ENERGY IMPLICATIONS OF SELF-DRIVING VEHICLES

Jooyong Lee
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
jylee3302@utexas.edu

Kara M. Kockelman, Ph.D., P.E.
(Corresponding Author)
Dewitt Greer Centennial Professor of Transportation Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu

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ABSTRACT

Despite saving drivers' time and decreasing the number of crashes, connected and self-driving or "autonomous" vehicles (CAVs) will increase vehicle-miles traveled (VMT) and thus will increase congestion, at least for some time. This is due to the potential for non-drivers to travel independently, to empty vehicles repositioning themselves, and to more low-density land development at the periphery of regions. Rising CAV will also impact every nation's energy use.

This paper estimates energy implications of and provides associated policy recommendations of CAVs under different use and technology scenarios. Some aspects of CAVs may deliver net energy savings, while others add energy consumption. Recognizing all vectors of impact, this paper estimates a net energy reduction of 11% to 55% versus the U.S.'s current ground-transportation conditions, depending on CAVs' drivetrain electrification. This work rank-orders the variable energy impacts of different behavioral changes and technologies and recommends the adoption of both CAVs with electric drivetrains to encourage more sustainable self-driving conditions in the United States, even as VMT and congestion rise.

KEYWORDS

Energy consumption; Connected and autonomous; Fully automated vehicle; Self-driving vehicle

INTRODUCTION

Early-stage connected, and semi- or highly-automated vehicles now exist in many cities of the world and are likely to be sold to fleet operators and private households and businesses in the future. These include vehicles with limited automation, such as the Waymo test vehicles, and cars being sold with automated emergency braking and/or lane-keeping assistance. The U.S. National Highway Traffic Safety Administration (NHTSA, 2018) relies on six levels of vehicle automation to facilitate communication in discussions of safety and deployment starting from Level 0, No Automation to Level 5, Full Automation.

Specifically, Level 2 automation refers to vehicle systems that control both steering and speed, assuming human driver performs the dynamic driving task, Level 3 automation assumes the vehicle performs dynamic driving task with the expectation that human driver will respond appropriately when needed, and Level 4 automation refers to vehicle systems that perform all driving tasks even if human driver does not respond appropriately to a request to intervene.. Tesla vehicles driving in "AutoPilot" mode currently fall somewhere between Level 2 and Level 3.

Fully automated and self-driving vehicles (AVs) will allow operators (no longer "drivers") to spend their travel time engaged in social interactions, viewing entertainment, work activities, or even sleeping. Requiring new vehicles to be connected (connected automated vehicles, CAVs) improves AV and existing-vehicle safety through active, high-frequency transmission of vehicle position, speed, direction, and acceleration rates. Self-driving vehicles would change not only the travel patterns, but also the economic structure, the shape of urban cities, and eventually the lifestyle of US citizens. Users of self-driving vehicles would be less reluctant to travel further distances, transportation workers—taxi and truck drivers—might become unemployed, and human and material exchange would increase.

Among the various changes that are anticipated, this paper focuses on energy implications from adoption of self-driving vehicles. CAVs could result in higher energy consumption, or a reduction in energy consumption. For example, while a smoother driving cycle would lower energy consumption, users of CAVs would make also additional trips, which would increase energy consumption. Self-driving vehicles would affect numerous areas related to energy consumption. Research and analysis should be performed to understand the implications of CAVs and establish appropriate energy policies. Since CAVs have not yet reached full market penetration rate (MPR), the information provided in this paper is largely based on a literature review and on simulation results.

This paper is organized as follows: the existing literature related to CAVs is reviewed and each impact that would be affected by the adoption of self-driving vehicles is categorized. Next, a scenario analysis is presented about potential changes in fuel consumption based on the rate of increase in market penetration of self-driving vehicles. Finally, the conclusion summarizes possible outcomes of increased use of CAVs.

SELF-DRIVING VEHICLES IMPACTS

Complete US adoption of CAVs will take decades, making CAVs' energy and emissions impacts challenging to anticipate. This section anticipates and quantifies the range of each impact. Some impacts are expected to reduce energy consumption, while others increase consumption. CAV adoption will affect vehicle use, traffic flows, and energy use, but also entire urban systems, social and economic interactions (Taiebat et al., 2018; Taiebat et al., 2019; Greenwald and Kornhauser, 2019). Appreciating all CAV energy impacts requires a careful look into human behaviors and infrastructure systems, among other sectors. This paper's estimates cannot comprehensively predict the future, but they can be used as a starting point to anticipate likely consequences of CAV adoption.

