Transportation Research Part D 77 (2019) 132–147

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Energy and emissions implications of automated vehicles in the U.S. energy system

Kristen E. Brown, Rebecca Dodder*

U.S. Environmental Protection Agency, 109 TW Alexander Dr., RTP, NC 27711, United States

ARTICLE INFO

Keywords:
Transportation
Automation
Automated vehicles
Scenario analysis
Air quality
Emissions

ABSTRACT

Vehicle automation has the potential to drastically transform transportation, with important implications for energy and the environment. There is considerable uncertainty regarding the impact of automation on travel demand and vehicle efficiency. We utilize the MARKet ALlocation (MARKAL) energy system model to examine four previously published scenarios that consider different effects of automation on efficiency and demand. We do not replicate detailed estimation of individual mechanisms but apply key outcomes from prior studies within a broader energy system framework. Our analysis adds insights on fuel switching, upstream impacts, and air emissions. MARKAL dynamically captures interactions between transportation and non-transportation sectors, which is important given that the revolutionary shifts from automation may invalidate static assumptions. Model results suggest that increasing travel demands from automation may boost fuel use and petroleum-based fuel prices, potentially increasing the market penetration of alternative-fuel vehicles. In contrast, dramatic efficiency improvements from automation could drive fuel prices lower, greatly reducing the competitiveness of alternative-fueled vehicles. Furthermore, these shifts could yield positive or negative environmental impacts. Some automation scenarios even resulted in counterintuitive results. For example, if high levels of efficiency improvement drive out alternative-fuel vehicles, such as battery electric and hybrids, a net worsening of air quality relative to the other scenarios could result. We also found system-level dynamics to be key. For example, reductions in liquid fuel prices led to increased consumption, and the resulting increase in air pollutant emissions offset a portion of the potential air quality benefits of automation.

1. Introduction

The sophistication of vehicle automation options range along a spectrum. On one end, the driver is in control, but the driving experience is augmented by features such as collision prevention, lane and side assistance, parking, and maintenance of safe driving distances. Many of these features are already in vehicles on the road. On the other end of the spectrum, the vehicle is capable of performing all driving functions under all conditions. Fully automated vehicles are being developed and tested in many markets in the U.S. and globally.

Much of the emphasis of research on automated vehicles (AVs) is on safety improvements, estimating the economic and social benefits of reducing vehicle collisions, providing greater roadway efficiency and less congestion, and expanding user groups (Fagnant and Kockelman, 2015, NHTSA, 2017). However, there are a number of mechanisms by which vehicle automation can either improve

* Corresponding author.
E-mail addresses: brown.kristen@epa.gov (K.E. Brown), dodder.rebecca@epa.gov (R. Dodder).

https://doi.org/10.1016/j.trd.2019.09.003

1361-9209/ Published by Elsevier Ltd.

or worsen public health and well-being, including air quality (Rojas-Rueda et al., 2017). Increasingly, researchers and decision makers are focusing on the impacts of vehicle automation on energy use and environmental outcomes, typically greenhouse gas (GHG) emissions (Greenblatt and Saxena, 2015, Greenblatt and Shaheen, 2015, Hula et al., 2018, Miller and Heard, 2016, Simon et al., 2015). Energy and CO_2 emissions changes from vehicle automation have also been examined within the broader context of what have been called the “Three Revolutions”: automated, shared and electric vehicles (Sperling, 2018). Studies have examined the role of vehicle automation within the context of shared mobility (Fagnant and Kockelman, 2014), electric vehicle penetration (Cox et al., 2018), or both (Iacobucci et al., 2018, Loeb et al., 2018). Some studies are also evaluating the interaction of automation and electric vehicle combinations and their connectivity to the grid (Wang et al., 2018). The life cycle impact of the additional vehicle components has also been evaluated (Gawron et al., 2018).

There are many individual technologies that contribute to vehicle automation and different mechanisms by which they affect energy use and emissions. Some recent papers have reviewed the literature on individual technologies and mechanisms and summarized the overall impacts. Taiebat et al. (2018) provide a systematic review of AVs and their environmental impacts, examining the impacts at four levels: vehicle, transportation system, urban system, and society. The analyses that are most useful to our modeling work aggregate up a range of mechanisms from the vehicle to the societal level. Another review (Anderson et al. 2016) focuses on the policy relevant implications of AVs, which includes some investigation into energy use, in addition to many safety impacts.

Rodier (2018) reviews studies assessing the travel effects and GHG emissions of automated vehicles, dividing scenario modeling into three categories: (1) simulations of route choice, primarily using dynamic traffic assignment models; (2) short to longer run modeling expanding beyond route choice to changes in time of day or mode choice, trip destination, and land use change; and (3) extrapolation studies, which take case studies and other analyses and combine a number of specific effects into a combined impact. These latter studies, which capture a range of specific effects or mechanisms at multiple scales, are of most interest for our energy system modeling. Brown et al. (2014) was one of the early extrapolation studies examining changes in energy use and carbon emissions at a broader scale. Given the many underlying uncertainties, their goal was to estimate the “upper-bound effects” of a range of impacts, both positive and negative. They estimated impacts of changes to efficiency, distances traveled, and travel speeds, to evaluate the impact on CO_2 emissions (Brown et al., 2014). Brown et al., also considered both efficiency improvements and penalties at the individual vehicle level. Broader system-wide efficiencies were considered as well. On the demand side, the authors considered expansion of autonomous vehicles into new user groups, as well as both increases in per capita miles traveled and reductions resulting from shared mobility and less searching for parking. They found the potential for “dramatic fuel savings,” but also potential increases in travel demand and energy use. Another study that estimates the bounds of automation, Stephens et al. (2016) calculated the potential changes in fuel use for connected and autonomous light duty vehicles while also considering potential changes in cost to the consumer. Wadud et al. (2016) developed four scenarios by adding ranges of estimates for several factors impacting energy use. In the methodology section and throughout, we will frequently refer to the Wadud et al. (2016) analysis and illustrative scenarios they developed. The Wadud et al. scenarios serve as the basis for the modeling described here.

While these studies have estimated ranges for impacts of automation on energy and fuel use, few studies have examined the effects of vehicle automation on the broader U.S. energy economy. The energy economy includes upstream fuel and electricity production and competition for energy from residential, commercial, and industrial needs. Changes in demand for transportation fuels may impact fuel prices and instigate fuel switching in other sectors. Traditionally, energy system models are more adept at developing projections that take into account factors such as high and low energy prices and supplies, levels of economic growth (e.g., AEO (EIA, 2016) side cases), specific policy measures and mitigation strategies (Loughlin et al., 2015, Rudokas et al., 2015, Thompson et al., 2014), and technology adoption under varying alternative assumptions about cost and performance (Aitken et al., 2016, Babaee et al., 2014).

AVs present a new challenge that does not necessarily fit any of these approaches. The challenge arises because AVs have the potential to overhaul travel norms by simultaneously changing end-use demands, vehicle stock and type, fuel use, and vehicle operations – all of which have their own effects on transportation energy projections. Greenblatt and Shaheen (2015) warned that “current trends will hardly apply” and that “energy analysts… will have to ‘watch this space’ carefully to prevent their projections from becoming inaccurate or (worse) irrelevant” (Greenblatt and Shaheen, 2015). Some energy system models are starting to take the first steps toward incorporating the impact of AVs on their projections. The Energy Information Administration (EIA) commissioned a study on energy impacts of Connected and Automated Vehicles (CAV) in order to “inform EIA of CAV’s technical status and the potential impacts on transportation energy use for incorporation into the National Energy Modeling System (NEMS) model” (EIA, 2017). More recently, an analysis using NEMS compared the 2018 reference case from the Annual Energy Outlook with two autonomous vehicle scenarios (EIA, 2018). However, both of the scenarios also included more widespread use of battery or hybrid electric vehicles (EVs). They found that transportation energy use was higher under both scenarios, with shifts in transportation fuel markets. Jones and Leibowicz (2019) developed an energy system optimization model to evaluate the impact of AV scenarios on electricity generation for a case study of Austin, TX. They found that with heavy sharing and electrification, AVs had the potential to reduce CO_2 emissions from both transportation and electricity generation.

For this paper, the focus is on the broader energy system impacts of AVs. The goal is to assess the extent of cross-sector impacts, in particular, on the electric power and petroleum sectors. Full energy system models are structured to capture these upstream effects on fuel supply markets (gasoline, diesel, electricity, biofuels, and compressed natural gas (CNG)) due to changes in light-duty vehicle demands. Because of the large uncertainties associated with AVs, we take a scenario-based approach that allows us to scope out a range of impacts and identify areas for future work. We do not attempt to replicate the detailed estimation of the impact of individual mechanisms, as done by Brown et al. (2014) and Wadud et al. (2016), but instead apply key outcomes (e.g., net vehicle miles traveled (VMT) changes) from those studies within a broader energy systems modeling framework.

2. Material and methods

This study utilizes the MARKAL (MARKet ALlocation) model, an energy system optimization model that generates scenarios of the evolution of the energy technology and fuel mix over multiple decades (Loulou et al., 2004). MARKAL uses assumptions of the future cost and operational parameters of technologies and energy sources to determine which technologies can satisfy projected consumer demands most cost effectively. The MARKAL model can represent energy systems at the global, national, regional, state/provincial, or community scale, and is typically run with a long-term horizon for future oriented energy planning and climate analysis. Most applications of the model capture the energy system from mining and extraction of fuels to end uses in transportation, buildings, and industry. MARKAL and other similar models are characterized as bottom-up models that start with a detailed techno-economic characterization of the full suite of energy technologies to build out the full energy system and its key sectors. For this analysis, the sectoral focus is on light-duty and heavy-duty vehicle travel demands, vehicle technology choices (e.g., conventional internal combustion engine, hybrid, plug-in hybrid, battery electric), and fuels. One of the benefits of using MARKAL relative to a transportation-only model is that interactions with non-transportation sectors can be modeled dynamically (DeCarolis et al., 2017). This feature is particularly important here since vehicle automation has the potential to create revolutionary shifts in transportation, making static assumptions about the supply and cost of electricity, petroleum products, and other fuel sources problematic. Results from this model can highlight potential interactions with other energy sectors and emissions sources.

