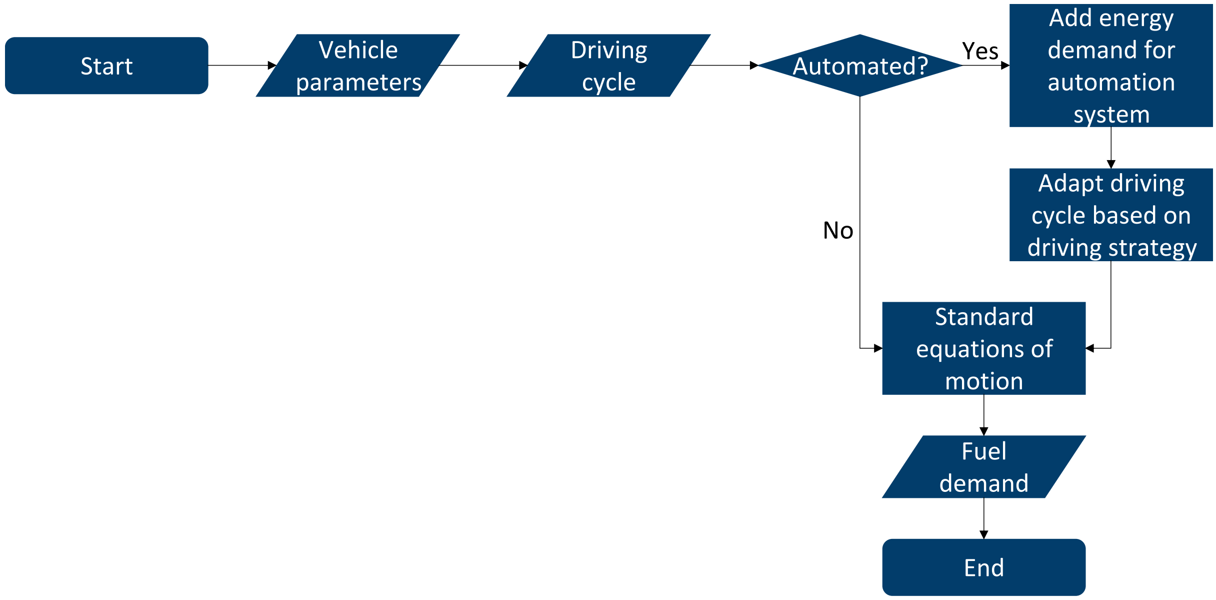

Fig. 3. Methodology for the calculation of the vehicle fuel demand.

additional power demand (1800 W) was estimated to reduce the driving range of a Chevrolet Bolt by up to 11.5 %.

Gawron et al. (2018) assumed the computational system for automated vehicles to consist of two Nvidia Drive PX2s with a power demand of 96 W each, making the total power demand for the computational system around 192 W. They estimated the total energy demand to increase by about 2.2 kWh/100 km via the automation system, of which about 0.9 kWh/100 km could be attributed to the power demand of the computational system. The life cycle energy demand of a battery-electric vehicle was found to increase by 3.75 % through the automation system.

Lee and Kockelman (2019) assumed the power demand for the computational system to be 1000 W. This resembles the power demand of a CPU and GPU in a high-performance desktop PC and was estimated to increase the fuel energy demand by 4 % to 15 %.

Liu et al. (2019) investigated the energy increase caused by the automation system with respect to the sensors used, as well as the communication and computational systems. For the computational system of advanced automated vehicles, a Nvidia Drive Pegasus platform with a power demand of about 450 W was selected. For redundancy, the system was integrated twice, resulting in a total power demand of 900 W. The future energy demand was estimated to decrease by up to 34 % if computing performance increases by 100 %. The share of the computational system was found to be around 61 % of the overall increase in energy demand caused by the vehicle's automation. In total, the authors estimate that energy consumption could increase by about 5 kWh/100 km, which would reduce the range of electric vehicles by up to 25 %.

Agora (2021) used the estimates by Gawron et al. (2018) and Liu et al. (2019) as a basis and assumed further improvements for the development of the energy demand of computational systems. In total, the additional energy demand for the automation system was estimated to be 0.46 kWh/100 km for a level 4 vehicle in 2020 and, due to improvements in energy efficiency, only 0.27 kWh/100 km by 2050.

Schall et al. (2021) simulated the energy demand of the autonomous mover U-shift (a driving module with changeable transport capsules), assuming a power demand of 3000 W for the sensors and computation. Based on this, Sigle and Hahn (2022) estimated the energy demand for the automation system of an autonomous truck to be 2500 W.

The estimated power and energy demand of the automation system are summarized in Fig. 2.

To conclude our findings from the current literature: The additional energy demand of the automation system is quite diversely estimated and might have a large influence on the potential fuel economy of automated vehicles, but until now it has mostly been neglected in studies on the energy implications of changes in driving behavior and vehicle utilization resulting from the use of automated vehicles. Therefore, in our analysis, we wish to close this gap by assessing the impact of different driving strategies on fuel demand while also considering the additional power demand for the automation system. In this study, we alter the standard driving cycles of conventional vehicles to depict those of automated vehicles. We calculate the energy demand for those driving cycles to assess the impact of driving cycle changes on the energy demand of individual vehicles. In this process, we place great emphasis on the role of the energy demand of the automation system and perform a sensitivity analysis for it. This allows us to obtain a more realistic estimate of the impact of vehicle automation on the vehicle energy demand.

3. Methodology: Fuel demand calculation and driving cycle alteration

In this chapter, we will introduce the methodology used to study the impact of automated and connected driving on the fuel consumption of vehicles. The methodology is summarized in Fig. 3. We will analyze alterations of driving cycles through automated and connected driving. Starting with the impact of driving cycle smoothening, as was done by Liu et al. (2017), we then turn towards further potentials to adapt driving cycles for automated and connected vehicles. We propose the elimination of stops in city driving and reducing the speeds of freight trucks on highways.

We wish to study the impact of driving strategies separately from all other factors affecting fuel efficiency. Therefore, we take today's vehicles and drivetrain efficiencies and only make changes to the driving cycles. We vary the speed, acceleration, and number of stops within these to depict the driving style of automated vehicles.

3.1. Calculation of energy demand based on driving cycles

The basis of our analyses was provided by the Worldwide Harmonized Light Vehicles Test Cycle (WLTC)-3b and the World Harmonized Vehicle Cycle (WHVC). We used the former for fuel demand analyses of

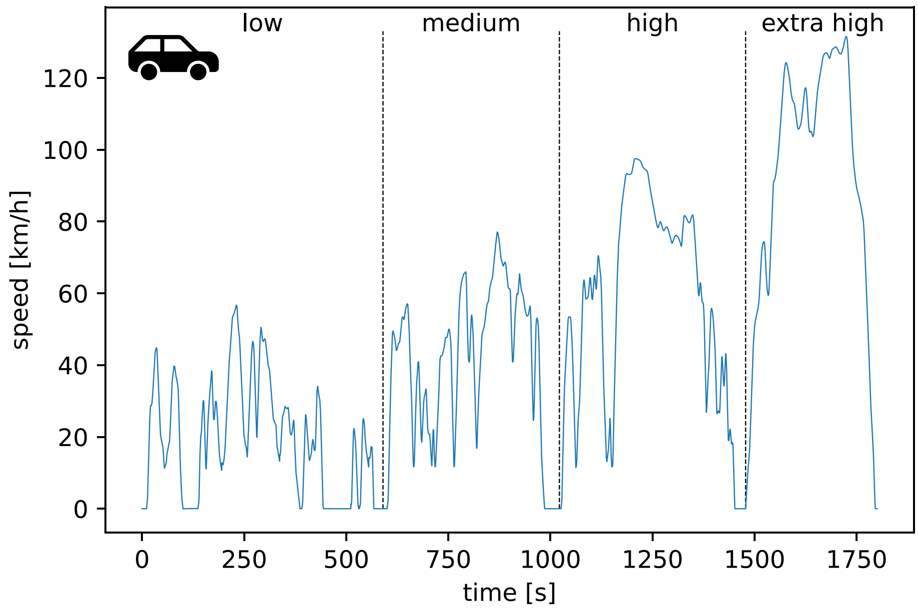

Fig. 4. WLTC-3b speed profile. The black dashed lines separate the four segments “low,” “medium,” “high,” and “extra high” (adapted from DieselNet, 2020a).

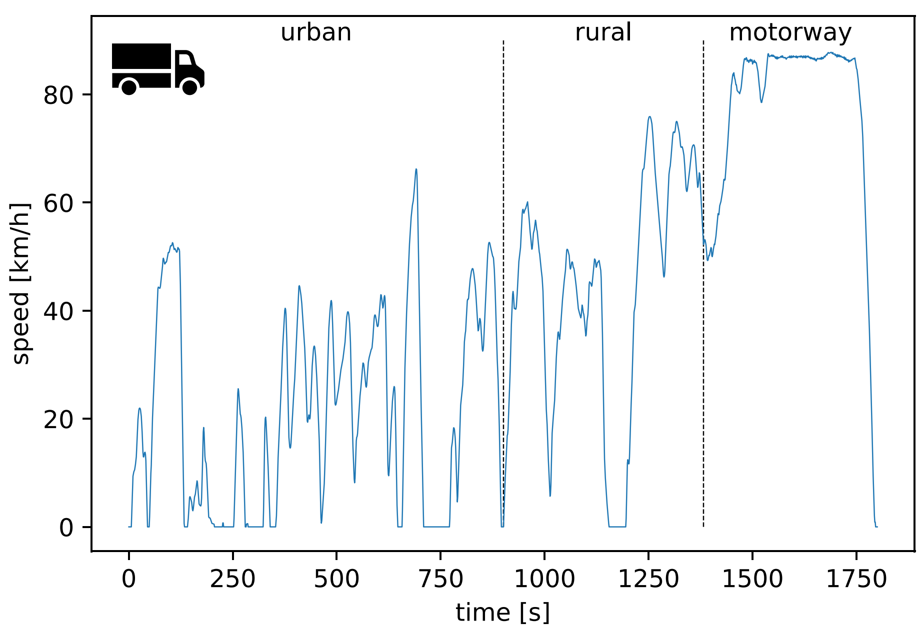

Fig. 5. WHVC speed profile. The black dashed lines separate the three segments “urban,” “rural,” and “motorway” (adapted from DieselNet, 2020b).

cars and the latter for heavy duty vehicles. Furthermore, we focus on motorway driving for heavy duty vehicles, as this makes up the largest share of their driving. For cars, we focus on highway driving for a comparison to heavy duty vehicles, as well as city driving, because automated vehicles are expected to be introduced through sharing services in cities (Narayanan et al., 2020). The driving cycle data is taken from DieselNet (2020a–b). The WLTC-3b consists of four segments (“low,” “medium,” “high,” and “extra high”) representing urban, sub-urban, rural and highway driving scenarios, of which we will use the first for city driving and the last for highway driving correspondingly. We will not use the other two parts because driving in sub-urban or rural areas is out of scope for our study. The WHVC consists of three segments (“urban,” “rural,” and “motorway”), of which we will only use the last for highway driving. Again, we will not use the other two parts because truck driving in urban or rural areas is out of scope for this study.

The WLTC-3b is shown in Fig. 4. It has a total duration of 1800s and covers a total distance of 23.266 km. The first segment (“low”/city driving) covers the first 589 s and 3.095 km. The vehicle has a maximum speed of 56.7 km/h during this segment and stands still for 146 s. The last segment (“extra high”/highway driving) covers the last 323 s and 8.254 km with a maximum vehicle speed of 131.5 km/h and a standstill time of 5 s.