This paper categorizes each impact into four categories as follows:

- The travel demand change category includes possible changes of users' travel behavior because of CAV implementation.
- The driving details category includes possible changes in vehicle performance, such as the change in acceleration / deceleration scheme, as well as the adoption of shared automated vehicles.
- The multi-vehicle operation category includes interaction among multiple CAVs and infrastructures.
- The powertrain energy source category explains the outcome of a new power source—fueling the transition from gasoline-powered to electric vehicles—that could be applied to vehicle fleets in the future.

Travel Demand Changes Category

Better Route Choice

Drivers with CAVs might choose their travel route more efficiently than drivers without a connected environment. Automated vehicles without the driving task might have improved route choice capability through immediate judgment of traffic conditions in real time. For example, CAVs might find the shortest path of their trip more effectively by knowing the traffic conditions through communication. They might optimize their path to satisfy certain objectives, such as finding the path with fewer stops. When route choice algorithms are combined with automated vehicles' computing power, more effective trips can be made. For instance, SAVs can choose more effective routes that satisfy the needs of more passengers by allowing for dynamic ride-sharing (DRS) (with strangers casually carpooling together) en route. Additionally, the distance or travel time required for empty driving of an automated vehicle can be minimized by choosing the optimal route.

Route choice of CAVs will affect the traffic flow at both the individual level and system level. At the individual level, riders might travel more efficiently by choosing the best route required for their personal trip. At the system level, the congestion level can be lowered by dispersing each driver's path to avoid congestion. Past research (Gonder et al., 2016; Guo et al., 2013), indicates that the energy consumption would be reduced from enhanced route choice from as little as -5% to as much as -20%.

Newly Induced Trips from Under-served Population

CAVs can reduce or even eliminate the burden of the driving task, so that those who were unable to drive a vehicle could ride in CAVs. For example, senior adults and persons with disabilities would benefit from CAVs and increase their mobility options. By 2030, around 74 million seniors are expected to be living in the United States, which accounts for 26% of the US population (Harper et al., 2016). Moreover, those who used public transit for their work trips tend to rely on automobiles after retirement. If more CAVs make up the US vehicle fleet, these groups could maintain this usage, or it could increase (Harper et al., 2016). This is because a driver's license might not be required to ride in CAVs, since the required driving tasks are relatively low for CAVs relative to conventional vehicles.

Improvement of accessibility is another factor that would increase trips with this previously underserved population. Accessibility can be used to describe how well a location can be reached (Meyer et al., 2017), and with CAVs' reduced driving tasks, underserved populations would travel more easily than before. Thus, trips from both seniors and persons with disabilities could rise with the adoption of CAVs, resulting in increased energy use and emissions. Through the literature survey, research estimates the increased energy consumption from newly induced trips to be between 10-14%.

Shared Automated Vehicles – Increased VMT and Empty Driving

Shared automated vehicles (SAVs) are automated vehicles shared among riders on demand. Car sharing is available with conventional vehicles, such as carpooling, but SAVs would expand this service. SAVs might shift personal transportation choice from privately owned vehicles to a service offered through shared vehicles. Automated vehicles are more favorable for car-sharing than conventional vehicles and might be more accessible to potential users. Combined with the empty-driving capability, SAVs can act as an automated taxi. For example, a driverless vehicle could drive around empty, looking for possible passengers or seeking free parking, after its passengers exit.

Of course, use of roadways by empty SAVs requires energy use. SAV fleet size will be smaller than privately owned fleets because a single SAV can replace several conventional vehicles (Fagnant and Kockelman, 2018 ; Chen and Kockelman, 2016). However, SAV fleet vehicle-miles traveled (VMT) typically exceed conventionally driven VMT because of the empty driving in between passengers. (Heavy use of DRS can offset this added VMT (Martinez and Crist, 2015; Fagnant and Kockelman, 2018). This section considers the potential range of SAVs' energy impacts from empty-driving VMT. It is inevitable that a certain proportion of SAVs' VMT will be without passengers and minimizing this is important for SAV and transport system efficiency. Past research (Loeb et al., 2018; Loeb et al., 2019), estimates the increase in energy consumption from SAVs – without DRS – to be as low as 6% - or as much as 14%- compared to the current state of vehicle energy consumption.

Long-distance Travel with CAVs

With vehicle automation, the driving task is reduced, as the vehicle takes over the driving role. The burden required for driving would be reduced with CAVs, and riders of CAVs could focus on other activities. For example, riders could work, use portable cellular or wireless devices, chat with others, or even sleep during the ride. Consequently, the value of travel time with CAVs would be lower than that of conventional vehicles, and riders would be less reluctant to travel further distances in CAVs. Thus, long-distance travel, such as intra-urban, inter-regional travel, would increase with the adoption of CAVs. This paper assumes riders of CAVs will travel longer distances than drivers of conventional vehicles and that the added distances are holistic, including intra-urban, inter-regional, and even longer distance travel.

