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

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Introduction

Researchers have examined the impacts of vehicle automation on energy use and environmental outcomes (1-5). Energy and emissions changes from vehicle automation have been examined within the broader context of what have been called the "Three Revolutions": automated vehicles (AVs), shared vehicles, and electric vehicles (EVs) (6-10). In 2014, Brown, Gonder, and Repac (11) was one of the early studies examining changes in energy use and carbon emissions. Given the high range of uncertainty, their goal was to estimate the "upper-bound effects" of a range of impacts, both positive and negative. Wadud, MacKenzie and Leiby (12) extended this approach by adding ranges of estimates for the same factors identified by Brown et al., and by considering additional factors (12).

While these studies have estimated ranges of impacts on fuel use and emissions, we are not aware of modeling studies looking explicitly at the effects of vehicle automation on the broader U.S. energy economy. Traditionally, energy system models are adept at developing projections that consider alternative assumptions about factors such energy prices and economic growth (e.g., AEO (13) side cases), specific policy measures or mitigation strategies (14-16), and technology adoption under varying assumptions about cost and performance (17, 18).

For this paper, the focus is on the broader energy system impacts of AVs. The goal is to assess the extent of "knock-on effects" across sectors, focusing on the electric power and petroleum refinery sectors (19). Full energy system models are structured to capture these upstream effects on fuel supply markets due to changes in demands. We take a scenario-based approach that allows us to scope out a range of impacts and identify areas for future work. We apply key outcomes (e.g., net vehicle miles traveled (VMT) changes, efficiency) from those studies within a broader energy systems modeling framework.

Methodology

This study utilizes the MARKAL (MARKet ALlocation) model, an energy system optimization model that simulates the evolution of the energy technology and fuel mix over multiple decades (20). For this analysis, the focus is on light-duty vehicle (LDV) and heavy-duty vehicle (HDV) travel demands, vehicle technology choices, and fuels. One of the benefits of using this model relative to a transportation-only model is that interactions with non-transportation sectors can be simulated dynamically. 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.

For this analysis, we use the EPAUS9r database developed by the U.S. Environmental Protection Agency (EPA) to represent the U.S. energy system for a time horizon of 2005-2055 with 5-year time steps. Full documentation of the database and data sources for modeling inputs is available at Lenox et al. (21). While the EPAUS9r database includes 9 regions (U.S. Census Divisions), results here are shown only at the national level. We use version EPAUS9r_v16.1.0 of the database, which is calibrated to the 2016 Annual Energy Outlook (AEO).

The model solves endogenously for the use of gasoline, diesel, and alternative fuels such as biomass-based fuels, compressed natural gas (CNG), and electricity within the transportation sector, considering the projected evolution of vehicle technologies. The HDV and LDV sectors together determine the demands for transportation fuels, but also compete with other end-use demand sectors for refined petroleum products, natural gas, and electricity.

Given the high level of uncertainty surrounding future transportation demands and technologies, an analysis of how vehicle automation will impact the future energy system is best addressed through scenario analysis. Wadud et al. (12) reviewed several possible impacts of automated vehicles on the transportation system. The scenario definition is structured around the "ASIF" method of estimating changes in carbon emissions from transportation (22). This framework is summarized in Equation (1).

Emissions = **A**ctivity Level * Modal **S**hare * Energy **I**ntensity * **F**uel Carbon Content (1)

These scenarios focus on quantifying Activity Level and Energy Intensity. 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. (12) proposed ASIF multipliers for mechanisms that may transform the transportation system. The multipliers for individual mechanisms (e.g. car-sharing, congestion, right-sizing) were then aggregated into a demand and an efficiency multiplier for each scenario. Four very different scenarios were developed using these multipliers. The narratives and inputs for each scenario are fully documented in Wadud et al. The scenarios describe a wide range of responses to automation. "*Cake*" reaps nearly all AV emissions benefits without potential drawbacks. "*Stuck*" has a weaker response as regulations do not allow for higher levels of automation. "*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 to increase emissions. *"Dystopian"* represents full automation, which leads to significant changes in the transportation system, often in ways that increase emissions due to an increase in demand.

Table 1 shows the values taken from Wadud et al. and implemented in MARKAL. Travel end-use demand corresponds to Activity Level, and efficiency corresponds to Energy Intensity. The changes were applied as a fractional change multiplied by the values in the business as usual (BAU) future for MARKAL, which is calibrated on AEO projections. Multipliers remain constant after 2030. We also consider a BAU scenario that does not include vehicle automation.