The MARKAL model represents resource supply extraction and imports, major conversion technologies such as electric power generation and petroleum refineries, and end-use sectors including residential and commercial buildings, energy-intensive industries, and light- and heavy-duty transportation. The model uses linear programming to determine the least-cost solution for meeting the end-use energy demands, based on the costs and performance of current and future energy technologies, and the cost and supply of primary energy resources. The solution is subject to constraints, which typically reflect energy and environmental policies. The model solves using perfect foresight and outputs the energy technology and fuel mix at selected intervals for the full modeled time horizon. Results from MARKAL should not be interpreted as predictive, and generally multiple scenarios are run in order to gain insights into the drivers of technology or fuel penetration under different inputs and assumptions.

For this analysis, we use the EPAUS9r database developed by the U.S. Environmental Protection Agency (EPA). This database allows MARKAL to be applied to the U.S. energy system at the level of the nine U.S. Census Divisions, represented in Fig. 1, for a time horizon of 2005–2055 with 5-year time steps. The EPAUS9r database has been used in many analyses that investigate linkages between energy, climate, air quality, and water use. These include assessing the regional air quality impacts associated with climate mitigation options (Rudokas et al., 2015), the energy impacts of internalizing environmental and health damages (Brown et al., 2013, 2017), and the potential emissions impacts of widespread electric vehicle (EV) adoption (Keshavarzmohammadian et al., 2017). The model has also been proven to be a powerful tool for scenario analysis (Brown et al., 2018; Gamas et al., 2015). A retrospective analysis (Lenox and Loughlin, 2017) helps validate the model and highlight limitations. For EPAUS9r, demands, technologies, and resources are characterized at the regional level, while allowing interaction among the nine regions through trading. Full documentation of the database and data sources is available at Lenox et al. (2013). Because a large number of the inputs are linked to the EIA's NEMS, the database is updated biannually to reflect changes in technology costs, resource supply prices and availability, and energy and environmental policies, regulations and standards that are included in the NEMS projections for the Annual Energy Outlook (AEO). We use version EPAUS9r_v16.1.0 of the database, which is calibrated to the 2016 AEO. It should be noted that this version does not incorporate some recent additions to NEMS to reflect shared and automated vehicles (EIA, 2018).

The key sectors for this analysis are light-duty and heavy-duty transportation, as well as the sectors that provide transportation fuels: petroleum and biomass-based refineries, electric power generation, and natural gas production (including compressed natural gas (CNG)). In EPAUS9r, demands for VMT are defined based on regionally projected population growth and per capita VMT (EIA, 2005, US EPA, 2013). Light-duty vehicles (LDVs) are characterized according to combinations of vehicle classes (mini, compact, full size sedan, minivan, pick-up, small sport utility vehicle (SUV), and large SUV) and fuel types (diesel, gasoline, E85 (a mixture of

Fig. 1. The nine modeling regions (Census Divisions) represented in the US EPA MARKAL database.

gasoline with 85% ethanol), CNG, and electricity). Each vehicle-fuel combination is then represented by estimates of investment and operating costs, efficiency, fuel inputs, start year, lifetime, technology specific-discount rates, and time-of-day charging profiles for EVs (EIA, 2015). The model first characterizes an existing fleet and then determines vehicle retirement and investment in new vehicles over the modeling horizon to meet end-use demand.

The model also includes detailed emissions factors (US EPA, 2014a) for air pollutants (e.g., NO_x, SO_2, VOCs, PM_{10}, $PM_{2.5}$) and climate pollutants (CO_2, CH_4, black carbon), and incorporates all light-duty standards and regulations as inputs to either the emissions factors (e.g., Tier 3) (US EPA, 2014b) or constraints to the model (LDV GHG standards) (NHTSA and EPA, 2012). We assume that conventional and hybrid vehicles emit at the Tier 3 standards, even if efficiency is improved. Emissions from plugin hybrids are reduced by the fraction of driving assumed to be in the electric mode. Emissions from electricity use are accounted for in the electric sector.

The heavy-duty transportation sector follows a similar structure as the LDVs. For this analysis, we consider heavy-duty vehicles (HDVs) to include commercial, medium- and heavy-duty trucks. Short- and long-haul heavy-duty trucks are represented by a range of vehicle technologies (e.g., advanced engines and hybrids, fuel cell) and fuel types (e.g., diesel, gasoline, CNG, LPG (liquified petroleum gas), electric). As with the LDVs, detailed emissions factors that reflect emission standards are incorporated. The model also considers bus, air, rail, and marine transportation. While these subsectors are not directly modified in the scenarios, it is possible that changes to LDV and HDV transportation would impact these modes via shifts in fuel prices.

The model can solve for the use of gasoline, diesel, and alternative fuels (e.g., biomass-based fuels, CNG, and electricity) in each transportation subsector. The HDV and LDV sectors along with off-road transportation determine the demands for transportation fuels, but also compete with other end-use demand sectors that utilize refined petroleum products and upstream supplies of crude oil and natural gas. Similarly, to the extent that there is electrification within the fleet, the model must optimize while also considering demands for residential, commercial, and industrial electricity needs.

Although we advance the state of knowledge from previous work, there are some limitations of the model. Trajectories for technology costs and efficiencies are specified exogenously, so if a certain technology is adopted heavily in early years in these scenarios it is possible that the price would decrease faster than modeled. Similarly, if a technology is not developed in early years, the real-world price would be unlikely to come down, and the cost in the model may be unrealistically low in later years. The model also cannot include technologies for which we cannot currently project parameter values. Therefore, if automation leads to vehicle types or operational modes that are significantly different from those in use today, we will be unable to capture that impact in the model.

3. Theory and calculation

Given the high level of uncertainty surrounding vehicle automation, an analysis of its impacts on the future energy system is best addressed through scenario analysis. Wadud et al. (2016) reviewed several possible impacts of automated vehicles on the transportation system and defined the four scenarios used in this analysis. The scenario definition is structured around the "ASIF" method of estimating changes in carbon emissions from transportation (Schipper, 2002). This framework is summarized in the equation:

$$\text{Emissions of } CO_2 = \textbf{A}\text{ctivity Level} * \text{Modal } \textbf{S}\text{hare} * \text{Energy } \textbf{I}\text{ntensity} * \textbf{F}\text{uel Carbon Content} \quad (1)$$

The scenarios defined in Wadud et al. (2016) focus on quantifying changes in the Activity Level and Energy Intensity portions of Eq. (1). While discussed qualitatively, Wadud et al. (2016) did not include price-induced fuel switching in their analysis, and thus did not capture changes in fuel carbon content, the F in ASIF. The energy system modeling done here will expand the analysis to include fuel carbon content by allowing the model to endogenously choose alternative fuels or EV options. Wadud et al. (2016) determined a set of mechanisms that may cause changes to the transportation system as well as the appropriate ASIF multipliers. These mechanisms can affect individual vehicles or the broader network. The energy intensity of LDVs are affected by multiple mechanisms: platooning, congestion mitigation, eco-driving, de-emphasized performance, crash avoidance, right-sizing, higher highway speeds, and increased features for comfort. Right-sizing in particular increases vehicle efficiency, as use of much smaller vehicles requires significantly less fuel. Platooning, or driving vehicles closer together, improves the aerodynamics of the chain and can also have a large impact. De-emphasized performance refers to a shift in consumer preference away from fast acceleration when the consumer is more passenger than driver. LDV activity level can change through generalized cost of the drivers' time, new users, and car sharing. Fewer mechanisms affect HDVs because vehicle technologies are more standardized. Platooning and congestion mitigation can affect the energy intensity, and reductions in generalized cost of travel can impact HDV demand.

The scenarios defined by Wadud et al. (2016) describe a wide range of responses to automation. The scenarios assume "nearly complete penetration of automated vehicles" (Wadud et al. 2016) but are intended to be exploratory, not predictive. One scenario, titled "Have our cake and eat it too" which is referred to here as "*Cake*", reaps nearly all AV emissions benefits without the potential drawbacks. This is exemplified by the high efficiency gains shown in Table 1. This scenario assumes that policy and technology advance smoothly with significantly reduced accidents. Platooning, right-sizing, eco-driving, and de-emphasized performance provide significant efficiency improvements. Some driver engagement is still required, which limits the increased demand. "Stuck in the middle at Level 2" or "*Stuck*" has a weaker response as regulations do not allow for higher levels of automation, so drivers must remain engaged, and many of the mechanisms for emissions changes remain the same as in a business-as-usual (BAU) scenario, represented in Table 1 with multipliers close to one. There is a very small increase in demand due to reduced risk of accidents and slight efficiency improvements from some platooning and eco-driving opportunities. "Strong responses" or "*Strong*" represents a scenario in which many of the emissions benefits from *Cake* are realized, but consumer choice also leads to changes with the potential

Table 1
Fractional change in end use demand (DMD) and fuel efficiency (EFF) compared to BAU for each of the four scenarios.

LDV DMD	2020	2025	2030	HDV DMD	2020	2025	2030
Cake	1.2	1.4	1.67	Cake	1.13	1.26	1.43
Stuck	1.03	1.07	1.11	Stuck	1.03	1.07	1.11
Strong	1.2	1.4	1.68	Strong	1.2	1.41	1.68
Dystopian	1.2	1.4	1.65	Dystopian	1.14	1.27	1.45
LDV EFF	2020	2025	2030	HDV EFF	2020	2025	2030
Cake	1.30	1.86	4.32	Cake	1.09	1.20	1.39
Stuck	1.06	1.12	1.22	Stuck	1.05	1.11	1.20
Strong	1.26	1.71	3.27	Strong	1.09	1.20	1.39
Dystopian	0.91	0.84	0.76	Dystopian	1	1	1

to increase emissions. This scenario has the largest increases in demand but also includes some efficiency improvements. Departures from *Cake* include faster speeds, more power-draining amenities, and higher demand from lower cost of time, which all increase energy use compared to *Cake*. This scenario also has more car-sharing, which mitigates the increased demand. "Dystopian nightmare" or *"Dystopian"* represents full automation, which leads to significant changes in the transportation system, but mostly in ways that increase emissions. Examples include an increase in demand due to the decreased cost of time associated with being a passive participant. This scenario has large increases in demand, and LDVs are actually less energy efficient than today due to higher speeds and more features.