The WHVC is show in Fig. 5. It has a total duration of 1800 s and covers a total distance of 20.072 km. The last segment (“motorway”/ highway driving) covers the last 419 s and 8.926 km with a maximum vehicle speed of 87.8 km/h and a standstill time of 5 s.

For the driving cycles, we calculate the mechanical energy demand of the vehicles using the standard equations of motion considering the acceleration as well as the forces for overcoming rolling and air resistance at each timestep, taking vehicle mass and size into account. We do

Table 1
Vehicle parameters for the mid-sized car and semi-truck; see: [1] (Kraus et al., 2021); [2] (Grube, 2014); [3] (Cox, 2018); [4] (Helms et al., 2022); [5] (Sigle and Hahn, 2022); [6] (Lee and Kockelman, 2019).

Parameter	Mid-sized car	Semi-truck
Vehicle mass m_{veh} [kg]	1508 [1]	12,243 [1]
Passenger/freight mass m_{load} [kg]	116 [1]	12,491 [1]
Frontal area $A_{frontal}$ [m^2]	2.25 [1]	8.38 [1]
Air drag coefficient c_d	0.267 [1]	0.53 [1]
Rolling resistance coefficient c_r	> 0.008668 [2]	0.0068 [1]
Vehicle electronics power demand P_{elec} [W]	600 [3][4]	8660 [5]
Automation system power demand P_{aut} [W]	1000 (+2000/-800) [6]	1000 (+2000/-800) [6]

not consider any road gradients in the driving cycles. The mechanical forces for each timestep t are described by the following equations:

$$F_{aero}(t) = \frac{1}{2}\cdot\rho_{air}\cdot A_{front}\cdot c_d\cdot v^2(t) \tag{1}$$

with the air density ρ_{air} (1.225 kg/m^3), the frontal area of the vehicle A_{front}, the air drag coefficient c_d, and the vehicle velocity $v(t)$.

$$F_{roll}(t) = [m_{veh} + m_{load}]\cdot g\cdot c_r(t) \tag{2}$$

with the base vehicle mass v_{veh}, the passenger/freight mass m_{load}, the gravitational constant g (9.81 m/s^2), and the rolling resistance coefficient $c_r(t)$, which is assumed to be a constant for the semi-truck and described by the following equation adapted from Grube (2014) for a mid-sized car:

$$c_r(t) = 0.008668 + 0.0016745\cdot\frac{v_{kmh}(t)}{100} + 0.0002758\cdot\left[\frac{v_{kmh}(t)}{100}\right]^4 \tag{3}$$

with $v_{kmh}(t)$ being the vehicle velocity in km/h instead of m/s.

$$F_{acc}(t) = [[1.02\cdot m_{veh}] + m_{load}]\cdot a(t) \tag{4}$$

with the vehicle acceleration $a(t)$. The factor 1.02 is used to calculate the effective rotational mass of the vehicle.

All vehicle parameters used for the calculations can be found in Table 1.

The total mechanical force is calculated as the sum of the three individual forces:

$$F_{mech}(t) = F_{aero}(t) + F_{roll}(t) + F_{acc}(t) \tag{5}$$

The momentary mechanical energy demand is then calculated by multiplying the total force at a timestep with the current speed and length of the timestep τ:

$$E_{mech}(t) = F_{mech}(t)\cdot v(t)\cdot\tau(t) \tag{6}$$

It is important to note at this point that the momentary mechanical energy demand might be negative for timesteps in which the vehicle decelerates. With respect to recuperation, this energy can be reused. Therefore, we differentiate the energy demand into positive and negative.

In addition, we consider the auxiliary energy demand for vehicle electronics and the automated driving system based on their respective power demands. The momentary auxiliary energy demand is then given by:

$$E_{aux}(t) = [P_{elec} + P_{aut}]\cdot\tau(t). \tag{7}$$

For the vehicle electronics, we assume auxiliary power demands P_{elec} of 8660 W for the semi-truck based on estimates by Sigle and Hahn (2022) (with the main contributions of 1800 W for the power steering pump, 4500 W for the air compressor, and 2000 W for heating and air conditioning) and 600 W for the mid-sized car based on estimates by Cox (2018) and Helms et al. (2022). It should be noted that the assumed energy demand for heating and air conditioning is much larger for the semi-truck. However, as we will discuss later, higher auxiliary energy demands do not affect the fuel demand for semi-trucks as much as for mid-sized cars because the mechanical energy demand is much larger for semi-trucks. As presented in chapter 2, the estimates for the energy demand of the automation system vary strongly. Therefore, we assume an auxiliary power demand P_{aux} of 1000 W for our calculation, which is in line with the assumption by Lee and Kockelman (2019) and presents a middle value for the studies presented. We will vary the power demand of the automation system for our analyses of car driving cycles, as it has a large impact on the auxiliary energy demand of cars. We do not vary it for the truck driving cycles, because the impact on the auxiliary energy demand is much smaller for those. To arrive at the final energy/fuel demand of the vehicle, the mechanical and auxiliary energy demands must be adjusted for energy conversion and transmission efficiencies. These efficiencies vary for different drivetrains like internal combustion engine vehicles and battery–electric vehicles. We only consider battery–electric vehicles and present the efficiencies for these. For the auxiliary energy demand, the battery efficiency η_{bat} and transmission efficiency η_{trans} must be considered. For the mechanical energy demand, the engine efficiency η_{engine} must be considered further. In the case of recuperation, the auxiliary energy demand can directly be served by the recuperation energy, in which case only the transmission efficiency η_{trans} is relevant. Recuperation energy above the auxiliary energy demand will be transferred to the battery considering the transmission efficiency η_{trans}. The efficiencies used in this paper can be found in Table 2.

Table 2
Component efficiencies for the mid-sized car and semi-truck (based on (Kraus et al., 2021)).

Efficiencies	Value
Electrical engine η_{engine}	0.885
Transmission η_{trans}	0.951
Battery η_{bat}	0.931

In order to make our fuel demand model accessible for validation, we provide our complete approach. In addition to using the standard equations of motion, we also disclose all vehicle parameters and assumptions needed for our fuel demand calculation. We use this fairly simple approach instead of more complex environmental models to filter out the areas of fuel consumption which are affected by changes in the driving behavior.

After these remarks on the determination of the vehicle energy demand for driving cycles, we will present the changes in driving cycles that we make in this study in the next section.

3.2. Altering driving cycles for automated and connected vehicles

Automated and connected vehicles have different driving characteristics compared to conventional, human-driven ones. Therefore, driving cycles for automated and connected vehicles might differ from traditional driving cycles. We will introduce probable changes to justify those we use for our analyses in the following.

3.2.1. The effect of (C)ACC on highway driving: Smoother driving cycles

First, automated driving might lead to more uniform driving patterns. Because of the planning horizon of the automated vehicle, it will only drive with the necessary amount of acceleration and deceleration. It will be able to react to events early and therefore prevent hard braking maneuvers. This results in a smoother driving cycle. As such a behavior is already introduced with driver assistance systems like adaptive cruise control (ACC), there may not be further benefits of fully automated vehicles for smooth driving cycles. Considering vehicle communication (cooperative adaptive cruise control (CACC)), on the other hand, might further increase the planning horizon and therefore the smoothening

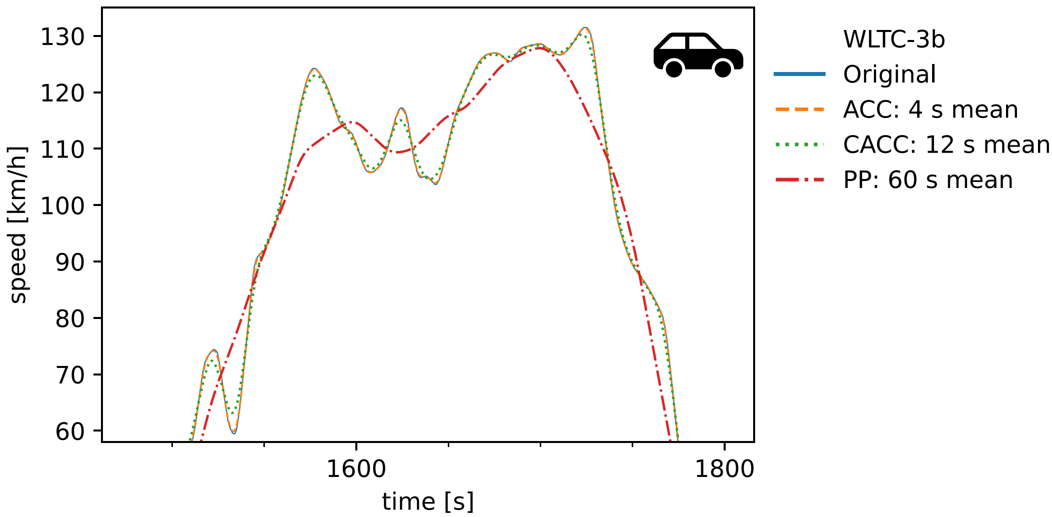

Fig. 6. WLTC-3b highway driving segment ("extra high"). The original driving cycle is shown as a solid blue line. The adaptive cruise control (ACC) driving cycle (4 s moving average) is shown as a dashed orange line. The cooperative adaptive cruise control (CACC) driving cycle (12 s moving average) is shown as a dotted green line. The perfect prediction (PP) driving cycle (60 s moving average) is shown as a dash-dotted red line. Note that the original driving cycle is mostly concealed by the other driving cycles. Furthermore, the acceleration and deceleration phases at the beginning and end of the cycle are cropped because they do not differ significantly between the different variants. (Original driving cycle adapted from DieselNet, 2020a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

effect. Suarez et al. (2022) showed that more aggressive acceleration behavior increases vehicle fuel demand, and therefore we expect that smoother driving cycles will reduce vehicle fuel demand.

To assess the effects of driving cycle smoothing, we calculate the moving average of the speed profile over a certain time window for (C) ACC. We use the moving average to depict the planning horizon of the vehicles instead of other smoothening methods like a polynomial fit, for which the interpretation of the fit parameters would be more difficult. In addition to smoothened (C)ACC driving cycles, we introduce the perfect prediction driving cycle for automated vehicles. This depicts a scenario in which all vehicles are automated and the driving cycles of the vehicles are strongly optimized to reduce acceleration and deceleration phases. We implement it in the same way as (C)ACC, but with a much larger time horizon. We also limit our analyses of smoothened driving cycles to highway driving, as city driving is more complex and involves more unpredictable factors (such as pedestrians and cyclists), making long planning horizons unrealistic. The effects of driving cycle smoothening on fuel demand are presented in chapter 4.1.