The increase of long-distance travel with CAVs will affect competing travel modes, especially airline travel. It is expected that airline revenue would be reduced by 53%, and that travel to increased distances using personal vehicles would increase by 9.6% (LaMondia et al., 2016). Interregional travel, including use of a personal vehicle to travel to locations 500 miles or further, would increase with the implementation of CAVs. As a result, the increased travel distance with CAVs would increase energy consumption for the ground transportation sector. However, airline travel would continue to be chosen by travelers for distances of 1,000 miles or more (Perrine et al., 2016). The analysis results from previous literature (LaMondia et al., 2016; Perrine et al., 2016) predict the increased rate of energy consumption to be from 6% to 18%.

Driving Details Category

Faster Travel from Improved Driving Skill

One of the benefits of vehicle automation is the control technique obtained from advanced sensors, networking capability, and artificial intelligence. Through the assistance or even full control of a vehicle from these techniques, the driving skills of CAVs will be improved in contrast to conventional human-driven vehicles. For instance, CAVs might be driving at faster speeds with closer spacing to the lead vehicle, while ensuring safety. Moreover, CAVs' enhanced safety devices may lead to speed-limit increases on certain roadways.

With the increase of travel speed, capacity of the facility tends to increase. Thus, future road infrastructure with CAVs would have a larger capacity compared to that of current infrastructure and congestion would decrease. Faster travel speeds would ensure reduced travel time; thus, riders of CAVs would benefit from the improved traffic conditions caused by using CAVs. However, if the performance of powertrain and efficiency of fuel sources used in CAVs are equal to that of current vehicles, faster travel of CAVs would consume more energy, and thus emit more emissions. Through the literature survey (Lee et al., 2018; Brown et al., 2014), this paper estimates the change in energy consumption from the faster travel speed of CAVs to increase from 7% to as much as 30% - as compared to current conditions.

Smoother Driving Cycle

Unlike the expectation from "Faster travel from improved driving skill" section, CAVs might have a smoother driving cycle in contrast with conventional human-driven vehicles. This is because the control techniques of CAVs can be used to remove redundant driving cycles that are unfavorable for vehicle durability, increase fuel consumption, etc. For instance, by knowing downstream traffic conditions, CAVs' stop-and-go driving cycles while decelerating can be smoothed by being better prepared for downstream conditions. During acceleration, CAVs can drive in a way to maintain its cruising speed, so that acceleration noise can be smoothed. Through interaction with traffic signals, the vehicle's acceleration or deceleration can be smoothed to reduce stopping using the information about signal cycles. Smoother driving cycles have been determined to have lower emissions than noisy driving cycles related to non-automated driving methods (Liu et al., 2017).

Another smoothing strategy for CAVs is to intentionally drive in an eco-friendly way. Unlike the smoother driving cycle designed for effective driving described above, the eco-friendly driving strategy can result in both smoother driving cycle and reduced energy consumption. CAVs' eco-driving ability can be an improvement over the driving behavior of human drivers, since control techniques can utilize efficient eco-driving skills while incorporating traffic conditions received via communication and sensors. It is known that dynamic eco-driving strategy of human drivers reduces fuel consumption and lowers CO_2 emissions (Barth et al., 2009). When such a strategy is accompanied with CAVs' advanced control technique, energy savings can be greater than that of conventional human drivers. This paper estimates the energy consumption from smoother driving cycles would decrease to between -10% and -20% of current energy use (Liu et al., 2017; Barth et al., 2009).

Computer and Sensor Power Demands

The computers and sensors used in automated vehicles deliver better performance and an improved driving experience to passengers when compared to vehicles without automation. However, the additional devices and equipment required for automation use additional energy. For example, an automobile air-conditioner (A/C) usually provides a more pleasant driving environment when it is used, but fuel economy is decreased due to the additional load required to operate the A/C. Steady-state air-conditioning in a sedan requires 1,000 W of energy loads, which results in a 15% decrease in fuel economy compared to 500 W base-line energy loads (Farrington & Rugh, 2000).

The energy use of CAV system will vary according to the level of automation; it is difficult to predict how much energy would be required. In a life-cycle assessment analysis, a CAV system is determined to have, at most, 4% greater emissions during its lifetime compared to a vehicle without this system (Gawron et al., 2018). However, this estimate is based on life-cycle analysis; therefore, actual energy consumption on the road could exceed this estimate.