The ASIF multipliers for individual mechanisms developed in Wadud et al. (2016) were combined to create a demand and efficiency multiplier for each of the LDV and HDV scenarios. Travel demand corresponds to impacts on Activity Level and efficiency corresponds to Energy Intensity. The demand values are multiplied by the VMT required for each vehicle class in the business as usual (BAU) scenario in MARKAL. The BAU future is based on AEO projections. The efficiency values are multiplied by each vehicle type's fuel efficiency in MARKAL as defined in the BAU, creating more (or less) fuel efficient vehicles per mile traveled. Table 1 shows the values used in MARKAL, which represent a fractional change from BAU. It was assumed that changes linearly increase until 2030 at which time they remain constant (as multipliers to the BAU). Demand still increases over time in all future years and vehicle efficiency improves in response to regulation. For ease of comparison and to ensure the changes take hold within the model time horizon, a simplistic view of the timeline has been assumed here, but it is likely that the scenarios would playout on different timelines.

We tested efficiency and travel demand changes both separately and together to determine how each affects the overall results. Twelve scenarios were tested. For each of the four scenarios described by Wadud et al. (2016), we ran a *combined impacts* scenario that models all of the changes as described, a scenario that only considers the *efficiency* improvements described in that scenario, and a scenario that only considers the *demand* changes. We consider the scenarios described above, as well as a BAU scenario that does not include vehicle automation. The BAU is based on the EPAUS9r MARKAL baseline as calibrated to the AEO 2016 reference case.

4. Results and discussion

Our modeling showed similar transportation sector results to those of Wadud et al. By using MARKAL, we are also able to investigate implications for refineries, upstream electric power generation, and criteria pollutant emissions as well as fuel switching, which are the unique contributions of this analysis. Fuel use, or the total amount of energy required to power vehicles, is shown in Fig. 2. As the name may suggest, the *Stuck* scenario is most similar to a future without automation: the transportation sector uses only slightly less total fuel than the BAU and has little electrification. The *Cake* scenario requires the least energy of all scenarios and has the largest fraction of conventionally fueled vehicles. *Strong* is very similar to *Cake*, although *Strong* has slightly more fuel use. The single mechanism *Strong* cases act as bounding scenarios for HDV fuel use. The *Strong* efficiency scenario represents strong emissions benefits from efficiency whereas demand increases lead to the highest emissions disbenefits. In the *Dystopian* scenario, there is an increase in alternative fuel vehicles compared to other scenarios to address the much larger overall need for transportation energy, but gasoline and diesel use remain high as well. The LDV sector has a larger range of responses to the scenarios due to the larger range of mechanisms that can change efficiency and demand compared with the HDV sector. Below, we highlight key changes observed in LDVs and HDVs including fuel type, and upstream sectors such as refineries. We then examine the implications for emissions of GHG and select air pollutants. To compare the full range of impacts across scenarios, it is assumed that all changes begin immediately and progress quickly, however different mechanisms are likely to impact transportation on different time scales in reality.

4.1. Light-duty vehicles

Significant differences are reported among scenarios for LDV fuel use, both in quantity and type of fuel. Fig. 3 shows fuel use by type in 2050 for the BAU and 12 scenarios. EVs are more efficient than gasoline vehicles, so the percentage of VMT using EVs is larger than the fraction of fuel use shown in Fig. 3. Fuel use by region and type is shown in terms of VMT for the four combined scenarios and the reference case in Fig. A5. Even by 2050, *Stuck* does not diverge substantially from BAU. In *Cake* and *Strong*, efficiency is the

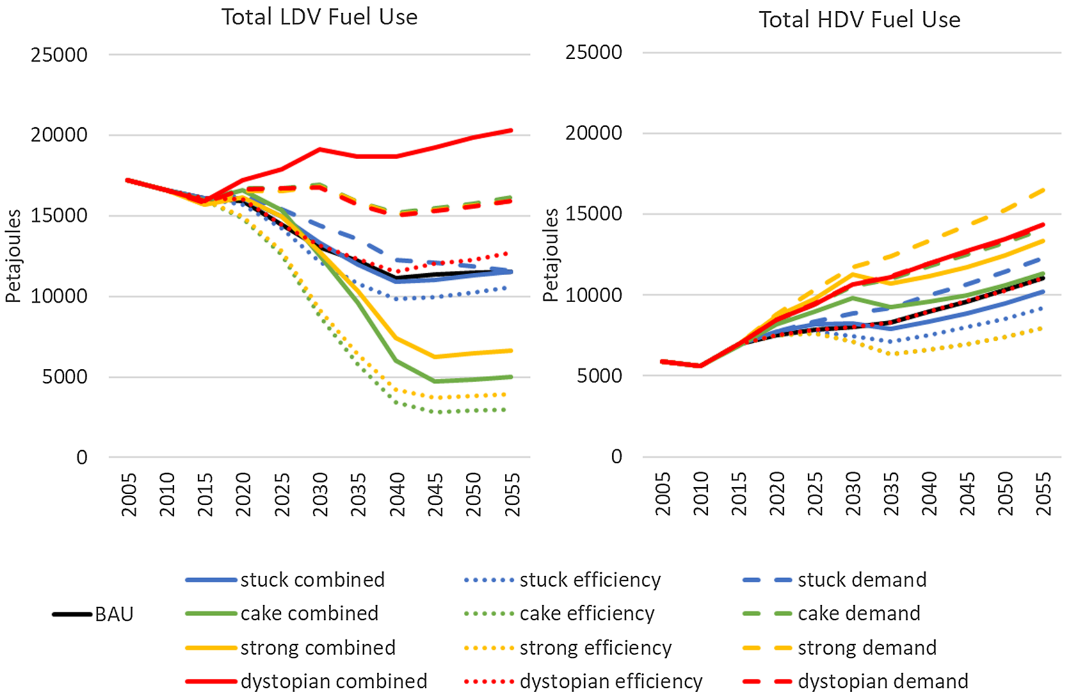

Fig. 2. Total fuel used in LDV and HDV vehicles for each of the twelve vehicle automation scenarios and a reference case (BAU) without automation.

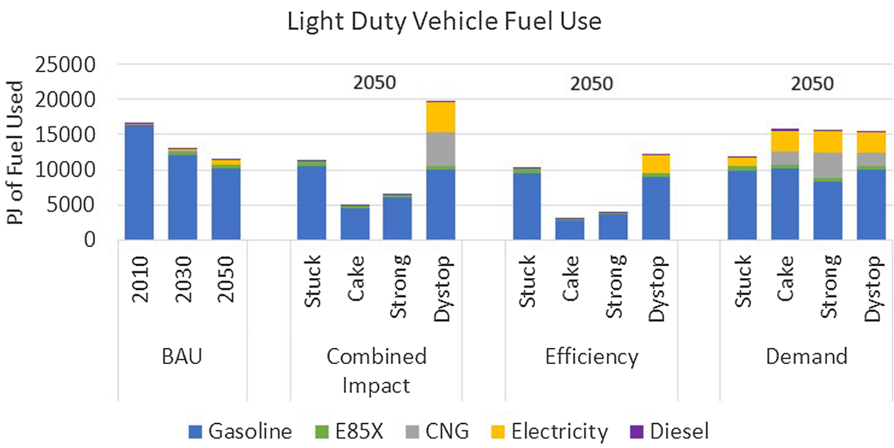

Fig. 3. Light-duty vehicle fuel use modeled in 2050. We show the combined impact of both changes in all scenarios, which would mimic the Wadud et al. (2016) results. We also run each scenario with only the Efficiency changes and only the Demand changes to gain insights into the relative impact of each set of drivers. Results are displayed in those categories, as well as a BAU result without vehicle automation. E85X represents a fuel blend of ethanol and gasoline such that the ethanol can constitute as much as 85% of the total fuel use for flex fuel vehicles.

main factor affecting LDV fuel use. Nearly all vehicles run on gasoline, but only require roughly a third to half of the fuel required for BAU. Similarly, in all scenarios in which only efficiency is improved (all "Efficiency" cases except *Dystopian*, which has an efficiency penalty), LDVs are mostly fueled using gasoline. The Efficiency and Demand only cases are not intended to represent realistic scenarios, but they provide insight into the most important drivers in each scenario. The *Dystopian* future is driven by high demand and requires much more fuel than any other scenario (e.g., over 70% more than the 2050 BAU). This scenario has a much larger adoption rate of alternative fuel vehicles, in response to the high gasoline prices that are driven up due to high demand. This response offsets some of the fuel increase indicated in Wadud et al., which did not consider fuel-switching. Analogously, in each of the scenarios where only demand is altered, there is an increase in alternative fuel vehicles, including both EVs and CNG.

It is important to keep in mind when looking at these results that the qualities of automation that would tend to favor electric- or fuel cell-powered autonomous vehicles are not evaluated here. For example, the larger batteries in EVs could potentially provide automated performance more seamlessly than a conventionally-fueled vehicle. Instead, the increase in electrification shown in these results comes only from changes in the price and availability of gasoline due to the large shifts in fuel alone.