We assume a planning horizon of 130 m for ACC, 400 m for CACC, and 2000 m for perfect prediction. This translates into 4 s, 12 s, and 60 s planning horizons for cars following the WLTC-3b with a speed of 120 km/h and of 6 s, 18 s, and 90 s for trucks following the WHVC with a speed of 80 km/h. The chosen planning horizons are in line with the typical ranges of radar and lidar sensors of up to 250 m. For ACC we set the planning horizon to about half the maximum detection range of the sensors to account for the fact that obstacles and vehicles limit the effective range of the sensors. For CACC the vehicles can make use of the data of other vehicles they are communicating with and thereby increase

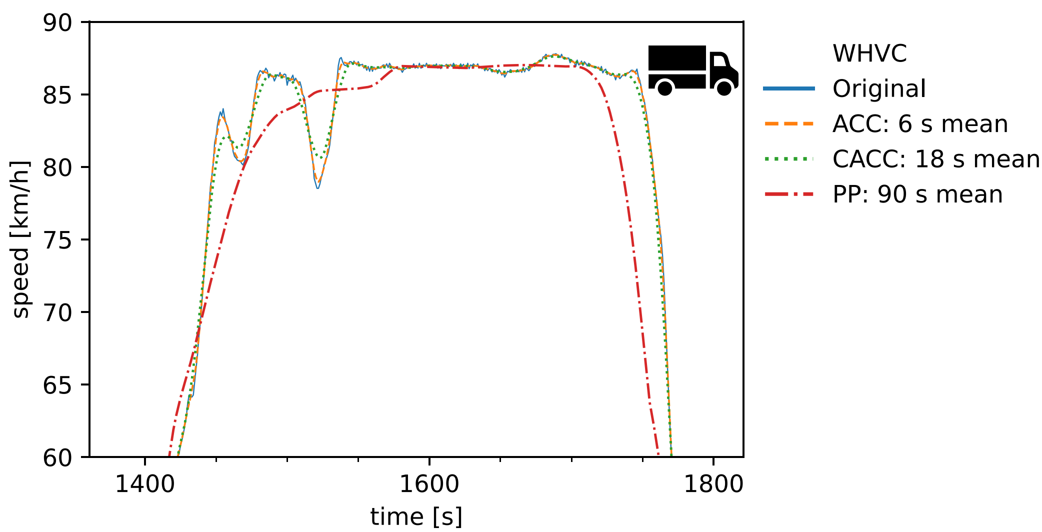

Fig. 7. WHVC highway driving segment ("motorway"). The original driving cycle is shown as a solid blue line. The adaptive cruise control (ACC) driving cycle (6 s moving average) is shown as a dashed orange line. The cooperative adaptive cruise control (CACC) driving cycle (18 s moving average) is shown as a dotted green line. The perfect prediction (PP) driving cycle (90 s moving average) is shown as a dash-dotted red line. Note that the original driving cycle is mostly concealed by the other driving cycles. Furthermore, the acceleration and deceleration phases at the beginning and end of the cycle are cropped because they do not differ significantly between the different variants. (Original driving cycle adapted from DieselNet, 2020b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

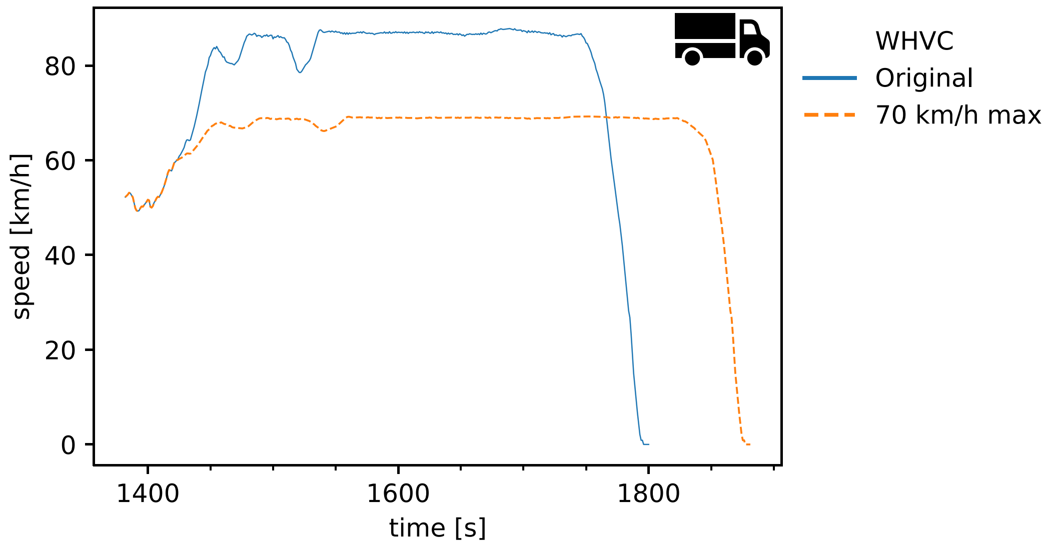

Fig. 8. WHVC highway driving segment ("motorway"). The original driving cycle is shown as a solid blue line. The speed-reduced driving cycle is shown as a dashed orange line. (Original driving cycle adapted from DieselNet, 2020b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

their planning horizon considerably. We set the planning horizon to 400 m to account for this but also consider that there are still non-communicating vehicles among the communicating ones, reducing the planning horizon through unpredictable behavior. For perfect prediction we assume that all vehicles are automated and communicate with each other. We set 2000 m as the planning horizon to avoid reducing the driving cycles completely to a single driving speed. Having only a single driving speed would not be appropriate because there may be different speed limits due to curves, construction sites, or other road features that require an adjustment of the driving speed. We implement this by applying a moving average with the respective time horizon over the driving cycles. The original highway driving segments and the smoothened driving segments for the WLTC-3b and WHVC are depicted in Fig. 6 and Fig. 7, respectively.

The WLTC-3b highway driving speed profile is already smooth in its original form, and therefore the ACC speed profile with a 4 s moving average does not differ much from the original speed profile. The CACC speed profile with a 12 s moving average, on the other hand, weakens short speed fluctuations that last up to a few seconds. For the WHVC highway driving speed profile, the ACC already shows an effect, as the original speed profile features high frequency fluctuations. The effect of the CACC is like that of CACC for the WLTC-3b. Perfect planning leads in both cases to strongly altered driving cycles with strong acceleration and deceleration only at the beginning and end.

3.2.2. Reducing truck driving speeds on highways

A second option to alter driving cycles is to change maximum driving speeds. We analyze this option for the highway driving of freight trucks. In conventional road freight operations, reducing driving speeds to save fuel is not profitable, as driver wages increase with longer driving times and these costs (in combination with the freight value of time) outweigh savings in fuel costs (Bray and Cebon, 2022). In addition, the driving hours of human truck drivers underlie strict limitations to ensure driver performance and decrease accident risks. The EU regulations are fixed in Regulation (EC) 561/2006 (EU, 2006) and the changes made to it (EU, 2009; EU, 2014; EU, 2016; EU, 2020). Drivers are only allowed to drive for nine hours per day and must take a 45-minute break after every 4.5 h of driving. Eliminating driver costs and driving time restrictions via fully automated truck driving will enable slower driving speeds for fuel-saving. It was shown by Bray and Cebon (2022) that reducing the target driving speed of a 29.5 t semi-truck from 90 km/h to 70 km/h reduces operational costs by 4 % when considering vehicle capital costs, fuel costs, and the freight value of time costs without driver costs. In this study, we reduce the maximum driving speed from about 90 km/h to 70 km/h by linearly scaling down excess speeds above 60 km/h to one third:

$$v_{70} = \begin{cases} v, & v \leq 60 \\ 60 + \dfrac{v-60}{3}, & v > 60 \end{cases} \tag{8}$$

This method keeps the driving behavior of the trucks at lower speeds unchanged and only affects higher driving speeds. Furthermore, in comparison to a hard cut-off at 70 km/h this method adjusts the acceleration behavior up to this point and therefore prevents kinks in the graph.

We alter the WHVC highway driving segment by reducing speeds in excess of 60 km/h to one third, as described above. Instead of a maximum speed of 87.6 km/h, we arrive at 69.3 km/h. Furthermore, we adapt the length of each timestep so that the vehicle still covers the same distance within the driving cycle. The modified driving cycle is shown in Fig. 8. It now takes the vehicle 81 s (18.9 %) longer to cover the distance of the driving cycle.

The effects of reduced driving speeds on fuel demand are presented in chapter 4.2. Further options for altering freight transport when no driver is needed anymore include shifting to nighttime operation to reduce peak traffic and so reduce traffic jams. Such effects and the implications of automated driving for traffic network performance are not analyzed in this paper, however.

3.2.3. Eliminating stops during city driving

A last option for altering driving cycles via automated and connected driving concerns city driving. Frequent starting and stopping increases fuel consumption, because even with recuperation, not all of the energy from a vehicle can be regained when decelerating. Hence, reducing/eliminating stopping from city driving might decrease fuel consumption in vehicles. We alter the WLTC-3b city driving cycle by removing stopping times (removing traffic lights) and setting the minimum driving speed to 10 km/h. For a smoother transition to that value, we linearly scale down speeds below 12.5 km/h to one fifth. The new driving speed is described by the following equation:

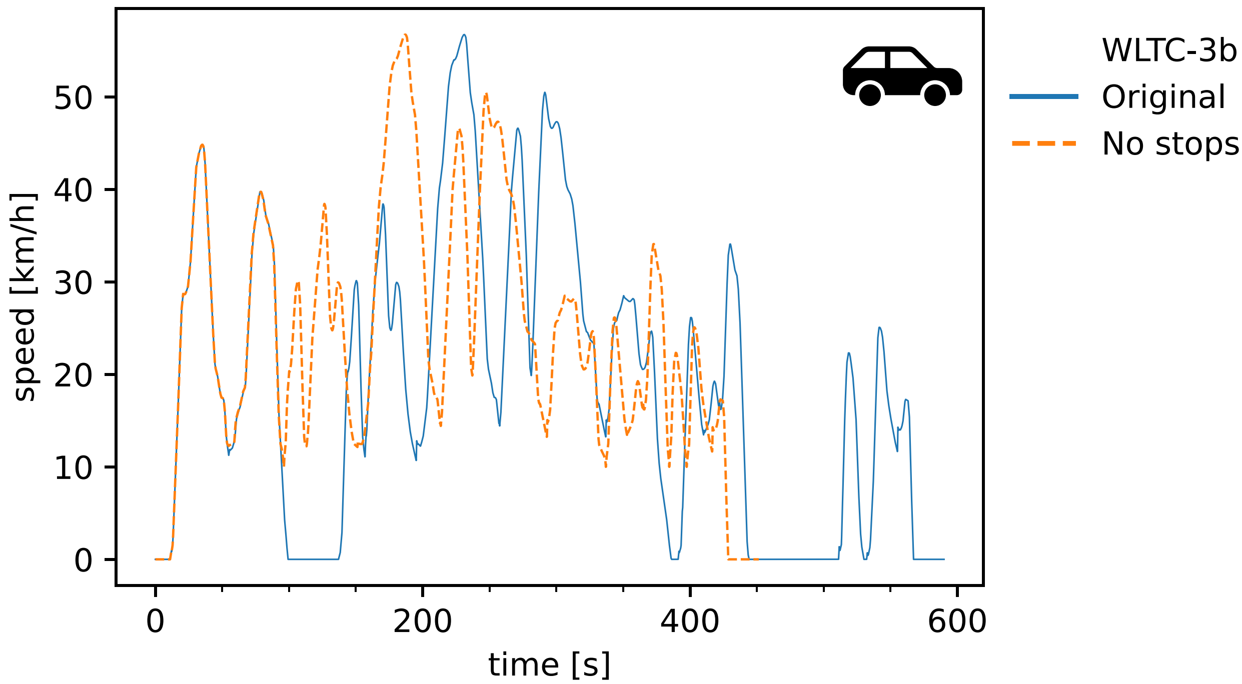

Fig. 9. WLTC-3b city driving segment ("low"). The original driving cycle is shown as a solid blue line. The driving cycle without stops is shown as a dashed orange line. (Original driving cycle adapted from DieselNet, 2020a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$v_{no-stop} = \begin{cases} v, & v \geq 12.5 \\ 10 + \frac{v}{5}, & v < 12.5. \end{cases} \tag{9}$$

We still decrease the speed of the vehicles instead of always keeping higher driving speeds to depict the behavior at intersections. Vehicles from different directions might cross the intersection at the same time with coordinated pathways and reduced speeds to reduce the risk of collisions. The length of each time step is adjusted such that the driving cycles still cover the same driving distance. The resulting driving cycle is shown in Fig. 9.