In this paper, a CAV system is estimated to use additional 1,000 W of auxiliary load. This amount of auxiliary load is required to operate steady-state air-conditioning. It is also reasonable to assume a CAV system would use 1,000 W, since the power supplies installed on a desktop PC with a high-performance CPU and GPU usually have around 1,000 W or more wattage. Based on this assumption, this paper estimates a CAV system would increase the energy consumption from 4% to as much as 15%.

Multi-vehicle Operation Category

Vehicle-to-vehicle (V2V) and Platooning

Vehicle-to-vehicle (V2V) refers to communication through networking technologies, such as dedicated short-range communication (DSRC). The adoption of V2V technology enables velocity synchronization and closer spacing among vehicles, which will eventually lead to platooning of vehicles. Platooning can improve string stability (Li et al., 2017; Talebpour et al., 2016) and increase capacity (Zhao et al., 2013), since vehicles will be driving with reduced acceleration noise and maintaining closer spacing with the preceding vehicle. Apart from improved traffic flow, platooning can reduce fuel consumption and emissions through a smoother driving cycle (Gonder et al., 2012), the ability to send downstream traffic condition to vehicles in upstream (Li et al., 2015), and drag reduction (Alsabaan et al., 2013). Reduced acceleration noise in the driving cycle results in a smoother driving cycle with minor differences in the acceleration rate. Since vehicles in the upstream can receive the traffic condition downstream through V2V, upstream vehicles can adjust to the downstream conditions better than before. Closer spacing among vehicles in the platoon will lead to reduced aerodynamic drag. These three factors will lead to greater reductions in fuel consumption and emissions, as compared to vehicles without V2V platooning.

Through the literature survey, the energy and emissions reduction from V2V and platooning is estimated to be from 7% to 35% (Li et al., 2017; Talebpour et al., 2016; Zhao et al., 2013; Gonder et al., 2012; Li et al., 2015; Alsabaan et al., 2013). However, past research assumed that V2V was applied to the cruising status of moving vehicles, where vehicles are platooning along a lengthy passage of roadway, such as a highway. In fact, cruising traffic flow is rarely observed on non-highways, such as roads in an urban network, so the estimates of V2V's energy reduction should be modified. According to FHWA travel statistics, highway travel in the United States comprises between 33% (interstate highway and expressway) and 55% (including major arterial roads) of all distance traveled. (Wadud et al., 2016). Based on these statistics, this research is applied to the rate of highway travel to modify the energy reductions of V2V for the highway-traveling scenario. Therefore, the consumption rate from V2V implementation is assumed to be changing from at least -2% (=-7%*33%) to at most -19% (=-35%*55%) when compared to conventional vehicles. This estimate was derived from assuming all other travel that does not take place on the highway is non-highway travel and the intersection management technique will affect the travels on those networks.

Shared Automated Vehicles – Enhanced Fuel Economy

Although SAVs may have adverse impacts on energy use as speculated above, they also have the potential to save energy when operated in an efficient way. Through vehicle right-sizing, SAVs can have various size options that fit the users' demand. If vehicle size can be optimized to enhance fuel economy, SAV can save energy required for travel. With dynamic ride-sharing (DRS), passengers with similar origin-destination can share their travel by taking SAV ride together.

On-demand travel of SAVs would increase trip efficiency, so that excessive energy use can be minimized. The trips that are not required to match the rider's demand, such as searching for a parking lot, can also be minimized to further reduce the energy consumption rate. Vehicle right-sizing can introduce smaller vehicles with smaller engines that still match the demand of riders and increase energy savings. Passengers' travel demand can be served with fewer vehicles by dynamic ride-sharing and reduced emissions. Past research (Fagnant et al., 2014), estimates the change in energy consumption from SAVs to be as little as -5% to as much as -12% compared to the current state.

Vehicle-to-infrastructure (V2I) and Connected Intersection

Vehicle-to-infrastructure communication, or V2I, is nearly analogous to V2V. However, V2I is communication protocol between vehicle and infrastructure, instead of communication between vehicles. Infrastructure with V2I communication include intersections, lane markers, and parking meters, but this paper focuses on connected intersection management with and without traffic signals. When smart intersections can be operated with automated vehicles, speed control of individual vehicles can be easily manipulated to obey the existing speed advisory system, which is subject to the driver's obedience of the rules. With the adoption of V2I to intersections, vehicles' stop delay can be reduced (Lee et al., 2012; Niu et al., 2013a), vehicles will be eco-friendlier (Qian et al., 2011; Rakha et al., 2011; Niu et al., 2013b), and the vehicles upstream can better adjust to the traffic conditions downstream (Sanchez et al., 2006). Furthermore, autonomous intersection management (AIM) can be implemented, where traffic signals are not in place (Carlino et al., 2013; Fajardo et al., 2011; Sharon et al., 2017). This type of intersection can manage the traffic by checking the trajectory of each vehicle and reserving the intersection to the target vehicle that should pass. In this way, collision between vehicles can be prevented, while minimizing stopping delay.