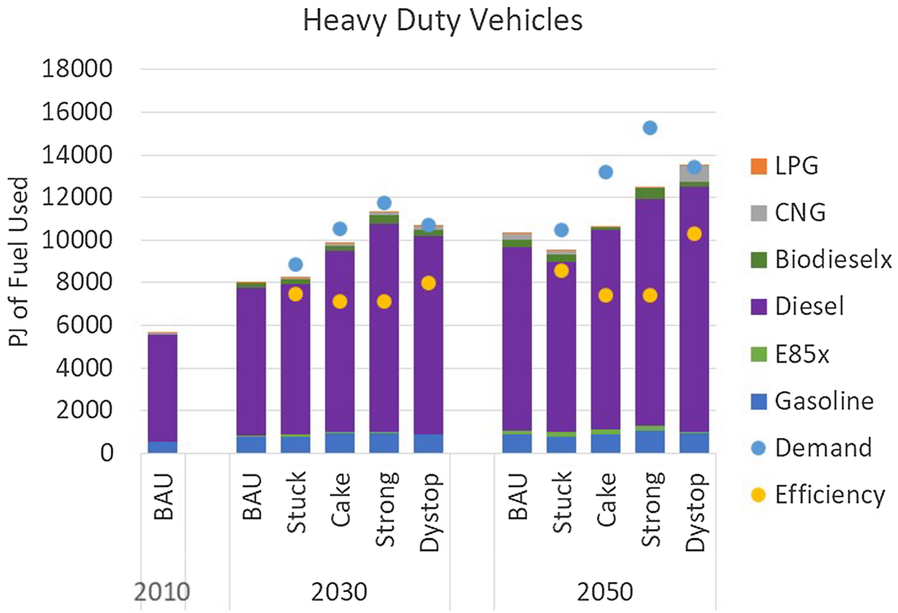

Fig. 4. Fuel use for heavy-duty vehicles in 2030 and 2050. The stacked bars represent fuel use for the scenarios where both demand and efficiency are modified. The dots represent the total fuel use when only efficiency (yellow dots) or demand (blue dots) are changed. E85X represents a fuel blend of ethanol and gasoline such that the ethanol can constitute as much as 85% of the total, Biodieselx represents a blend up to 20% biodiesel. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Heavy-duty vehicles

In all scenarios, diesel fuel remains firmly dominant for HDVs, as demonstrated in Fig. 4. Total demand for fuel varies widely across scenarios. Although all scenarios that consider efficiency alone have lower fuel use than the BAU, *Stuck* is the only scenario that has lower fuel use in 2050 when both efficiency and demand changes are considered. All combined impact scenarios had higher fuel use than BAU in 2030. Heavy-duty efficiency does not change from BAU in the *Dystopian* scenario, therefore the combined and demand change scenarios are the same. When demand is large enough, CNG breaks into a larger share of the market as seen for the *Dystopian* scenario. The *Cake* and *Strong* demand only scenarios also have larger CNG use than other scenarios.

4.3. Refineries

Due to large changes in demand for petroleum-based transportation fuel, the output from refineries also changes, as shown in Fig. 5. Not only are different quantities of oil required from scenario to scenario, but the split of petroleum products output from refineries also differs. In 2050, gasoline output from the combined impact *Cake* and *Strong* scenarios is 14% and 18% of total output, respectively, compared to 52% in 2010 and 29% in the 2050 BAU. This change in the refinery output mix may impact fuel price and emissions even more than indicated by the model. This dynamic arises because MARKAL shows that an increase in total oil demand will increase prices according to the supply curve, and there are limits to what ratios of products are feasible from a refinery. Significantly different product fractions may come with cost and emissions impacts that are not fully captured in the model (Young et al. 2019). For instance, very low gasoline use combined with increased demand for diesel will still require oil, but the output fractions would differ from base assumptions, which may alter emissions portfolios and commodity prices.

In scenarios where total refinery output is greater than about 30,000 PJ, there is always more EV and CNG use. An increase in EV use above this threshold indicates that petroleum becomes sufficiently expensive to warrant an increase in vehicle electrification despite the higher capital cost of EVs. The efficiency-only *Dystopian* scenario also has high electrification even though the total quantity of refined products is below the threshold. There is an efficiency penalty for LDVs in this scenario (see Table 1), so moving toward more efficient EVs is a logical response to the higher cost of fuel per VMT.

4.4. Emissions

In our model, emissions of most air pollutants do not change with vehicle efficiency because we assume that vehicle manufacturers meet Tier 3 tailpipe emissions standards on a mg/mile basis. Therefore, higher efficiency does not reduce the per mile emissions rates. Most air pollutant emissions are tied to VMT, so an increase in demand will directly correspond to an increase in emissions. However, emissions signatures for different fuels are not the same, therefore fuel switching that occurs in some scenarios leads to differences in emissions. CH_4 and CO_2 emissions are directly tied to fuel use thus are affected by efficiency measures.

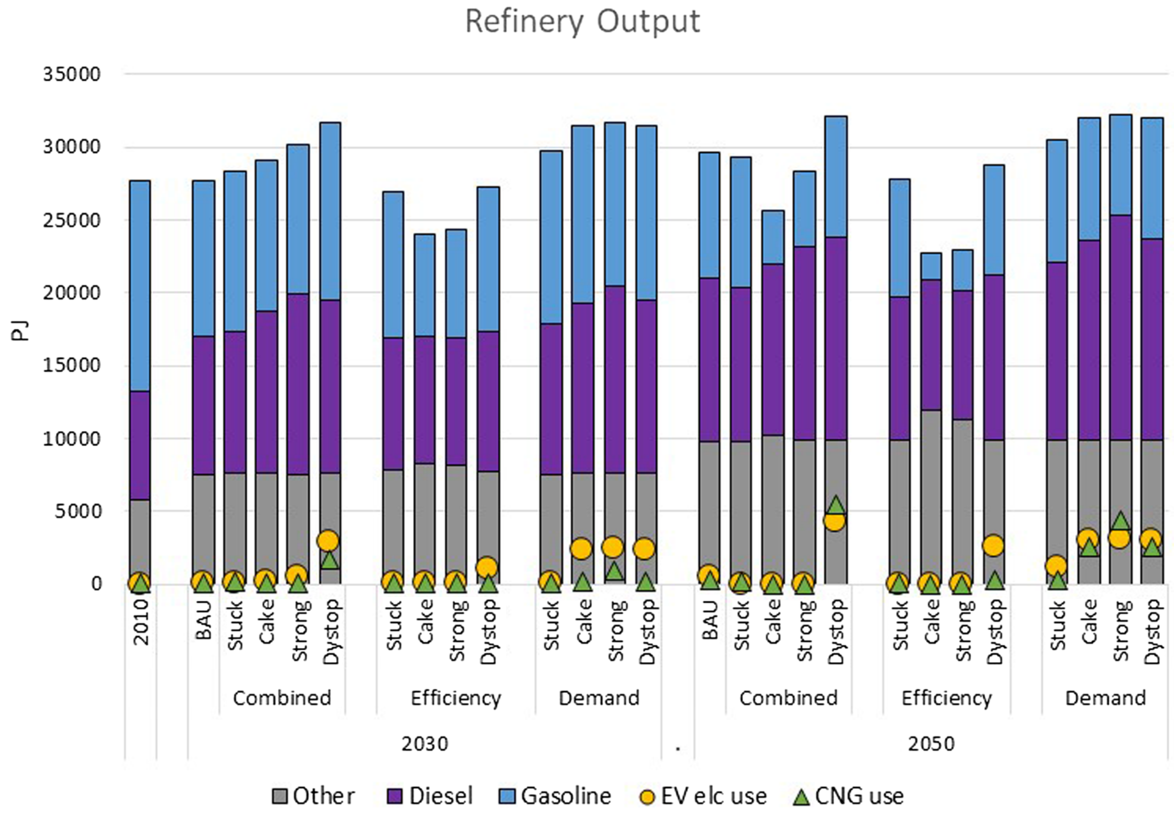

Fig. 5. Output of refinery products for various scenarios presented as stacked bars. EV elc (electricity) use and CNG use are not petroleum products but are presented to help illustrate trends in fuel switching. Other petroleum products include distillates, feedstock, petroleum coke, jet fuel, fuel oil, LPG, and asphalt.

Transportation-related emissions in 2050 from each scenario are presented in Fig. 6. In 2014, more than half of U.S. NO_x was emitted from transportation (EPA, 2015), so changes in transportation NO_x can significantly impact overall environmental burden. Variations in NO_x emissions are most heavily impacted by HDV, specifically total VMT driven using diesel. Increasing VMT from non-electric LDVs also increases NO_x emissions. Thus, *Stuck* has the lowest 2050 NO_x emissions because that scenario has the least demand. For *Cake* and *Strong*, the combined effect scenarios have higher emissions than the demand scenarios, despite using less fuel and traveling the same distance. The VMT for the combined impact and demand cases of a scenario is the same, and emissions are determined by vehicle type and miles driven. High demand without efficiency improvements leads to shifts away from petroleum due to rising prices for refined petroleum products, lowering total NO_x emissions compared to the combined impact cases. In addition to changes directly attributable to the scenarios, there is a large (almost 40%) decrease in NO_x from marine shipping in the combined impact *Dystopian* scenario because of a shift to more efficient diesel ships. This is an example of the type of cross-sector impacts that can be captured in MARKAL, because increases in fuel prices meant that more expensive ships are cost effective due to the reduced need for fuel. Although fleet turnover in shipping is low, this analysis has a long time-frame. Also, MARKAL has perfect foresight, meaning that the operator 'knows' that fuel prices will impact their future business. The magnitude of this cross-sector impact may be overestimated in MARKAL, but the insight that automation will have wide-ranging impacts is likely to hold true.

Only a small fraction of SO_2 emissions are from transportation (EPA, 2015). The largest change in total energy-related SO_2 emissions relative to BAU in 2050 is 4%. Changes in direct SO_2 emissions are up to 9 kt higher than BAU, as shown in Fig. 6. Transportation-related SO_2 changes are driven by indirect emissions associated with electricity generation for EVs and are small relative to other sources of SO_2. Scenarios with high vehicle electrification have higher transportation related SO_2 emissions because SO_2 emissions associated with electricity generation are higher than those associated with vehicles.