For the first 100 s, the driving cycle stays the same as the original

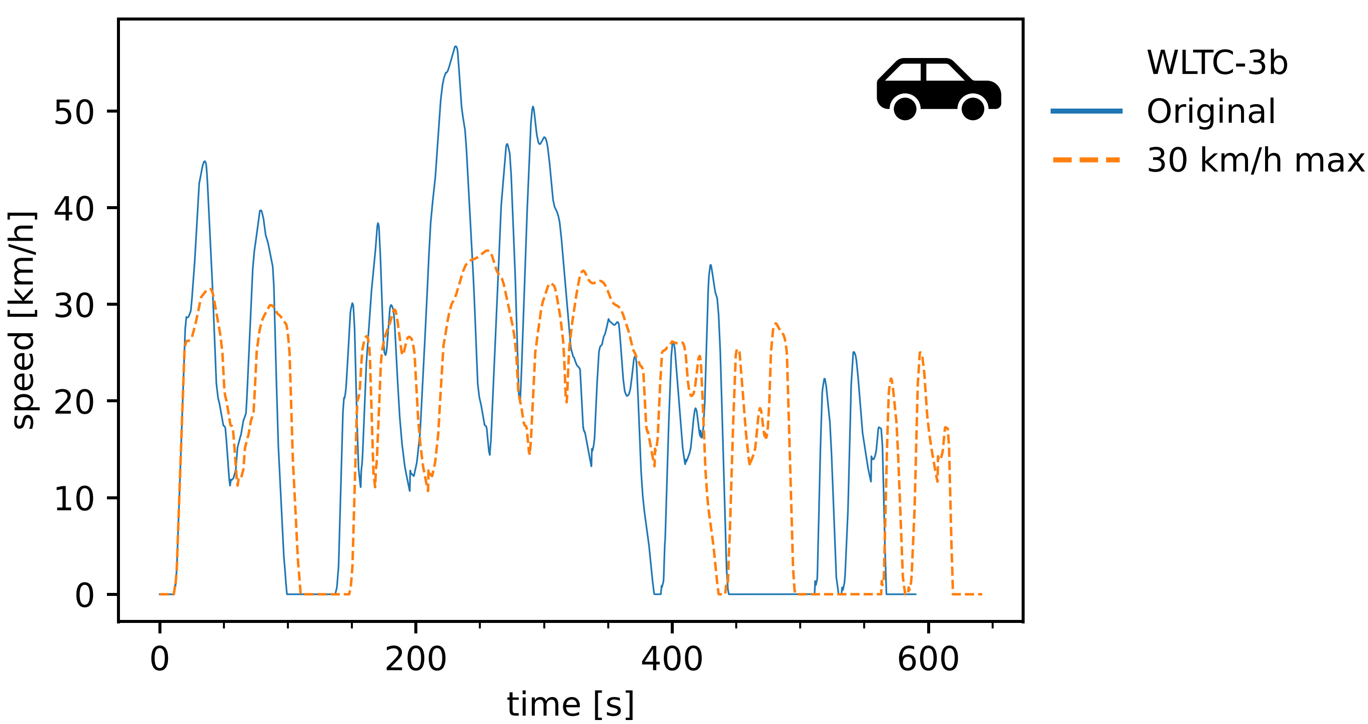

Fig. 10. WLTC-3b city driving segment ("low"). The original driving cycle is shown as a solid blue line. The speed-reduced driving cycle is shown as a dashed orange line. (Original driving cycle adapted from DieselNet, 2020a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

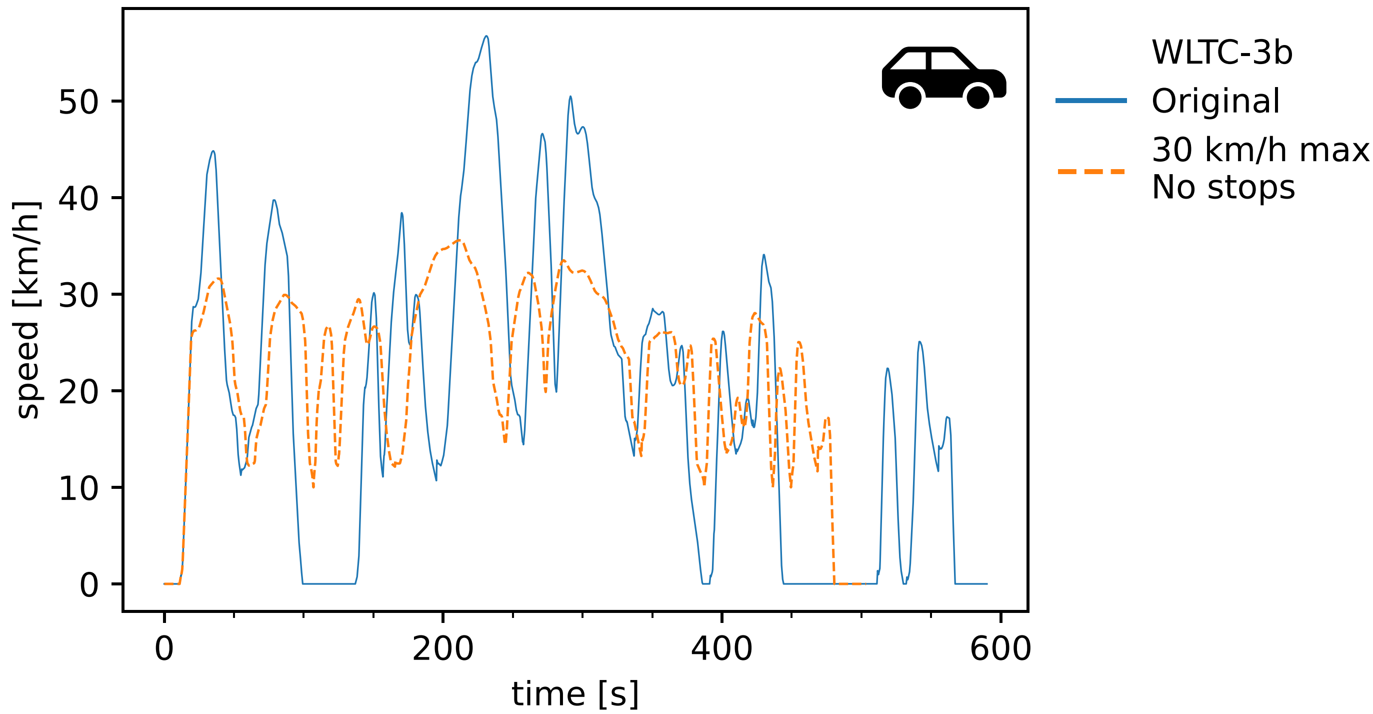

Fig. 11. WLTC-3b city driving segment ("low"). The original driving cycle is shown as a solid blue line. The speed-reduced driving cycle without stops is shown as a dashed orange line. (Original driving cycle adapted from DieselNet, 2020a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

one. However, when the first stop occurs at 100 s in the original driving cycle, the vehicle speed in the new driving cycle does not go below 10 km/h and the vehicle does not wait for around 50 s; instead, it continues its driving. In total, the vehicle finishes the new driving cycle 139 s (24 %) faster than the original one.

Driving times can be reduced when stops are eliminated from the driving cycle and vehicles do not need to wait at traffic lights for long periods of time anymore. However, this is a highly advanced assumption for a scenario in which all vehicles are automated and the traffic flow is managed perfectly (without traffic lights). This alteration and its effect on fuel consumption are therefore to be seen as the maximum possible (utopian) scenario. A more moderate assumption would be that the vehicles communicate with the traffic lights to adjust their speed in order to arrive at the traffic light when it turns green so that no waiting time is needed for the vehicle. However, overall travel time cannot be reduced by this method. Nevertheless, fuel consumption can be altered by slower driving speeds. We investigate the effect of reducing driving speeds on fuel consumption at first isolated and afterwards in combination with eliminating stops.

3.2.4. *Reducing city driving speeds*

The driving speed reduction for city driving is performed in the same way as for the highway driving and is described by the following equation:

$$v_{30} = \begin{cases} v, & v \leq 25 \\ 25 + \dfrac{v-25}{3}, & v > 25. \end{cases} \tag{10}$$

The length of each timestep is adjusted such that the same distance is covered in each. The resulting driving cycle is shown in Fig. 10.

In particular, the segment of the original driving cycle between 200 and 350 s is affected by the speed reduction. The reduced speed reduces the acceleration and deceleration of the vehicle during this time period. Furthermore, this time period is stretched compared to the original driving cycle, which reduces the acceleration and deceleration of the vehicle even further. Overall, it takes 52 s (8.8 %) longer for the vehicle to finish the driving cycle; the average speed therefore drops to 17.4 km/h. It should be noted that "30 km/h max" is to be understood as a speed limit for the driving cycle that is exceeded at some points in the same way as the 50 km/h speed limit for the original driving cycle.

3.2.5. *Eliminating stops and reducing city driving speeds*

In a final attempt, we combine the two approaches of eliminating stops and reducing driving speeds. The resulting driving cycle is shown in Fig. 11.

The time savings of eliminating stops outweigh the additional time for driving at lower maximum speeds, so that the new driving cycle is 87 s (15 %) shorter than the original one.

The resulting driving cycle does not depict the scenario of adjusting driving speeds to arrive at traffic lights in time. In such a scenario the overall travel time could not be reduced as it is the case for our driving cycle. Instead, the driving cycle combines the two approaches of reducing driving speeds and eliminating stops to benefit from the fuel savings of both. We therefore expect the lowest fuel demand for this driving cycle.

For city driving, we do not propose a strongly smoothened driving cycle like we did for highway driving, as interactions with other road users like cyclists or pedestrians make such perfect driving forecasts impossible. Furthermore, vehicles reduce their speeds when turning, which is specific to a certain location and cannot be smoothened. Further aspects of slower driving speeds such as reduced noise and pollution in cities, as well as safety benefits, will not be considered in this paper.