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
Cake	1.2	1.4	1.67
Stuck	1.03	1.07	1.11
Strong	1.2	1.4	1.68
Dystopian	1.2	1.4	1.65

HDV DMD	2020	2025	2030
Cake	1.13	1.26	1.43
Stuck	1.03	1.07	1.11
Strong	1.2	1.41	1.68
Dystopian	1.14	1.27	1.45

LDV eff	2020	2025	2030
Cake	1.30	1.86	4.32
Stuck	1.06	1.12	1.22
Strong	1.26	1.71	3.27
Dystopian	0.91	0.84	0.76

HDV eff	2020	2025	2030
Cake	1.09	1.20	1.39
Stuck	1.05	1.11	1.20
Strong	1.09	1.20	1.39
Dystopian	1	1	1

Findings

Our results are similar to the Wadud et al. scenarios, but also model broader energy system impacts, through "knock-on" effects due to changes in fuel demand and prices. In particular, these results highlight potential implications for refineries, upstream electric power generation, and fuel switching, which are unique contributions of this analysis.

Both quantity and type of fuel differ significantly across the scenarios for LDVs. Figure 1 shows fuel use and type in 2050. Even by 2050, *Stuck* does not diverge substantially from BAU. In *Cake* and *Strong*, efficiency is the main factor affecting LDV fuel use. Nearly all vehicles run on gasoline, but require roughly a third to half of the fuel required for BAU. The *Dystopian* future is driven by high demand and requires much more fuel than any other scenario. This scenario has a much larger adoption rate of alternative fuel vehicles, responding to 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.

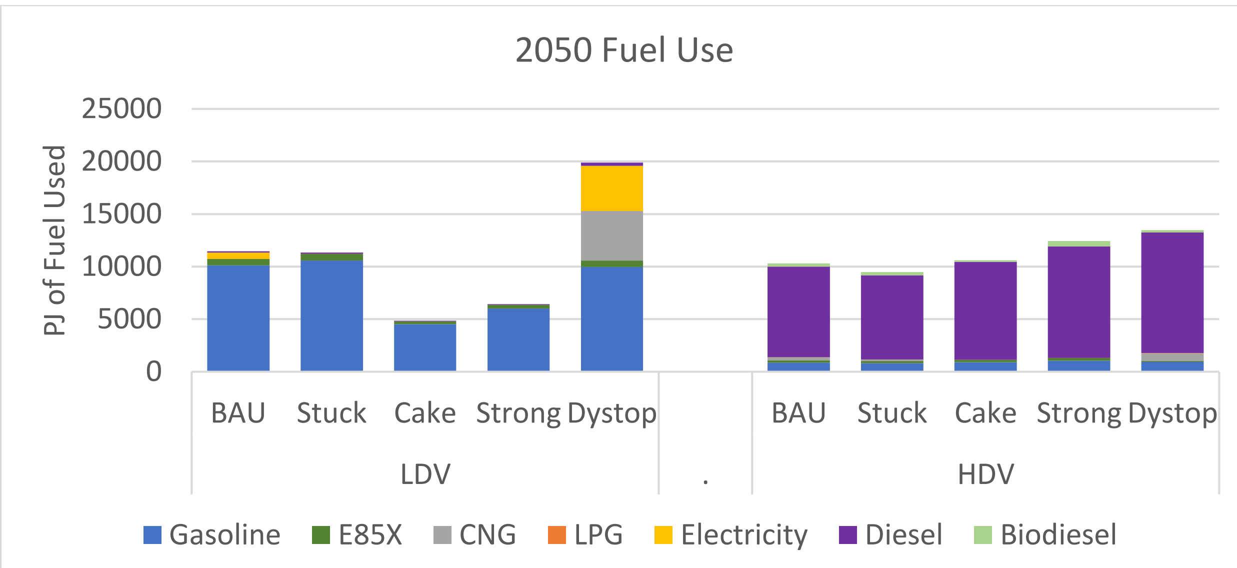

FIGURE 1 Light-duty and Heavy-duty vehicle fuel use in 2050. The combined impact results are shown as well as a BAU result without vehicle automation. E85X represents a fuel blend of ethanol and gasoline such that the ethanol can constitute as much as 85% of the total.

Total fuel demand varies widely across scenarios. In all scenarios, diesel remains the dominant HDV fuel. When demand is large enough, CNG breaks into a larger share of the market.

Due to large changes in demand for petroleum-based transportation fuel, the output from refineries must also undergo changes. Not only are different quantities of oil required from scenario to scenario, but the mix of petroleum products produced by refineries also differs. In scenarios where total refinery output began to exceed 30,000 PJ, there is a shift toward more EV and CNG use. An increase in EV use above this threshold indicates that petroleum-based fuels become sufficiently expensive to warrant an increase in vehicle electrification despite the higher capital cost of EVs.