Because CO_2 emissions are directly tied to fuel use, they exhibit the most variation among scenarios. CO_2 reductions are driven by the large efficiency improvements in some scenarios. Demand is still important for CO_2, and expanded demand leads to greater emissions due to increases in fuel use. The CO_2 results echo the fuel use results (Figs. 3 and 4), which is expected based on the ASIF framework. Over a quarter of U.S. GHG emissions in 2015 (EPA, 2017) came from transportation, so changes in transportation emissions can be important to overall emissions levels.

Methane (CH_4) emissions also vary across scenarios. Fig. 7 presents the emissions results graphically. Almost all CH_4 emissions are upstream, therefore we evaluate changes across the whole energy system. Increases related to transportation could be associated with either CNG vehicles or EVs, as natural gas produces 38–60% of electricity in 2050, depending on the scenario. When efficiency is

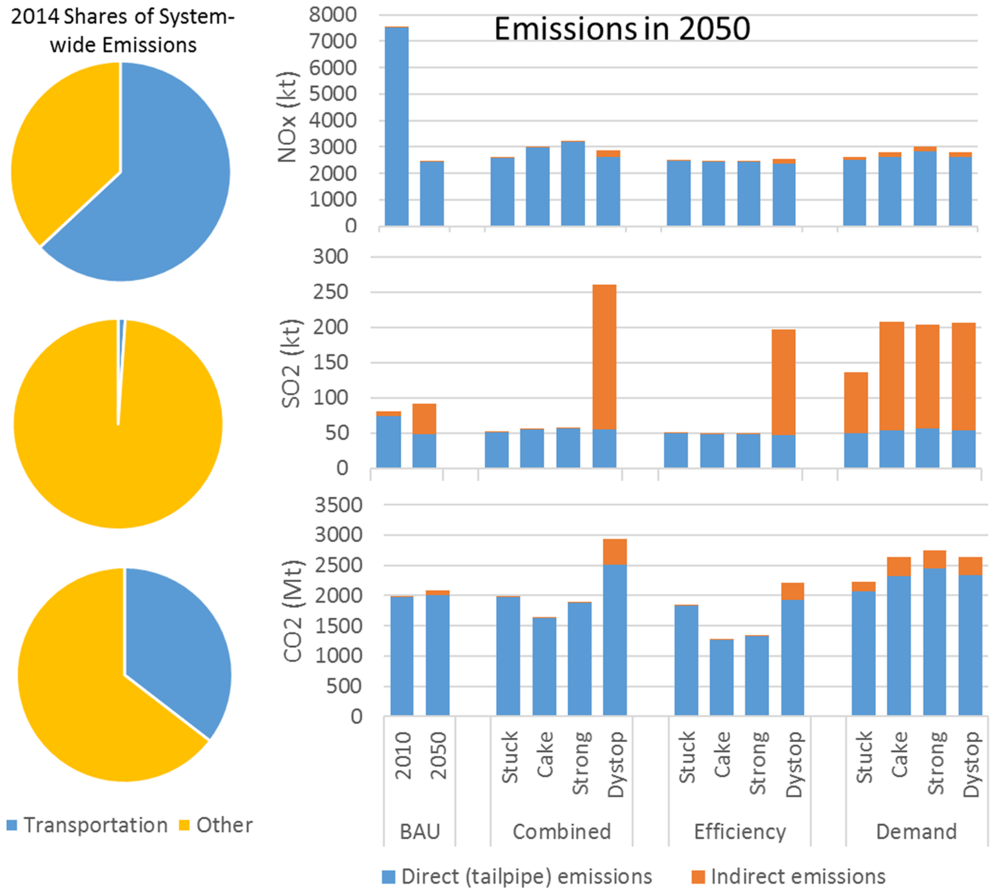

Fig. 6. Transportation related emissions of three pollutants of concern in 2050 for a range of automated futures. Direct emissions refer to tailpipe emissions from vehicles while indirect emissions are those that occur at power plants but are associated with electricity use in vehicles. This does not include full life cycle emissions such as those associated with vehicle manufacturing or disposal. To provide context, the pie charts show the proportion of 2014 energy-related emissions that come from the transportation sector based on the National Emissions Inventory (EPA, 2015). The BAU emissions in model years 2010 and 2050 are shown for reference, as well.

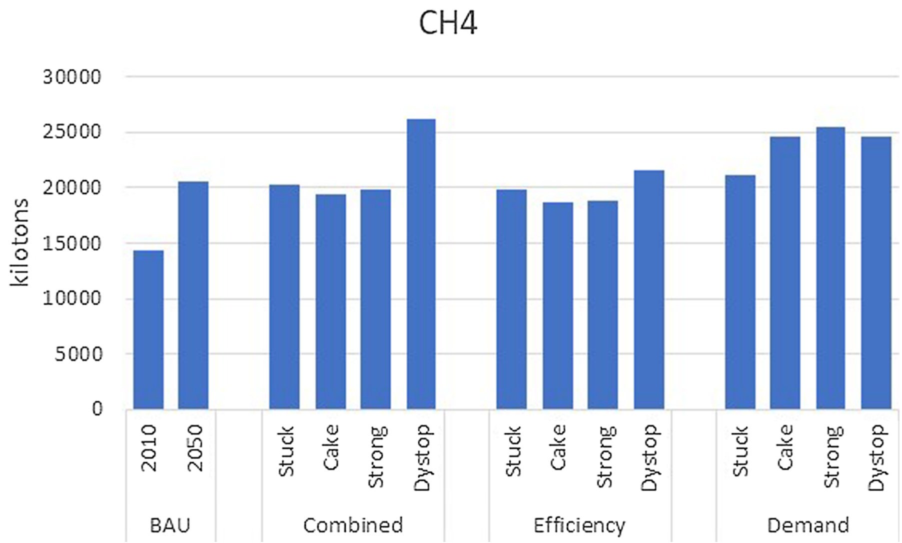

Fig. 7. Methane (CH_4) emissions in 2050 from the US energy system.

improved (alone or combined with demand) in the *Stuck*, *Cake*, and *Strong* scenarios, CH_4 emissions decrease because there are fewer electric and CNG vehicles than for BAU. There are increases in CH_4 from BAU in all *Dystopian* scenarios. The largest increases occur in the combined scenario, where 27% more CH_4 is released in 2050 compared to BAU. In all scenarios with increased demand only, CH_4 emissions are greater than BAU.

As shown in the appendix (Figs. A1–A4), the relative ranking of scenarios from highest to lowest for direct emissions of volatile organic compounds (VOC), particulate matter (PM), organic carbon (OC), and black carbon (BC) is similar. Some pollutants vary more than others, but the perturbations are similar as they are all based on VMT and fuel type. We evaluate total transportation emissions. Therefore, the impact of vehicle automation on transportation emissions is influenced by the share of emissions originating from highway transport. For example, at most 20% of BC is emitted from road vehicles, so the perturbations are smaller as a percentage of the total transportation emissions. The combined impact scenarios for *Strong* and *Cake* have higher emissions than the other scenarios because these scenarios have the largest quantity of combustion driven VMT.

4.5. Regionality

Depending on which vehicle types and fuels are adopted in a region, these scenarios could lead to either an increase or decrease in regional air pollutant emissions. The proportion of EVs is quite uniform across all nine regions in the four automation scenarios, with a slightly lower percentage of EVs in regions 1 and 9. This may be due to stringent renewable portfolio standards (RPS) in region 9 (the West Coast) that make expansion of the grid for a very large increase in EV use more expensive than in other regions. In all scenarios including BAU, biofuel vehicles are concentrated in region 3, the Midwest, with some biofuel vehicles in the adjacent regions 4 and 6. Most ethanol is produced from crops grown in this portion of the country. When CNG vehicles are used, penetration varies among regions, with 28–36% of VMT in regions 3, 4, 7, and 8 using CNG in the Dystopian combined scenario in 2050. All eastern regions have less than 15% of vehicles running on CNG, and the west coast has no CNG vehicles. Natural gas prices vary regionally due to availability and transportation required to access natural gas. Fig. A5 represents fuel use by region. Future work could more closely examine the differential regional air quality impacts from shifts in vehicle emissions as well as upstream emissions for fuels and electricity.

4.6. Comparison

Fig. 8 compares our results to those predicted by Wadud et al. (2016). They predicted percentage changes in fuel use and CO_2 emissions due to assumed changes in demand and efficiency but did not consider fuel switching as part of their implementation of the ASIF equation. As a result, percent changes in fuel use resulted in the same percent changes in CO_2 emissions. The bars in Fig. 8 only account for direct roadway emissions, not upstream or other transportation emissions. Considering upstream emissions related to biomass carbon uptake or electricity generation could shift these values.