4. Use case analyses: Fuel demand for automated vehicles

We present the changes in fuel demand arising from the driving cycle alterations described in the previous chapter. Starting with an analysis of the impact of (C)ACC on highway driving cycles in the form of smoothening, we will subsequently turn to the impacts of reduced

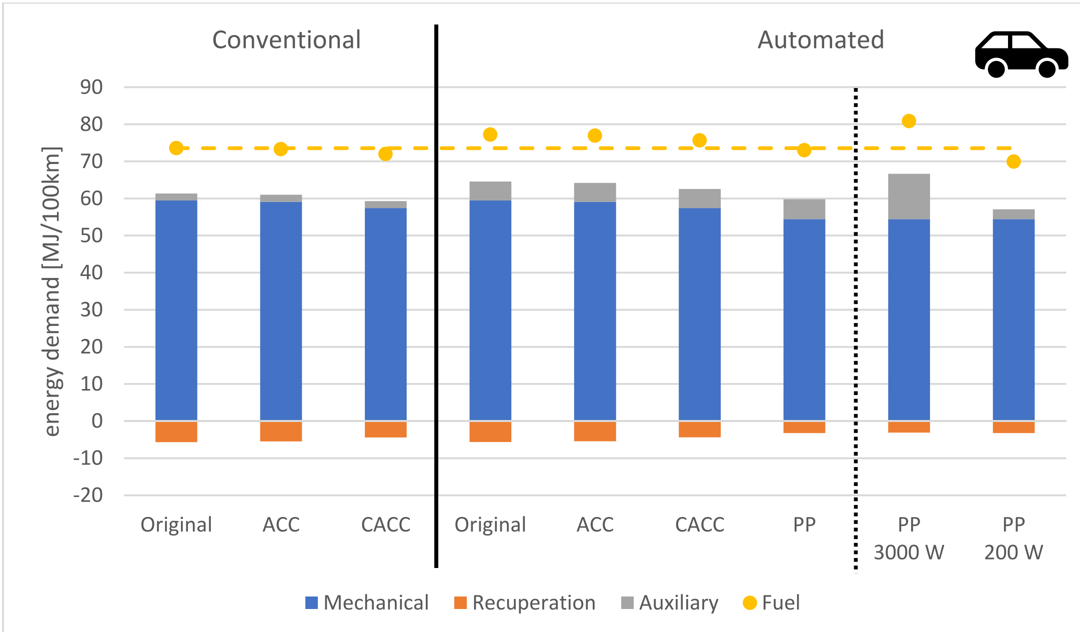

Fig. 12. Energy demand for the WLTC-3b highway driving segment ("extra high") calculated for a battery-electric mid-size car. (ACC: adaptive cruise control, 4 s moving average; CACC: cooperative adaptive cruise control, 12 s moving average; PP: perfect prediction, 60 s moving average).

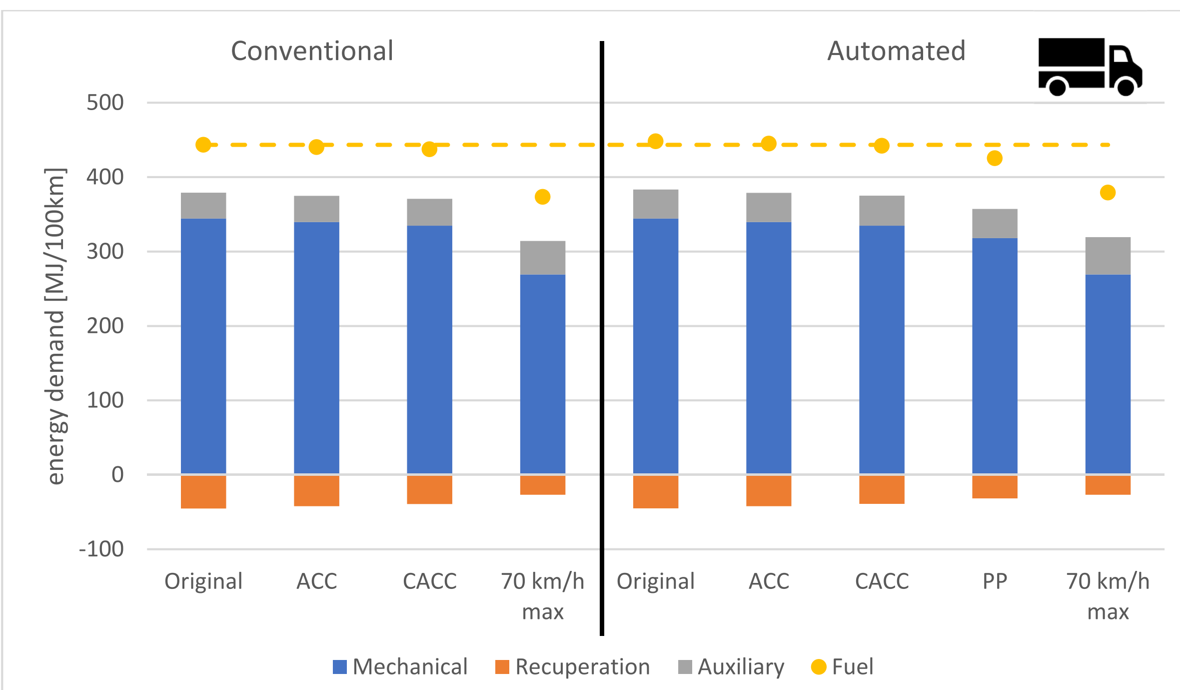

Fig. 13. Energy demand for the WHVC highway driving segment ("motorway") calculated for a battery-electric semi-truck. (ACC: adaptive cruise control, 6 s moving average; CACC: cooperative adaptive cruise control, 18 s moving average; PP: perfect prediction, 90 s moving average).

driving speeds and fewer stops during city driving.

4.1. The effect of (C)ACC on highway driving: Smoother driving cycles

The energy demand for the driving cycles and styles (original, ACC, CACC, and perfect prediction) is shown in Fig. 12 and Fig. 13, respectively (see also Tables A1 and A2 in the Appendix A). The energy demand is calculated for a conventional vehicle and a fully automated one that incorporates the energy demand for the automation system.

For the original WLTC-3b highway driving cycle, the mechanical energy demand of a conventional mid-sized car is 59.45 MJ/100 km, 5.69 MJ/100 km (9.6 % of the mechanical energy demand) can be recuperated, and the vehicle electronics require about 1.90 MJ/100 km (3.2 % of the mechanical energy demand) auxiliary energy demand.

The introduction of ACC leads to a 0.6 % decline in the mechanical energy demand, whereas the recuperated energy declines by 3.9 % and the auxiliary energy demand remains unchanged, resulting in an overall 0.4 % decrease in fuel energy demand. The introduction of CACC leads

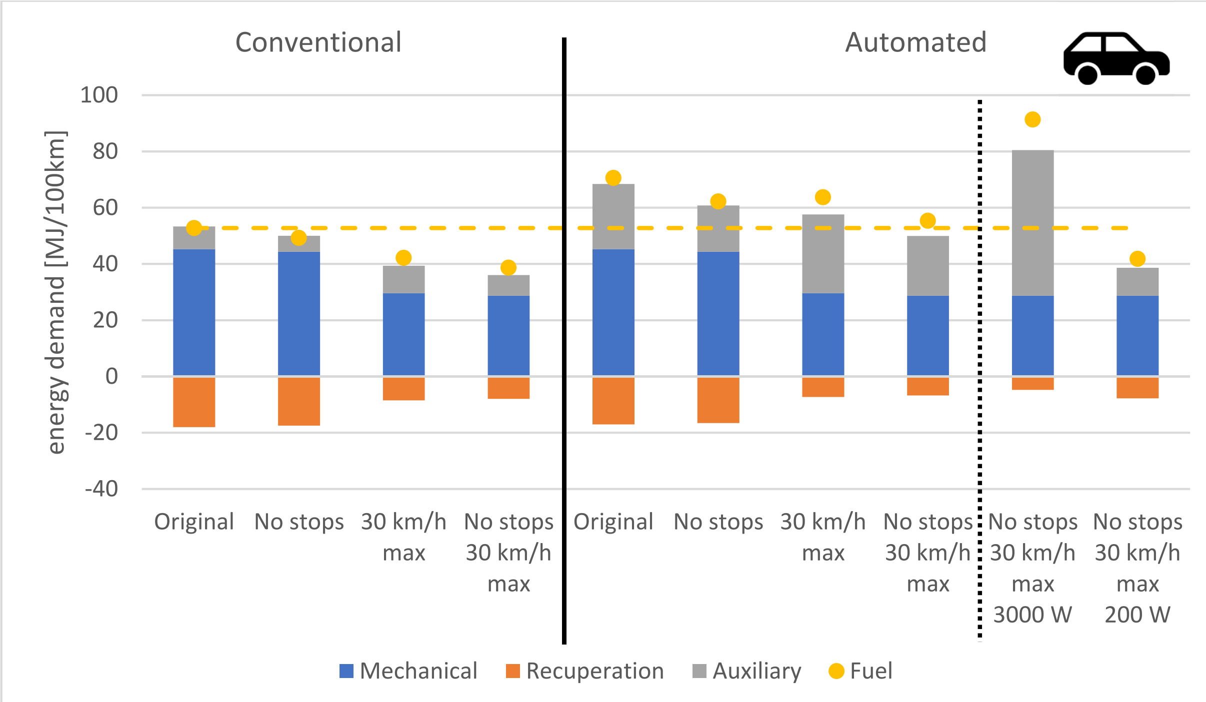

Fig. 14. Energy demand for the WLTC-3b city driving segment ("low") calculated for a battery-electric mid-sized car.

to the same effect but stronger decreases of 3.4 % for the mechanical energy demand and 22.5 % for the recuperated energy, resulting in an overall 2.2 % decrease in fuel energy demand.

For the automated vehicle, the mechanical energy remains unchanged, while the auxiliary energy demand increases strongly by 3.21 MJ/100 km (169 %) through the energy demand for the operation of the automation system. The recuperation slightly decreases by 0.7 % as a larger part of the excess mechanical energy is used to balance the auxiliary energy demand. This leads to an increase in overall fuel energy demand of 5 %.

The introduction of ACC and CACC leads to the same effects as for the conventional vehicle, resulting in a 0.4 % and 2.0 % decrease in fuel energy demand, respectively. The introduction of perfect prediction leads to an 8.4 % decrease in mechanical energy demand, a 43.0 % decrease in recuperation energy, and a 4.5 % increase in auxiliary energy demand, resulting in a 5.5 % decrease in fuel energy demand. Compared to the original driving cycle of the conventional vehicle, the benefits in mechanical and recuperation energy demand through ACC and CACC are outweighed by the additional auxiliary energy demand of the automation system, resulting in an overall fuel energy demand increase of 4.6 % and 2.8 %, respectively. In contrast, the benefits of perfect prediction outweigh the additional energy demand, resulting in an overall fuel energy demand decrease of 0.8 %.

For perfect prediction, we vary the auxiliary energy demand of the automation system for two more scenarios (PP 3000 W and PP 200 W). In the first, we increase the energy demand to 3000 W and in the second, we reduce the energy demand to 200 W, reflecting the upper and lower bound of the energy demand values for the automation system presented in chapter 2.

The higher energy demand for the automation system increases the auxiliary energy demand for the automated vehicle by 129 %. In this case, the auxiliary energy demand even exceeds the mechanical energy demand by 48.5 %. All benefits from the adaptations of the driving cycles are outweighed by the additional energy demand for the automation system. Moreover, overall fuel demand increases by 9.9 % compared to the original driving cycle of the conventional vehicle.

The lower energy demand for the automation system, on the other hand, reduces the auxiliary energy demand by 50.2 %. The additional energy demand of the automation system is lower than the gains accrued by the foresighted driving style. Therefore, the overall fuel demand decreases by 4.9 % compared to the original driving cycle of the conventional vehicle.

For the original WHVC highway driving cycle, the mechanical energy demand of the conventional semi-truck was 344.23 MJ/100 km. Because of the higher vehicle weight compared to the mid-sized car and lower driving speeds, the energy demand for acceleration is proportionally larger than the energy demand needed to overcome air resistance and hence more energy can be recuperated, totaling 45.20 MJ/100 km (13.1 % of the mechanical energy demand). Auxiliary energy demand also makes up a higher share of the total energy demand, needing about 34.95 MJ/100 km (10.2 % of the mechanical energy demand).