Figure 2 compares fuel use and emissions results with those predicted by Wadud et al. (12). CO_2 emissions reductions are driven by the large efficiency improvements in *Cake* and *Strong*. Conversely, expanded demand leads to increases in emissions due to rises in fuel use, such as in *Dystopian*. In Wadud et al., the percent change in CO_2 was the same as that of fuel use (represented as a single outlined column in Figure 2). This is expected when using the ASIF framework since fuel switching was not included. In MARKAL, however, the shift away from petroleum and toward more efficient EVs in scenarios like *Dystopian* leads to lower transportation sector emissions and fuel use compared to the results from Wadud et al.

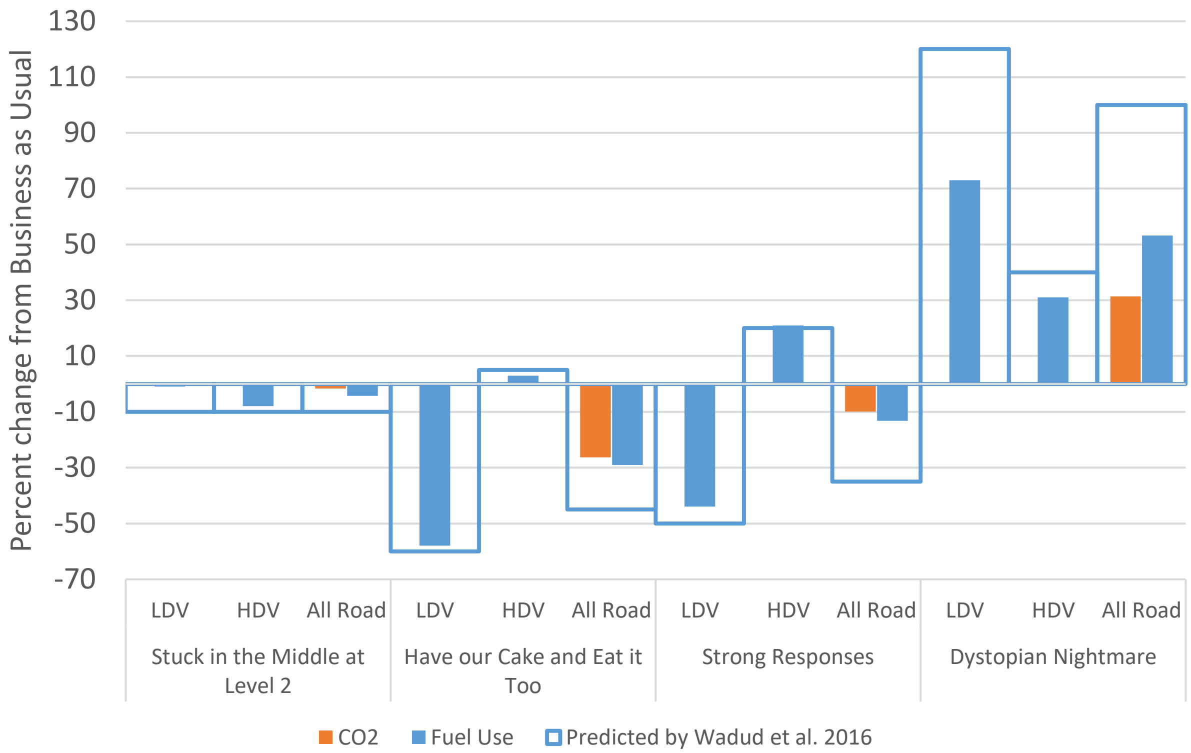

FIGURE 2. A comparison of percentage changes from the BAU to the four vehicle automation scenarios. MARKAL-based changes in fuel use (blue) and roadway CO_2 emissions (orange) are presented for LDV, HDV and both. MARKAL results are compared against the percent change from the original Wadud et al. (12) scenario results, shown as an outline representing both CO_2 and fuel use. These are comparisons in 2050 assuming full AV penetration. Only tailpipe emissions are shown here.

Conclusion

As shown in Figure 2 the percent changes in CO_2 emissions and fuel use for each scenario in Wadud et al. were the same because there was no fuel switching. 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 magnitude of the shifts tends to be smaller when implemented in MARKAL, which captures additional system dynamics. These may include a shift toward purchasing more efficient or alternative-fueled vehicles if high fuel demand increases the cost of petroleum-based fuels.

Differences between these results and those in Wadud et al. may also be due to variations in baseline assumptions for HDV versus LDV demands. Additionally, the final net changes are smaller than predicted in *Dystopian*, where price feedback effects mitigated the large increases in fuel use and emissions relative to those modeled using the ASIF approach. Being able to capture system-wide effects, including upstream changes in the electric sector, refineries, and natural gas supplies illustrates the additional insights that a full energy system modeling framework can provide. This represents an early step in understanding the role of energy system modeling in assessing vehicle automation impacts, by using multipliers to model changes in end-use demands and efficiency for both LDVs and HDVs. Future work remains to develop more detailed characterization of automated vehicles (cost, efficiency, distribution across vehicles classes) and their associated changes in demands.

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