The modeling work described in this paper includes additional mechanisms by which the future transportation system can diverge from a BAU scenario. When implementing the scenarios in a full energy system model, the general pattern and the direction of changes match those predicted in Wadud et al. However, the shifts in both fuel use and CO_2 emissions projected in MARKAL tend to

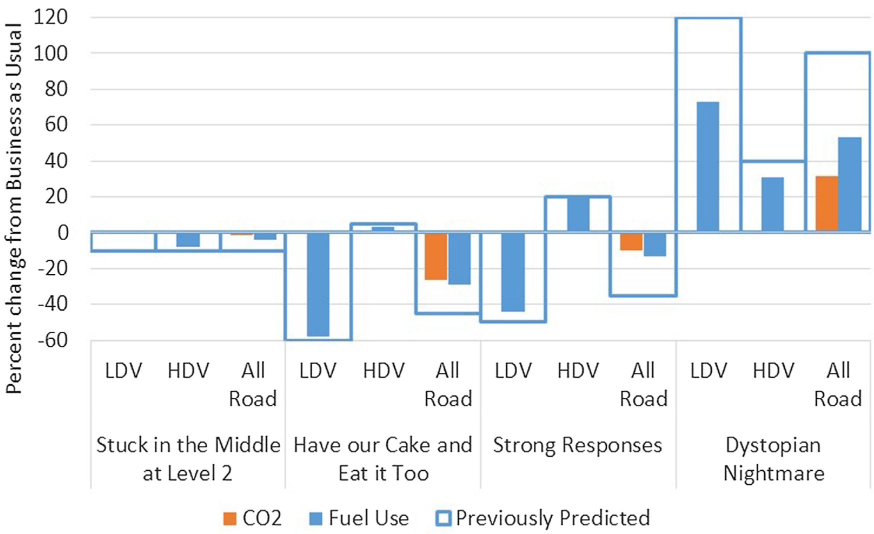

Fig. 8. A comparison of percentage changes from the BAU to the four scenarios with vehicle automation. Changes in fuel use and roadway CO_2 emissions are presented and compared against the predicted percent change from the original Wadud et al. (12) scenario results. The outline corresponds to both the bars within it because the methodology in Wadud et al. leads to equivalent changes in CO_2 and fuel use. These are comparisons in 2050 assuming full AV penetration, as was done in Wadud et al. Only tailpipe emissions are considered.

be smaller than those predicted in Wadud et al. Since MARKAL results have substantially smaller changes in CO_2 emissions compared to MARKAL fuel use, fuel switching appears to be an important component in calculating CO_2 emissions changes. This is because high demand scenarios shift toward lower carbon fuels, reducing emissions, while low demand scenarios use even less low carbon fuels than the BAU. The fuel use changes are also smaller than predicted in Wadud et al. The discrepancy in fuel use is strongest for Dystopian where vehicle choices are much different from BAU. There may be a shift toward purchasing more efficient vehicles if high fuel demand increases the cost of fuels. Although ASIF may describe changes to vehicle types, other economic factors captured in MARKAL can drive consumer choices to reduce the impact of automation.

Differences in fuel use may also be due to different baseline assumptions for heavy- versus light-duty vehicle demands since the LDV and HDV percentages match more closely than the All Road percentages. This difference is an example of why using multiple modeling techniques is important to illuminate where projections may be dependent on underlying assumptions or modeling methodologies. Additionally, the changes modeled in MARKAL for all parameters are smaller than predicted by Wadud et al. in *Dystopian*, where accounting for fuel cost and allowing fuel switching leads to a feedback effect that decreases the impacts compared to the ASIF model. These insights illustrate the benefits of using a modeling framework that captures system-wide effects. The suite of vehicles available is the same in all scenarios, including BAU. It is possible that as advances in automation occur, vehicle offerings would also change. As a result, we may be underestimating fuel switching.

5. Conclusions

Automation may increase or decrease fuel use depending on how automation affects vehicle efficiency, demand, and shifts in vehicle and fuel type. We expect that the changes to these attributes will be sufficiently large that the surrounding system cannot be assumed to remain static. Capturing feedbacks between the broader energy system and the transportation sector (e.g. via fuel supply and price) is an important factor in this analysis and was modeled dynamically with the MARKAL model. The fuel and vehicle parameters are important determinants of overall fuel use and emissions. The results of these modeled scenarios can be used to help determine potential unintended consequences of vehicle automation, and thus inform future policy responses to address negative impacts.

Many of our modeling results were as expected, but some surprises were revealed as well. Without strong impacts on the driving experience (i.e., VMT changes), the impact of automation on energy and emissions is small. However, when demand for travel is high, fuel prices increase, which can mitigate the rise in energy use by inducing shifts in fuel and vehicle type. The *Cake* and *Strong* scenarios exhibit counterintuitive results for criteria pollutant emissions: improved efficiency increases emissions by reducing the use of alternative vehicles. Because most air pollutants are determined only by vehicle type and miles traveled (based on the assumption that conventional vehicles emit at the standards), scenarios with the same demand for travel and more conventional vehicles have higher emissions.

These results should be considered in future technology and policy development, to ensure that the benefits of automated vehicles can be realized while minimizing negative impacts on human health and the environment. These results indicate that demand is an important driver for energy use and emissions. We did not model pricing structures or policy restrictions that could target the drivers of demand such that high levels of automation do not lead to harmful increases in air pollution. Decreased cost of time leads to an increase in emissions, but an increased monetary cost or a high level of vehicle sharing could reduce negative impacts associated with this. Changes associated with automated vehicles impact not only air quality and climate policy, but also fuel taxes. Based on the fuel switching and demand changes here, it will be important to consider not only the value of fuel taxes, but the entire framework around vehicle fees, as discussed in Leiby and Rubin (2018). Another important finding of this paper relates to adoption of alternative fuels. Only the very high demand scenarios in this analysis prompted increases in alternative fuels and electrification, meaning if increasing the use of alternative fuels is a specified goal, additional policy mechanisms may be required and were not modeled here. Society should not assume that automation will necessarily lead to an increase in alternatively fueled vehicles. This coordination has often been assumed in previous studies, "but environmental and energy imperatives are NOT what's motivating [vehicle automation]" (Greenwald and Kornhauser, 2019). It is important to realize that the various transportation revolutions may not all advance at either a unified pace or in a coordinated manner. Although many observers anticipate or hope that technology advancement will reduce emissions, the results of this analysis reinforce that emissions reductions are usually driven by policy while other consumer preferences, such as comfort and cost, are primarily market driven.

Further work is warranted on this topic. Although these results include significant shifts in the vehicle fuel source due to energy system feedbacks, there are additional reasons why automation might accelerate fuel shifting, in particular, vehicle electrification (Weiss et al., 2017). Factors could include consumer choice, vehicle compatibility between EVs and automation, battery requirements for AV features, and automation allowing driverless charging.

Assumptions about the timing of the shift toward automation and when efficiency and demand impacts would occur, should also be refined. We have assumed all changes start immediately and progress quickly and linearly. Different scenarios are likely to achieve their ultimate impact along different timelines, and some benefits may occur faster than others. For instance, platooning may require that most vehicles on the road are autonomous and can communicate before benefits are achieved, whereas many eco-driving benefits can be immediately realized on any vehicle with the required technology. Determining how energy systems models can characterize changes impacting a portion of new vehicles (e.g. increased features) as well as changes that impact the entire on-road fleet (e.g. congestion mitigation) is an area for future study. The penetration levels discussed in Bush et al. (2019) present another characteristic that may be studied in conjunction with timing. Further in the future, even deeper levels of automation, such as those discussed in Vahidi and Sciarretta (2018) may lead to larger impacts that considered here. Future work will continue to examine these upper and lower bounds of mechanisms that impact energy efficiency and travel demand.

Results presented here may be limited by current model representation of refinery flexibility and outputs. The petroleum industry may be able to evolve to produce the needed products under a very different demand regime. Yet, these changes may lead to additional impacts on emissions and fuel prices. This analysis illustrates the need for research to assess the changing air emissions impacts of different levels of crude throughput, fuel product mix, and associated refinery configurations (Young et al., 2019). The possibility of large shifts also reveals places where manufacturers of alternative fuels or energy storage devices can focus their efforts to maximize the competitiveness of their own technology. These results indicate that a shift in fuel demand and fuel mix is likely with automated vehicles, but how that shift plays out may vary based on how mature different technologies are at the time of the divergence as well as how well those technologies integrate with vehicle automation. For instance, fuel cell technologies are comparatively underdeveloped relative to other mobile technologies, which is why they do not appear in these results. However, it is possible these vehicles would integrate well with automation. If the technology were to develop faster than assumed in this modeling exercise, those vehicles might become major players in a future automated vehicle market.

6. Disclaimer

The views expressed in this article are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency.

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.

Appendix A

Emissions results presented in the appendix represent the transportation sector only (tailpipe). Emissions represented are for 2050 unless otherwise indicated.

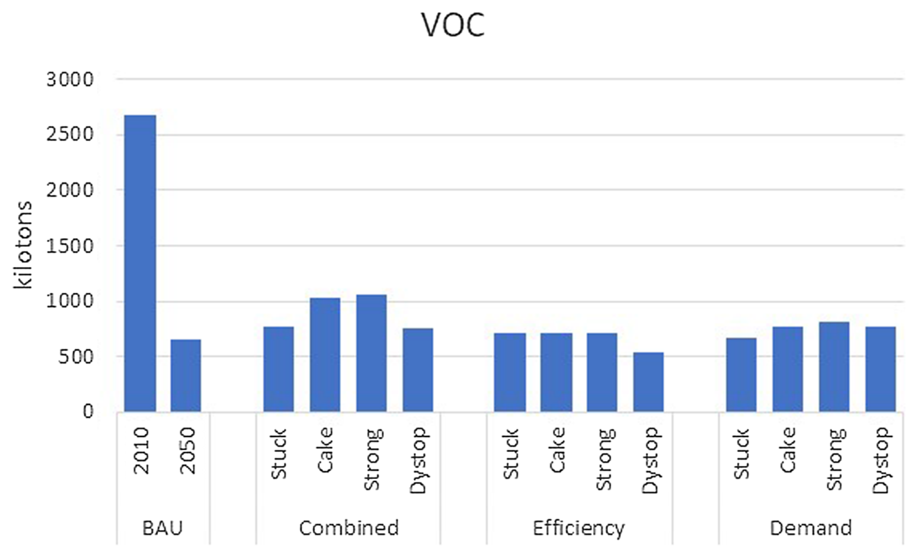

Fig. A1. VOC emissions in 2050 from the transportation sector.