The introduction of ACC leads to a 1.3 % decline in the mechanical energy demand, whereas the recuperated energy declines by 6.7 % and the auxiliary energy demand increases by 0.7 %, resulting in an overall 0.7 % decrease in fuel energy demand. For CACC, the mechanical energy demand decreases by 2.8 %, recuperation decreases by 13.3 %, and auxiliary energy demand increases by 3.3 %, resulting in an overall 1.4 % decrease in fuel energy demand.

For the automated vehicle, the auxiliary energy demand increases by 4.07 MJ/100 km (11.6 %), with all other energy demands remaining unchanged. This leads to an increase in overall fuel energy demand of 1.0 %.

Introducing ACC and CACC for the automated vehicle leads to the same changes in mechanical energy demand and recuperation as for the conventional one, resulting in a 0.7 % and 1.3 % decrease in fuel energy demand, respectively. The introduction of perfect prediction leads to a 7.6 % decrease in mechanical energy demand, a 29.9 % decrease in recuperation energy, and a 0.3 % increase in auxiliary energy demand, resulting in a 5.0 % decrease in fuel energy demand. Compared to the original driving cycle of the conventional vehicle, the additional energy demand for the automation system outweighs the reductions in mechanical energy demand through ACC, resulting in an overall 0.3 % increase in fuel demand. However, for CACC and perfect prediction, the reductions in mechanical energy demand dominate, so that overall fuel demand decreases by 0.3 % and 4.0 %, respectively.

In conclusion, smoother driving cycles may lead to fuel efficiency gains for automated semi-trucks, whereas for mid-sized cars, the additional energy demand of the automation system outweighs the gains. However, further benefits may come from platooning or reductions in traffic jams, as described in chapter 2, but we do not consider these effects in our analysis.

4.2. Reducing truck driving speeds on highways

The effects of reducing truck driving speeds (70 km/h max) are shown in Fig. 13 (see also Table A2 in the Appendix A).

Reducing the driving speed of the conventional vehicle leads to a strong decrease in the mechanical energy demand of 21.8 %. Recuperated energy also decreases strongly by about 40.7 %. Auxiliary energy, however, increases via the longer driving time at lower speeds by about 28.8 %. This results in an overall fuel energy demand decrease of 15.8 %.

For the automated semi-truck, reducing the driving speed does not change the mechanical energy and recuperation, with the only difference being the auxiliary energy demand. Between the original and speed-reduced driving cycle, the auxiliary energy demand again increases by 28.7 %, resulting in a 15.3 % overall decrease in fuel energy demand. Compared to the original driving cycle for the conventional vehicle, the savings in mechanical energy demand outweigh the additional energy demand for the automation system, resulting in a 14.5 % decrease in overall fuel energy demand.

In conclusion, reduced driving speeds may lead to large fuel efficiency gains for conventional as well as automated semi-trucks.

4.3. Eliminating stops during city driving

We now turn to city driving for cars. We eliminate stops during the city driving cycle and set the minimum driving speed to 10 km/h, as described in chapter 3.2. The effect of this on the energy demand is shown in Fig. 14 (see also Table A3 in the Appendix A).

For the original driving cycle, the conventional mid-sized car has a mechanical energy demand of 45.28 MJ/100 km. Because of frequent deceleration phases, a large amount of energy can be recuperated. In total, 18.04 MJ/100 km can be recuperated (39.8 % of the mechanical energy demand). Furthermore, the auxiliary energy demand is high because of the low driving speeds and an assumed constant power demand. The auxiliary energy demand is 8.07 MJ/100 km (17.8 % of the mechanical energy demand).

Eliminating stops from the driving cycle has minor effects on the mechanical energy demand and recuperation, as only acceleration and deceleration phases at low speeds are cut out, resulting in a 2.1 % and 3.2 % reduction, respectively. The main difference arises in auxiliary energy demand, which decreases by 30.1 %. The difference is primarily caused by the 139 s faster completion of the driving cycle. Overall, the vehicle fuel energy demand decreases by 6.6 % via the elimination of stops in the driving cycle.

For the automated vehicle in the original driving cycle, 15.09 MJ/100 km are added to the auxiliary energy demand for the operation of the automation system, which is an increase of about 187 %. Furthermore, the recuperation energy is reduced by 5.4 %, as more excess mechanical energy is used to compensate for the additional auxiliary energy demand. In total, this results in a 33.7 % increase in vehicle fuel demand.

Eliminating stops from the driving cycle again primarily influences the auxiliary energy demand. Mechanical energy demand and recuperation energy decrease by 2.1 % and 3.0 %, respectively, whereas the auxiliary energy demand decreases by 29.0 %. In total, the fuel energy demand decreases by 11.8 %. Compared to the original driving cycle of the conventional vehicle, the fuel energy demand increases by 17.9 %, as the additional energy demand for the automation system outweighs by far the energy savings of a shorter driving time.

4.4. Reducing city driving speeds

We now present the influence of reducing city driving speeds to 30 km/h. Driving speeds are altered as described in chapter 3.2. Speeds in excess of 30 km/h are reduced to one third for the WLTC-3b city driving. The effect on the energy demand of the vehicle is shown in Fig. 14 (see also Table A3 in the Appendix A).

Reducing the maximum driving speed leads to a decrease in the mechanical energy demand of 34.6 %. At the same time, recuperation decreases by 52.9 %, as the deceleration phases in the driving cycle are not as strong anymore. Furthermore, the auxiliary energy demand increases by 20.7 %. The increase is larger than merely the time increase of the driving cycle (8.8 %) because the auxiliary energy demand will be directly covered by the excess mechanical energy during deceleration phases, which is balanced before calculating recuperation energy and auxiliary energy demand. The recuperation is unable to cover the auxiliary energy demand as much as at 50 km/h, and therefore the remaining auxiliary energy demand increases. Nevertheless, the total fuel demand decreases by about 20.1 % for the reduced speed driving cycle.

For the automated vehicle, reducing the speed decreases the recuperation energy by 57.3 %, while increasing the auxiliary energy demand by 20.7 %. The increase in auxiliary energy demand is outweighed by the decrease in mechanical energy demand, resulting in an overall decrease in fuel energy demand of 9.8 %. However, in comparison to the original driving cycle of the conventional vehicle, the increase in auxiliary energy demand greatly outweighs the decrease in mechanical energy, resulting in an overall fuel energy demand increase of 20.7 %.

4.5. Eliminating stops and reducing city driving speeds

We now look at the effect of combining the approaches of eliminating stops and reducing driving speeds from the previous sections. In this way, the benefits of both approaches are combined. In particular, the standing times (156 s total), which add to the energy demand through the power demand for the operation of the automation system (1000 W), are eliminated, which lowers the energy demand by about 5 MJ/100 km. As the fuel-saving aspects of the two modifications are independent of each other, the benefits of the modifications should add up, resulting in higher total fuel savings. The overall effect on fuel demand is shown in Fig. 14 (see also Table A3 in the Appendix A).

The reduction in the maximum driving speed and elimination of stops leads to a decrease in the mechanical energy demand of 36.6 %. Because of the lower acceleration and deceleration rates, recuperation decreases strongly, by 56.0 %. Lastly, the auxiliary energy demand decreases by 9.4 %, as the time savings from eliminating the stops outweigh the additional time it takes because of the slower driving speeds.

For the automated vehicle, eliminating stops and reducing driving speeds reduces the recuperation energy even further, by 60.3 %, because a larger part of the excess mechanical energy is directly used to serve the auxiliary energy demand. On the other hand, the auxiliary energy demand decreases by about 8.2 %, which is less than for the conventional vehicle, even though a larger portion of the recuperation is used, as the energy demand is simply much larger. Overall, fuel energy demand decreases by 21.6 %. The decrease is less than for the conventional vehicle, as the auxiliary energy demand has a higher share for the automated vehicle and decreases less than the mechanical energy demand. Compared to the original driving cycle for the conventional vehicle, the decrease in mechanical energy demand and recuperation nearly offsets the increase in auxiliary energy demand, resulting in a 4.9 % increase in vehicle fuel demand.

We retain the changes to the driving cycle and again vary the auxiliary energy demand of the automation system to 3000 W and 200

W for two more scenarios.

The higher energy demand for the automation system increases the auxiliary energy demand for the automated vehicle by 144 %. In this case, the auxiliary energy demand even exceeds the mechanical energy demand by 80.2 %. All benefits from the adaptations of the driving cycles are outweighed by a large margin by the additional energy demand for the automation system. Overall, fuel demand increases by 73.2 % compared to the original driving cycle of the conventional vehicle.

The lower energy demand for the automation system, on the other hand, reduces the auxiliary energy demand by 53.2 %. The additional energy demand of the automation system is lower than the gains through the lower driving speeds and omitted stops. Therefore, the overall fuel demand decreases by 20.1 % compared to the original driving cycle of the conventional vehicle.

5. Discussion

The effects of driving cycle smoothening for the highway driving of conventional vehicles were shown to be in the low percentage area (-2.2 % for the mid-sized car and −1.4 % for the semi-truck). The absolute fuel energy demand for a semi-truck in WHVC highway driving was almost six times the energy demand for a mid-sized car in WLTC-3b highway driving. Therefore, the absolute energy demand declines through ACC and CACC is larger for semi-trucks. Nevertheless, the relative decrease in energy demand for the WLTC-3b is almost two times higher than for the WHVC in the case of CACC. However, when considering an additional energy demand of 1000 W for the automation system, the advantage of the car diminishes. The energy demand of the automation system nearly offsets the fuel efficiency gains for semi-trucks (-0.3 %) and even leads to an increase in the energy demand for mid-sized cars (+2.8 %). However, for the strongly-altered perfect prediction driving cycles of automated vehicles, fuel efficiency increased for both vehicle types (-4.0 % for semi-trucks and −0.8 % for mid-sized cars). It should be noted that reducing acceleration and deceleration phases has a much weaker impact on the fuel demand for electric vehicles than it has for combustion vehicles. The calculated fuel savings should therefore be seen as a lower bound for the impact of driving cycle smoothening. Furthermore, the vehicle weights for the mid-sized car is assumed rather light in our study. This leads to a conservative estimation of the benefits of vehicle automation on vehicle fuel demand as higher vehicle weights would lead to stronger fuel demand decreases through lesser acceleration and deceleration. In addition to that, further benefits may come from platooning or the reduction of traffic jams, as described in chapter 2, but these effects were not considered in our analysis.

We further analyzed the potential for reducing truck driving speeds on highways, reducing driving speeds above 60 km/h to one third, resulting in a maximum driving speed of 69.3 km/h instead of 87.6 km/h, which led to a decrease in mechanical energy demand of 21.8 %. This is in line with the results from Bray and Cebon (2022), in which a target speed reduction from 90 km/h to 70 km/h for a 29.5 t semi-truck was found to reduce mechanical energy demand by 26 %. The difference between the results can be attributed to different vehicle masses, as well as rolling and air resistance factors. Considering the additional energy demand for the automation system, the overall fuel energy demand was found to decrease by 14.5 %. Slower driving speeds could therefore be an option for automated trucks to save costs and reduce CO_2 emissions at the same time.