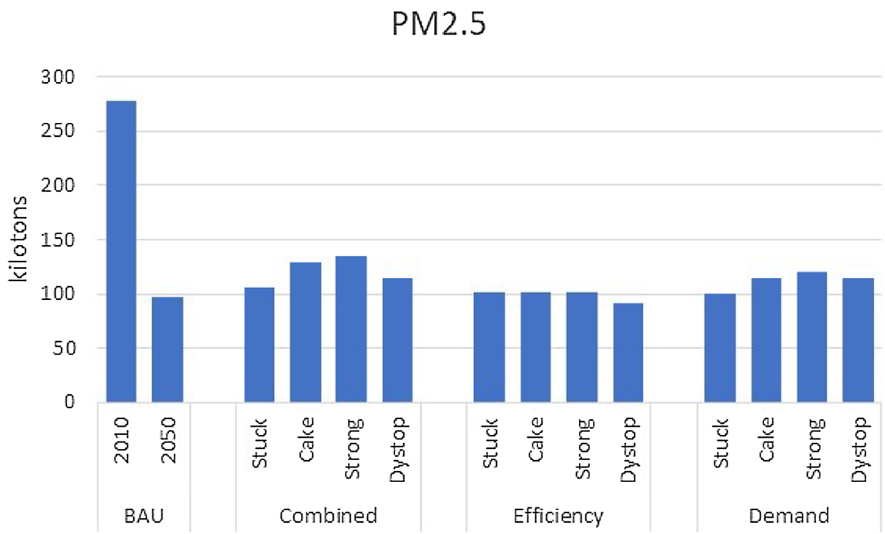

Fig. A2. $PM_{2.5}$ emissions in 2050 from the transportation sector.

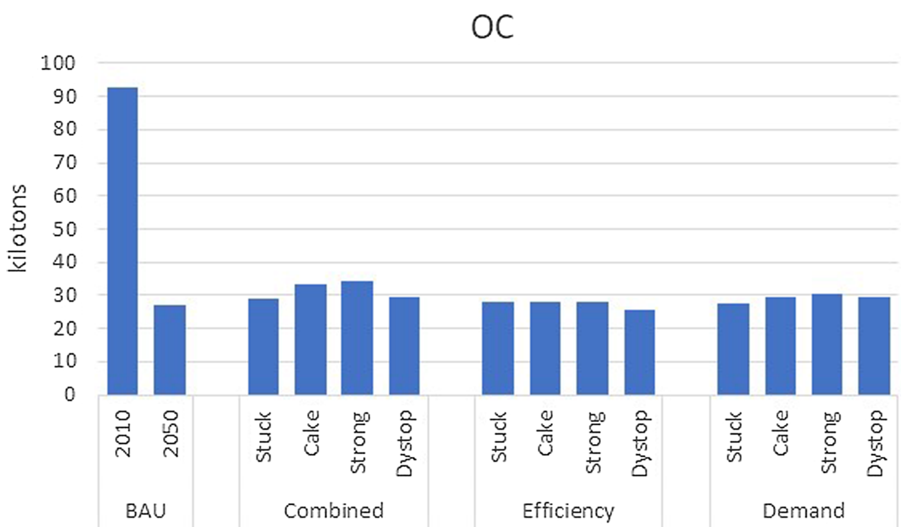

Fig. A3. Organic Carbon emissions in 2050 from the transportation sector.

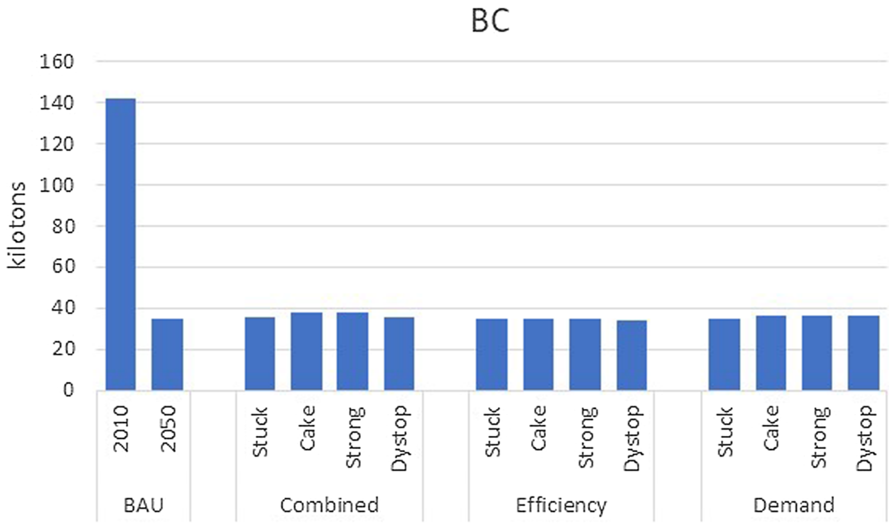

Fig. A4. Black carbon emissions in 2050 from the transportation sector.

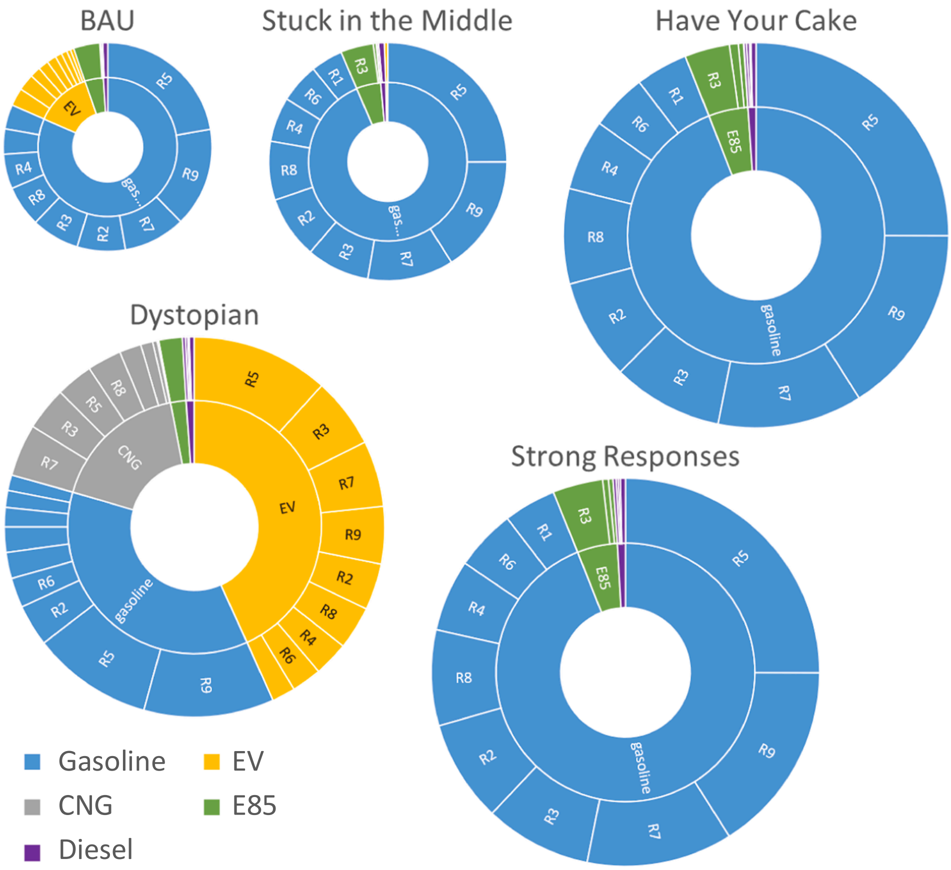

Fig. A5. Miles traveled by light duty vehicles represented by region and fuel type. The BAU case does not include automated vehicles and the four *combined* scenario results are represented. The size of the circle is scaled by total VMT in each case, and slice size represents VMT using a particular fuel in a particular region.

References

Aitken, M.L., Loughlin, D.H., Dodder, R.S., Yelverton, W.H., 2016. Economic and environmental evaluation of coal-and-biomass-to-liquids-and-electricity plants equipped with carbon capture and storage. Clean Technol. Environ. Policy 18, 573–581. https://doi.org/10.1007/s10098-015-1020-z.

Anderson, J.M., Kalra, N., Stanley, K.D., Sorensen, P., Samaras, C., Oluwatola, O.A., 2016. Autonomous Vehicle Technology: A Guide for Policymakers. RAND Corporation, Santa Monica, CA. https://www.rand.org/pubs/research_reports/RR443-2.html (accessed August 15, 2018).

Babaee, S., Nagpure, A.S., Decarolis, J.F., 2014. How much do electric drive vehicles matter to future U.S. emissions? Environ. Sci. Technol. 48, 1382–1390. https://doi.org/10.1021/es4045677.

Brown, A., Gonder, J., Repac, B., Meyer, G., Beiker, S., 2014. Road vehicle automation. In: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation. Springer, Cambridge.

Brown, K.E., Henze, D.K., Milford, J.B., 2013. Accounting for climate and air quality damages in future U.S. electricity generation scenarios. Environ. Sci. Technol. 47, 3065–3072. https://doi.org/10.1021/es304281g.

Brown, K.E., Henze, D.K., Milford, J.B., 2017. How accounting for climate and health impacts of emissions could change the US energy system. Energy Policy 102, 396–405. https://doi.org/10.1016/j.enpol.2016.12.052.

Brown, K., Hottle, T., Bandyopadhyay, R., Babaee, S., Dodder, R., Kaplan, P., Lenox, C., Loughling, D., 2018. Evolution of the United States energy system and related emissions under varying social and technological development paradigms: plausible scenarios for use in robust decision making. Environ. Sci. Technol. 52 (14), 8027–8038. https://doi.org/10.1021/acs.est.8b00575.

Bush, B., Vimmerstedt, L., Gonder, J., 2019. Potential energy implications of connected and automated vehicles: exploring key leverage points through scenario screening analysis. Transp. Res. Rec 0361198119838840.

Cox, B., Mutel, C.L., Bauer, C., Mendoza Beltran, A., van Vuuren, D.P., 2018. Uncertain environmental footprint of current and future battery electric vehicles. Environ. Sci. Technol. 52, 4989–4995. https://doi.org/10.1021/acs.est.8b00261.

Decarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., 2017. Formalizing best practice for energy system optimization modeling. Appl. Energy 194, 184–198. https://doi.org/10.1016/j.apenergy.2017.03.001.

EIA, U.S., 2005. Household Vehicles Energy Use. DOE/EIA-0464(2005), Washington, DC. https://www.eia.gov/consumption/residential/pdf/046405.pdf (accessed January 12, 2014).

EIA, U.S., 2015. Annual Energy Outlook 2015 with projections to 2040. Annual Energy Outlook. US Energy Information Administration, Washington, DC.

EIA, U.S., 2016. Annual Energy Outlook 2016. Anual Energy Outlook. Energy Information Administration, Washington, DC.

EIA, U.S., 2017. Study of the Potential Energy Consumption Impacts of Connected and Automated Vehicles. U.S. Department of Energy, Washington, DC. https://www.eia.gov/analysis/studies/transportation/automated/pdf/automated_vehicles.pdf (Accessed June 3, 2018).

EIA, U.S., 2018. Autonomous vehicles: uncertainties and energy implications. Issues in Focus from the Annual Energy Outlook 2018. Department of Energy, Washington, DC.

EPA, U.S., 2013. ICLUS Integrated Climate and land-Use Scenarios. https://www.epa.gov/iclus/iclus-downloads#tab-1 (accessed January 12, 2016).

EPA, U.S., 2014. MOVES2014b Latest Version of Motor Vehicle Emission Simulator November 2015. https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves (accessed December 14, 2015).

EPA, U.S., 2014. Control of Air Pollution from Motor Vehicles: Tier 3 Motor Vehicle Emission and Fuel Standards. RIN 2050-AQ86. Washington, DC: FR 2014-04-28.

EPA, U.S., 2015. National Emission Inventory (NEI) Air Pollutant Emission Trends Data. Available: https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data.

EPA, U.S., 2017. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2015. US Environmental Protection Agency, Washington, D.C.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part A: Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp. Res. Part C Emerg. Technol. 40, 1.

Gamas, J., Dodder, R., Loughlin, D., Gage, C., 2015. Role of future scenarios in understanding deep uncertainty in long-term air quality management. J. Air Waste Manage. Assoc. 65 (11), 1327–1340. https://doi.org/10.1080/10962247.2015.1084783.

Gawron, J., Keoleian, G., de Kleine, R., Wallington, T., Kim, H., 2018. Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects. Environ. Sci. Technol. 52 (5), 3249–3256. https://doi.org/10.1021/acs.est.7b04576.

Greenblatt, J., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. Nat. Clim. Change 59 (9), 860.

Greenblatt, J.B., Shaheen, S., 2015. Automated vehicles, on-demand mobility, and environmental impacts. Curr. Sustain. Renew. Energy Rep. 2, 74–81. https://doi.org/10.1007/s40518-015-0038-5.

Greenwald, J.M., Kornhauser, A., 2019. It's up to us: policies to improve climate outcomes from automated vehicles. Energy Policy 127, 445–451.

Hula, A., Snapp, L., Alson, J., Simon, K., 2018. The environmental potential of autonomous vehicles. In: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation 4. Springer International Publishing, Cham.

Iacobucci, R., McLellan, B., Tezuka, T., 2018. Modeling shared autonomous electric vehicles: potential for transport and power grid integration. Energy 158, 148–163. https://doi.org/10.1016/j.energy.2018.06.024.

Jones, E., Leibowicz, B., 2019. Contributions of shared autonomous vehicles to climate change mitigation. Transp. Res. Part D: Transp. Environ. 72, 279–298. https://doi.org/10.1016/j.trd.2019.05.005.

Keshavarzmohammadian, A., Henze, D.K., Milford, J.B., 2017. Emission impacts of electric vehicles in the US transportation sector following optimistic cost and efficiency projections. Environ. Sci. Technol. 51, 6665–6673. https://doi.org/10.1021/acs.est.6b04801.

Leiby, P., Rubin, J., 2018. Efficient fuel and VMT taxation for automated vehicles. Transportation Research Board 97th Annual Meeting, Washington, DC. No. 18-05439.

Lenox, C., Dodder, R., Gage, C., Loughlin, D., Kaplan, O., Yelverton, W., 2013. EPA US Nine-region MARKAL Database: Database Documentation. US EPA, Cincinnati, OH.

Lenox, C., Loughlin, D., 2017. Effects of recent energy system changes on CO_2 projections for the United States. Clean Technol. Environ. Policy 19 (9), 2277–2290. https://doi.org/10.1007/s10098-017-1417-y.

Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Transp. Res. Part C: Emerg. Technol. 89, 222–233. https://doi.org/10.1016/j.trc.2018.01.019.

Loughlin, Daniel H., Kaufman, Katherine R., Lenox, Carol S., Hubbell, Bryan J., 2015. Analysis of alternative pathways for reducing nitrogen oxide emissions. J. Air Waste Manage. Assoc. 65 (9), 1083–1093. https://www.tandfonline.com/doi/full/10.1080/10962247.2015.1062440https://doi.org/10.1080/10962247.2015.1062440.

Loulou, R., Goldstein, G., Noble, K., 2004. Documentation for the MARKAL Family of Models. Energy Technology Systems Analysis Programme, Paris, France.

Miller, S.A., Heard, B.R., 2016. The environmental impact of autonomous vehicles depends on adoption patterns. Environ. Sci. Technol. 50, 6119–6121. https://doi.org/10.1021/acs.est.6b02490.

NHTSA, EPA, U.S., 2012. 2017 and later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards. RIN 2060–AQ54; RIN 2127–AK79, Washington, DC: FR-2012-10-15.

NHTSA, 2017. Automated Driving Systems 2.0: A Vision for Safety. Department of Transportation. https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/13069a-ads2.0_090617_v9a_tag.pdf (accessed November 15, 2018).

Rodier, C., 2018. Travel Effects and Associated Greenhouse Gas Emissions of Automated Vehicles. National Center for Sustainable Transportation, UC Davis. https://escholarship.org/uc/item/9g12v6r0 (accessed June 19, 2019).

Rojas-Rueda, D., Nieuwenhuijsen, M., Khreis, H., 2017. Autonomous vehicles and public health: literature review. J. Transp. Health 5, S13. https://doi.org/10.1016/j.jth.2017.05.292.
Rudokas, J., Miller, P.J., Trail, M.A., Russell, A.G., 2015. Regional air quality management aspects of climate change: impact of climate mitigation options on regional air emissions. Environ. Sci. Technol. 49, 5170–5177. https://doi.org/10.1021/es505159z.
Schipper, L., 2002. Sustainable urban transport in the 21st century: a new agenda. Transp. Res. Rec. J. Transp. Res. Board 1792, 12–19. https://doi.org/10.3141/1792-02.
Simon, K., Alson, J., Snapp, L., Hula, A., 2015. Can transportation emission reductions be achieved autonomously? Environ. Sci. Technol. 49, 13910–13911. https://doi.org/10.1021/acs.est.5b05396.
Sperling, D., 2018. Three Revolutions: Steering Automated, Shared and Electric Vehicles to a Better Future. Island Press.
Stephens, T.S., Gonder, J., Chen, Y., Lin, Z., Liu, C., Gohlke, D., 2016. Estimated Bounds and Important Factors for Fuel Use and consumer Costs fo Connected and Automated Vehicles. Energy, D.O. (ED.). United States. https://doi.org/10.2172/1334242.
Taiebat, M., Brown, A., Stafford, H., Qu, S., Xu, M., 2018. A review on energy, environmental, and sustainability implications of connected and automated vehicles. Environ. Sci. Technol. 52 (20), 11449–11465.
Thompson, T.M., Rausch, S., Saari, R.K., Selin, N.E., 2014. A systems approach to evaluating the air quality co-benefits of US carbon policies. Nat. Clim. Change 4, 917.
Vahidi, A., Sciarretta, A., 2018. Energy saving potentials of connected and automated vehicles. Transp. Res. Part C: Emerg. Technol.
Wadud, Z., Mackenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part A: Pol. Pract. 86, 1–18. https://doi.org/10.1016/j.tra.2015.12.001.
Wang, A., Stogios, C., Gai, Y., Baughan, J., Ozonder, G., Lee, S., Posen, I., Miller, E., Hatzopoulou, M., 2018. Automated, electric, or both? Investigating the effects of transportation and technology scenarios on metropolitan greenhouse gas emissions. Sustain. Cities Soc. 40, 524–533. https://doi.org/10.1016/j.scs.2018.05.004.
Weiss, J., Hledik, R., Lueken, R., Lee, T., Gorman, W., 2017. The electrification accelerator: understanding the implications of autonomous vehicles for electric utilities. Electr. J. 30, 50–57. https://doi.org/10.1016/j.tej.2017.11.009.
Young, B., Hottle, T., Hawkins, T., Jamieson, M., Cooney, G., Motazedi, K., Bergerson, J., 2019. Expansion of the petroleum refinery life cycle inventory model to support characterization of a full suite of commonly tracked impact potentials. Environ. Sci. Technol. 53 (4), 2238–2248.

Glossary

AEO: Annual Energy Outlook
AV: Automated Vehicle
BAU: Business as Usual
CAV: Connected and Automated Vehicles
CH_4: Methane
CNG: Compressed Natural Gas
CO_2: Carbon Dioxide
E85: Gasoline and ethanol mixture with 85% ethanol
EIA: Energy Information Administration
EPA: Environmental Protection Agency
EPAUS9r: The nine-region database used in the MARKAL model
EV: Electric Vehicle
GHG: Greenhouse Gas
HDV: Heavy Duty Vehicle
LDV: Light Duty Vehicle
LPG: Liquified Petroleum Gas
MARKAL: MARKet ALlocation energy system model
NEMS: National Energy Modeling System
NO_x: Nitrogen Oxides
PJ: Petajoules
PM_{10}: Particulate Matter less than 10 μm in diameter
$PM_{2.5}$: Particulate Matter less than 2.5 μm in diameter
SUV: Sport Utility Vehicle
VMT: Vehicle Miles Traveled
VOC: Volatile Organic Compounds