Eliminating stops from city driving cycles was shown to reduce fuel demand by 6.6 % for conventional vehicles; therefore, one not only saves time but also reduces CO_2 emissions. The fuel demand of automated vehicles could even be reduced by 11.8 % through this measure, as their auxiliary power demand is higher because of the (constant) additional power demand for the automation system. As eliminating stops is an advanced assumption for the changes automated vehicles might bring to city driving cycles, the result represents an upper bound for fuel saving opportunities via optimized traffic flow. Reducing driving speeds for city driving was shown to diminish energy demand by around 20.1 % for conventional vehicles and so might also be a strong measure for reducing CO_2 emissions from motor vehicles in cities. For automated vehicles, however, decreasing maximum driving speeds from 50 km/h to 30 km/h was found to decrease fuel demand by just 9.8 % due to the additional energy demand for the operation of the automation system. Furthermore, the fuel demand of automated vehicles was in any case larger than the energy demand of conventional vehicles.

The energy demand for the operation of the automation system reduces the fuel efficiency benefits of automated driving strategies in all areas. For large semi-trucks, the additional energy demand is less significant, as the mechanical energy demand is almost six times higher than for mid-sized cars. The automation system was found to increase the energy demand for semi-truck highway driving by about 1.0 % while increasing the energy demand for mid-sized car highway driving by about 5.0 %. The increase in total energy demand for the mid-sized car is in line with the results from Lin et al. (2018), in which a 1000 W power demand for the automation system's computation processes was found to reduce the driving range of a Chevrolet Bolt by up to 6 %. In our case, this was enough to equalize the benefits of smoother driving on highways for mid-sized cars. For city driving, the impact of the additional power demand is even more severe. Through low driving speeds in cities (19.8 km/h average) compared to highways (90 km/h average), the power demand of the automation system increases the energy demand much more. We observed an increase of 33.7 % in fuel demand between the non-automated and automated WLTC-3b city driving cycles. When we increased the auxiliary energy demand of the automation system further, to 3000 W, the gains in mechanical energy demand when reducing maximum driving speeds for city driving from 50 km/h to 30 km/h were equalized by the increase in auxiliary energy demand due to the longer driving time. The high auxiliary energy demand was found to increase fuel demand for the speed-reduced driving cycle without stops by 73.2 % compared to the original driving cycle for the conventional vehicle. Such high auxiliary energy demands might not only be caused by the automation system but could also reflect the energy demand for vehicle heating at low temperatures (Küng et al., 2019) or air conditioning at high temperatures (Sigle and Hahn, 2022). Reducing the energy demand for the automation system was shown to be a key factor for achieving fuel savings for automated mid-sized cars. When a power demand of 200 W was assumed for the automation system, the proposed measures could reduce fuel demand and were not outweighed by the additional energy demand of the automation system (for both highway and city driving). The development of computational systems will lead to a reduction in the power demand of the automation system in the future. For the development of computing efficiency (computations per kWh), Koomey et al. (2011) noted a doubling every 1.57 years from 1946 to 2009. This would mean an increase in efficiency by a factor of about 83 within a decade. However, from 2000 to 2009, this rate slowed to a doubling every 2.6 years (Naffziger and Koomey, 2016), which would constitute an increase in efficiency by a factor of about 14 within a decade. Therefore, a reduction in power demand for the automation system from 1000 W to 200 W (a factor of five) could therefore already be achieved in about six years. The computational energy demand might therefore not be a problem for automated vehicles in the future, but as of now it must be considered a burden.

For automated trucks, the additional energy demand for the automation system may not even result in an increase in auxiliary energy demand, because other auxiliary energy demands might be reduced or even eliminated. As no driver is required anymore, heating and air conditioning for the driver cabin are no longer needed (Sigle and Hahn, 2022). For trucks, the energy demand could already be reduced by the proposed measures when considering the additional energy demand of the automation system. A reduced energy demand would therefore only increase the efficiency of the proposed measures.

For passenger vehicles, such decreases in the energy demand for

Table A1
Energy demand for the WLTC-3b highway driving segment (“extra high”) calculated for a battery-electric mid-sized car. (ACC: adaptive cruise control, 4 s moving average; CACC: cooperative adaptive cruise control, 12 s moving average; PP: perfect prediction, 60 s moving average).

	Energy demand [MJ/100 km]					
Vehicle	Driving cycle	Mechanical	Recuperation	Auxiliary	Fuel (BEV)	Comparison to conventional original
Conventional	Original	59.45	−5.69	1.90	73.56 (+/- 0 %)	–
	ACC	59.11	−5.47	1.89	73.28 (-0.4 %)	−0.28 (-0.4 %)
	CACC	57.41	−4.41	1.90	71.97 (-2.2 %)	−1.59 (-2.2 %)
Automated	Original	59.45	−5.65	5.11	77.22 (+/- 0 %)	+3.66 (+5.0 %)
	ACC	59.11	−5.44	5.08	76.92 (-0.4 %)	+3.36 (+4.6 %)
	CACC	57.41	−4.36	5.14	75.65 (-2.0 %)	+2.09 (+2.8 %)
	PP	54.44	−3.22	5.34	72.99 (-5.5 %)	−0.57 (-0.8 %)
	PP 3000 W	54.44	−3.09	12.21	80.85 (+4.7 %)	+7.29 (+9.9 %)
	PP200 W	54.44	−3.24	2.66	69.93 (-9.4 %)	−3.63 (-4.9 %)

heating or air conditioning are not feasible because passengers still travel within the vehicles and their comfort must be taken into account. The increase in fuel demand through the energy demand for the automation system might severely hinder automated vehicle uptake for cars in urban applications, as operational costs increase by a large margin and, in the case of battery–electric vehicles, the range of the vehicles decreases by the same factor. In particular, shared autonomous mobility concepts for urban areas could suffer from this. Furthermore, measures to increase traffic efficiency through automation technology will always face an uphill climb when considering vehicle energy demand, as the additional energy demand for the automation system must be overcome. The measures proposed in this paper, eliminating stops during city driving as well as reducing driving speeds, for example while reducing energy demand for conventional cars by 6.6 % and 20.1 %, respectively, were shown not to outweigh the additional energy demand of the automation system for mid-sized cars; on the contrary, fuel demand increased by a respective 17.9 % and 20.7 %. Again, it should be noted that the fuel savings are calculated for electric vehicles. The elimination of starts and stops would result in much larger fuel savings for combustion vehicles. The calculated fuel savings are therefore to be seen as a lower bound.

We did not consider network and traffic flow effects of automated vehicles in our study. Higher energy demands of individual vehicles might be omitted by fuel efficiency gains on the network level, e.g., through less jams. In such a case, early vehicle owners should be supported by the government, if necessary, to cover the higher costs associated with the higher energy demand of automated vehicles when penetration is too low for network effects to balance these out. Automated trucks driving at lower speeds should also be supported as not only fuel savings can be achieved but also safety levels on highways improved.

6. Conclusions

In this study, we investigated the influence of changes in driving strategies for automated vehicles. We altered the WLTC and WHVC standard driving cycles to depict the behavior of automated vehicles. For highway driving, we smoothened the driving cycles and found reduced fuel demands for automated trucks and no increased fuel demands for automated cars because the additional energy demand of the automation system outweighed the benefits of the smoother driving cycle for these. In further analyses, we altered the driving cycles by reducing maximum driving speeds and eliminating stops. A reduction in the driving speeds for trucks driving on highways from 90 km/h to 70 km/h was shown to strongly reduce fuel demand. For cars driving in cities, fuel demand could also be strongly reduced when reducing driving speeds from 50 km/h to 30 km/h. However, we found that this does not hold true when considering the additional energy demand for the automation system. For trucks, the additional energy demand did not matter much because of their high mechanical energy demand. For cars, on the other hand, the additional energy demand for the automation system was much larger compared to the mechanical energy demand. In addition to that lower driving speeds during city driving further increase its impact. Automated vehicles were found to have a much higher energy demand during city driving compared to conventional ones and even reducing driving speeds and eliminating stops was insufficient to outweigh the increase in energy demand. We conclude that the additional energy demand for the automation system could hinder the introduction of

Table A2
Energy demand for the WHVC highway driving segment (“motorway”) calculated for a battery-electric semi-truck. (ACC: adaptive cruise control, 6 s moving average; CACC: cooperative adaptive cruise control, 18 s moving average; PP: perfect prediction, 90 s moving average).

	Energy demand [MJ/100 km]					
Vehicle	Driving cycle	Mechanical	Recuperation	Auxiliary	Fuel (BEV)	Comparison to conventional original
Conventional	Original	344.23	−45.20	34.95	443.37 (+/- 0 %)	–
	ACC	339.65	−42.15	35.21	440.21 (-0.7 %)	−3.16 (-0.7 %)
	CACC	334.75	−39.17	36.12	437.32 (-1.4 %)	−6.05 (-1.4 %)
	70 km/h max	269.18	−26.80	45.00	373.36 (-15.8 %)	−70.01 (-15.8 %)
Automated	Original	344.23	−45.17	39.02	447.99 (+/- 0 %)	+4.62 (+1.0 %)
	ACC	339.65	−42.10	39.33	444.90 (-0.7 %)	+1.53 (+0.3 %)
	CACC	334.75	−39.14	40.31	442.08 (-1.3 %)	−1.29 (-0.3 %)
	PP	318.14	−31.68	39.14	425.41 (-5.0 %)	−17.96 (-4.0 %)
	70 km/h max	269.18	−26.78	50.22	379.28 (-15.3 %)	−64.09 (-14.5 %)

Table A3
Energy demand for the WLTC-3b city driving part (“low”) calculated for a battery electric mid-size car.

	Energy demand [MJ/100 km]					
Vehicle	Driving cycle	Mechanical	Recuperation	Auxiliary	Fuel (BEV)	Comparison to conventional original
Conventional	Original	45.28	−18.04	8.07	52.76 (+/-0%)	–
	No stops	44.35	−17.47	5.64	49.29 (-6.6 %)	−3.47 (-6.6 %)
	30 km/h max	29.63	−8.50	9.74	42.15 (-20.1 %)	−10.61 (-20.1 %)
	No stops30 km/h max	28.71	−7.93	7.31	38.67 (-26.7 %)	−14.09 (-26.7 %)
Automated	Original	45.28	−17.07	23.16	70.56 (+/-0%)	+17.80 (+33.7 %)
	No stops	44.35	−16.56	16.45	62.21 (-11.8 %)	+9.45 (+17.9 %)
	30 km/h max	29.63	−7.29	27.95	63.68 (-9.8 %)	+10.92 (+20.7 %)
	No stops30 km/h max	28.71	−6.78	21.25	55.34 (-21.6 %)	+2.58 (+4.9 %)
	No stops 30 km/h max3000 W	28.71	−4.75	51.75	91.36 (+29.5 %)	+38.60 (+73.2 %)
	No stops 30 km/h max200 W	28.71	−7.76	9.94	41.78 (-40.8 %)	−10.98 (-20.1 %)

automated vehicles through shared car fleets in cities, as the higher energy demand may make it less economically-feasible and severely reduce driving ranges for electric vehicles. For the future development of automation systems, it is therefore essential to keep computational power demands as low as possible while maintaining the necessary computational speed and reliability. Future studies regarding the energy demand of automated vehicles should further consider the energy demand of the automation system as an important factor and model potential developments for it.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Helmholtz Association under the program, “Energy System Design.”

Appendix A

Tables A1 – A3.

References

Agora, 2021. Agora Verkehrswende. On Autopilot to a More Efficient Future? How Data Processing by Connected and Autonomous Vehicles Will Impact Energy Consumption [WWW Document]. URL https://www.agora-verkehrswende.de/en/publications/on-autopilot-to-a-more-efficient-future/, https://www.agora-verkehrswende.de/en/publications/on-autopilot-to-a-more-efficient-future/ (accessed 1.10.23).

Bray, G., Cebon, D., 2022. Operational speed strategy opportunities for autonomous trucking on highways. Transp. Res. Part Policy Pract. 158, 75–94. https://doi.org/10.1016/j.tra.2022.01.014.

Campbell, M., Egerstedt, M., How, J.P., Murray, R.M., 2010. Autonomous driving in urban environments: approaches, lessons and challenges. Philos. Trans. r. Soc. Math. Phys. Eng. Sci. 368, 4649–4672. https://doi.org/10.1098/rsta.2010.0110.

Chen, Y., Gonder, J., Young, S., Wood, E., 2019. Quantifying autonomous vehicles national fuel consumption impacts: A data-rich approach. Transp. Res. Part Policy Pract. 122, 134–145. https://doi.org/10.1016/j.tra.2017.10.012.

Cox, B., 2018. Mobility and the Energy Transition: A Life Cycle Assessment of Swiss Passenger Transport Technologies including Developments until 2050 (Doctoral Thesis). ETH Zurich. https://doi.org/10.3929/ethz-b-000276298.

UK DfT, 2018. UK Department for Transport, Road Traffic Forecasts 2018.

DieselNet, 2020a. Emission Test Cycles: Worldwide Harmonized Light Vehicles Test Cycle (WLTC) [WWW Document]. URL https://dieselnet.com/standards/cycles/wltp.php (accessed 6.10.20).

DieselNet, 2020b. Emission Test Cycles: World Harmonized Vehicle Cycle (WHVC) [WWW Document]. URL https://dieselnet.com/standards/cycles/whvc.php (accessed 6.10.20).

Dong, Z., Shi, W., Tong, G., Yang, K., 2020. Collaborative Autonomous Driving: Vision and Challenges, in: 2020 International Conference on Connected and Autonomous Driving (MetroCAD). Presented at the 2020 International Conference on Connected and Autonomous Driving (MetroCAD), pp. 17–26. 10.1109/MetroCAD48866.2020.00010.

Eea, 2022. European Environment Agency, National emissions reported to the UNFCCC and to the EU Greenhouse Gas Monitoring Mechanism. accessed 12.23.22. https://www.eea.europa.eu/ds_resolveuid/cc4dcc3007b54c488d4e3d1c97623043.

EU, 2006. Regulation (EC) No 561/2006 of the European Parliament and of the Council of 15 March 2006 on the harmonisation of certain social legislation relating to road transport and amending Council Regulations (EEC) No 3821/85 and (EC) No 2135/98 and repealing Council Regulation (EEC) No 3820/85 (Text with EEA relevance) - Declaration, OJ L.

EU, 2009. Regulation (EC) No 1073/2009 of the European Parliament and of the Council of 21 October 2009 on common rules for access to the international market for coach and bus services, and amending Regulation (EC) No 561/2006 (recast) (Text with EEA relevance), OJ L.

EU, 2014. Regulation (EU) No 165/2014 of the European Parliament and of the Council of 4 February 2014 on tachographs in road transport, repealing Council Regulation (EEC) No 3821/85 on recording equipment in road transport and amending Regulation (EC) No 561/2006 of the European Parliament and of the Council on the harmonisation of certain social legislation relating to road transport Text with EEA relevance, OJ L.

EU, 2016. Corrigendum to Regulation (EC) No 561/2006 of the European Parliament and of the Council of 15 March 2006 on the harmonisation of certain social legislation relating to road transport and amending Council Regulations (EEC) No 3821/85 and (EC) No 2135/98 and repealing Council Regulation (EEC) No 3820/85 (OJ L 102, 11.4.2006), OJ L.

EU, 2020. Regulation (EU) 2020/1054 of the European Parliament and of the Council of 15 July 2020 amending Regulation (EC) No 561/2006 as regards minimum requirements on maximum daily and weekly driving times, minimum breaks and daily and weekly rest periods and Regulation (EU) No 165/2014 as regards positioning by means of tachographs, OJ L.

Feng, D., Haase-Schütz, C., Rosenbaum, L., Hertlein, H., Gläser, C., Timm, F., Wiesbeck, W., Dietmayer, K., 2021. Deep Multi-Modal Object Detection and Semantic Segmentation for Autonomous Driving: Datasets, Methods, and Challenges. IEEE Trans. Intell. Transp. Syst. 22, 1341–1360. https://doi.org/10.1109/TITS.2020.2972974.

FHWA, 2022. Federal Highway Administration, 2022 FHWA Forecasts of Vehicle Miles Traveled (VMT).

Gawron, J.H., Keoleian, G.A., De Kleine, R.D., Wallington, T.J., Kim, H.C., 2018. Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects. Environ. Sci. Technol. 52, 3249–3256. https://doi.org/10.1021/acs.est.7b04576.

Grube, T., 2014. Potentiale des Strommanagements zur Reduzierung des spezifischen Energiebedarfs von Pkw (Dissertation). Technische Universität Berlin, Jülich, Fak. V - Verk.- Maschinensysteme.

Helms, H., Bruch, B., Räder, D., Hausberger, S., Lipp, S., Matzer, C., 2022. Energieverbrauch von Elektroautos, Texte 160/2022. Umweltbundesamt.

Kamal, M.A.S., Taguchi, S., Yoshimura, T., 2016. Efficient Driving on Multilane Roads Under a Connected Vehicle Environment. IEEE Trans. Intell. Transp. Syst. 17, 2541–2551. https://doi.org/10.1109/TITS.2016.2519526.

Koomey, J., Berard, S., Sanchez, M., Wong, H., 2011. Implications of Historical Trends in the Electrical Efficiency of Computing. IEEE Ann. Hist. Comput. 33, 46–54. https://doi.org/10.1109/MAHC.2010.28.

Kraus, S., Reul, J., Grube, T., Linßen, J., Stolten, D., 2021. Vehicle Cost Analysis for Road Vehicles Until 2050, in: 30th Aachen Colloquium Sustainable Mobility. Aachen, pp. 1231–1256.

Küng, L., Bütler, T., Georges, G., Boulouchos, K., 2019. How much energy does a car need on the road? Appl. Energy 256, 113948. https://doi.org/10.1016/j.apenergy.2019.113948.

Lee, J., Kockelman, K.M., 2019. Energy implications of self-driving vehicles, in: Proceedings of the 98th Annual Meeting of the Transportation Research Board, Washington, DC, USA. pp. 13–17.

Lin, S.-C., Zhang, Y., Hsu, C.-H., Skach, M., Haque, M.E., Tang, L., Mars, J., 2018. The Architectural Implications of Autonomous Driving: Constraints and Acceleration, in: Proceedings of the Twenty-Third International Conference on Architectural Support for Programming Languages and Operating Systems. Association for Computing Machinery, New York, NY, USA, pp. 751–766.

Liu, J., Kockelman, K., Nichols, A., 2017. Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model, in: Transportation Research Board 96th Annual Meeting.

Liu, Z., Tan, H., Kuang, X., Hao, H., Zhao, F., 2019. The Negative Impact of Vehicular Intelligence on Energy Consumption. J. Adv. Transp. 2019, e1521928.

Massar, M., Reza, I., Rahman, S.M., Abdullah, S.M.H., Jamal, A., Al-Ismail, F.S., 2021. Impacts of Autonomous Vehicles on Greenhouse Gas Emissions—Positive or Negative? Int. J. Environ. Res. Public. Health 18, 5567. https://doi.org/10.3390/ijerph18115567.

Moubayed, A., Shami, A., Heidari, P., Larabi, A., Brunner, R., 2020. Cost-optimal V2X Service Placement in Distributed Cloud/Edge Environment, in: 2020 16th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Presented at the 2020 16th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), pp. 1–6. 10.1109/WiMob50308.2020.9253437.

Muratori, M., Holden, J., Lammert, M., Duran, A., Young, S., Gonder, J., 2017. Potentials for Platooning in U.S. Highway Freight Transport: Preprint (No. NREL/CP-5400-67618). National Renewable Energy Lab. (NREL), Golden, CO (United States). 10.4271/2017-01-0086.

Naffziger, S., Koomey, J., 2016. Energy Efficiency of Computing: What's Next? Electron, Des https://www.electronicdesign.com/technologies/microprocessors/article/21802037/energy-efficiency-of-computing-whats-next (accessed 2.10.23.

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. Transp. Res. Part C Emerg. Technol. 111, 255–293. https://doi.org/10.1016/j.trc.2019.12.008.

Pendleton, S.D., Andersen, H., Du, X., Shen, X., Meghjani, M., Eng, Y.H., Rus, D., Ang, M. H., 2017. Perception, planning, control, and coordination for autonomous vehicles. Machines 5, 6.

Roca-Puigròs, M., Marmy, C., Wäger, P., Beat Müller, D., 2023. Modeling the transition toward a zero emission car fleet: Integrating electrification, shared mobility, and automation. Transp. Res. Part Transp. Environ. 115, 103576 https://doi.org/10.1016/j.trd.2022.103576.

Schall, P., Sigle, S., Ulrich, C., 2021. Design Strategy for a Distributed Energy Storage in a Modular Mover, in: 2021 Sixteenth International Conference on Ecological Vehicles and Renewable Energies (EVER). Presented at the 2021 Sixteenth International Conference on Ecological Vehicles and Renewable Energies (EVER), pp. 1–5. 10.1109/EVER52347.2021.9456606.

Schubert, M., Kluth, T., Nebauer, G., Ratzenberger, R., Kotzagiorgis, S., Butz, B., Schneider, W., Leible, M., 2014. Verkehrsverpflechtungsprognose 2030 - Schlussbericht. Bundesministerium für Verkehr und digitale Infrastruktur.

Sigle, S., Hahn, R., 2022. Energy Consumption Comparison of Current Powertrain Options in Autonomous Heavy Duty Vehicles (HDV), in: 2022 Second International Conference on Sustainable Mobility Applications, Renewables and Technology (SMART). Presented at the 2022 Second International Conference on Sustainable Mobility Applications, Renewables and Technology (SMART), pp. 1–7. 10.1109/SMART55236.2022.9990489.

Slowik, P., Sharpe, B., 2018. Automation in the long haul: Challenges and opportunities of autonomous heavy-duty trucking in the United States. The International Council on Clean Transportation.

Suarez, J., Makridis, M., Anesiadou, A., Komnos, D., Ciuffo, B., Fontaras, G., 2022. Benchmarking the driver acceleration impact on vehicle energy consumption and CO2 emissions. Transp. Res. Part Transp. Environ. 107, 103282 https://doi.org/10.1016/j.trd.2022.103282.

Tsugawa, S., Jeschke, S., Shladover, S.E., 2016. A Review of Truck Platooning Projects for Energy Savings. IEEE Trans. Intell. Veh. 1, 68–77. https://doi.org/10.1109/TIV.2016.2577499.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part Policy Pract. 86, 1–18. https://doi.org/10.1016/j.tra.2015.12.001.

Yeong, D.J., Velasco-Hernandez, G., Barry, J., Walsh, J., 2021. Sensor and sensor fusion technology in autonomous vehicles: A review. Sensors 21, 2140.