The expected energy reduction from V2I varies among the literature but ranges between 13% to as much as 44% (Lee et al., 2012; Niu et al., 2013a; Qian et al., 2011; Rakha et al., 2011; Niu et al., 2013b; Sanchez et al., 2006; Carlino et al., 2013; Fajardo et al., 2011; Sharon et al., 2017). Similar to V2V, this reduction rate is modified with FHWA's non-highway travel rate in the United States, which is between 45% and 67%. Thus, the energy consumption rate from V2I implementation is assumed to be decreasing from at least -6% (=13%*45%) to at most -30% (=44**67%) when compared to conventional vehicles.

The limitations of V2I research conducted so far are: 1) research is constrained to the implementation of a single intersection, rather than multiple network-wide smart intersections, and 2) interaction among different approaches of the intersection are often neglected and are constrained to a single approach. When these areas are covered through future research, the estimates for the fuel reduction rate from V2I will be able to be derived more accurately.

Powertrain Energy Source Category

Electric and Hybrid Electric Vehicles

As technologies advance, energy and carbon-saving regulations take effect, and the public grows more concerned about mitigating climate change, there will be more vehicles equipped with electric motors in the future. Moreover, increased adoption of CAVs may well inspire greater adoption of electric and hybrid powertrains. Quarles' (2018) microsimulations of the US passenger vehicle fleet (which recognizes CAV technologies along with EV technologies) and others' forecasts of the future (Loeb et al. 2018, Loeb et al. 2019, Chen and Kockelman, 2016) suggest that electric powertrains will be the majority of United States and global vehicle powertrains by 2050. CAVs' empty-driving capabilities will allow EVs to self-charge without drivers. When charged inductively (or with a robotic arm), no humans need be present for the refueling (unlike with diesel and gasoline). This is particularly valuable for electric SAV fleets (Loeb et al. 2018, Loeb et al. 2019), when travelers do not have to worry about the range of the SAV being sufficient for their trip request (since only sufficiently charged SAEVs would be sent their way) or worry about charging times (since charging happens only when vehicles are unoccupied, as in Loeb et al., 2018 and Chen and Kockelman, 2016).

With the advent of CAVs, the likelihood of the adoption of electric motors or hybrid engines for powertrains might increase. Because electric vehicles do not have tailpipe emissions, vehicle emissions would be reduced. Although power plants that generate electricity might carry more emissions because of their increased electricity demands, this research does not cover emissions from power plants, instead focusing on tailpipe emissions and energy consumption from vehicles themselves. Past research (Hawkins et al., 2013; Al-Samari et al., 2017; Pitanuwat et al., 2015), suggests that the adoption of electric or hybrid vehicles would reduce the energy consumption of vehicles from -30% to as much as -70%.

Summary

In summary, improved driving performance would provide an enhanced traveling experience to the users of CAVs, though it might use more energy due to more active operation. If CAVs are designed to have better fuel economy through control techniques, it might save more energy than conventional vehicles. Considering all of these impacts, the change in fuel type is expected to have the biggest impact on energy use. In the end, the change in energy consumption rate will affect the change in emissions implications of self-driving vehicles. The results of this literature review are summarized in Table 1, assuming an already highly motorized country, like the U.S.

TABLE 1. Summary of Impacts

Category	Impacts	Description	Energy Impacts
Travel Demand Changes	Better Route Choices	Route choice based on real-time traffic data from connected environment	-5% to -20%
	New Trips from Under-served Populations	Motorized trips by limited drivers & non-drivers	+10% to +14%

	Shared Automated Vehicles – Empty Driving	SAVs traveling to next passenger, empty	+6% to +14%
	More Long-distance Travel	Longer distance travel caused from lower driving task of CAVs	+6% to +18%
Driving Details	Faster Travel from Improved Driving Skills	Fast & throughput-efficient driving cycle	+7% to +30%
	Smoother Driving Cycle	More fuel-efficient driving cycles	-10% to -20%
	Computer & Sensor Power Demands	Energy for sensors, on-board computing, vehicle control & navigation	+4% to +15%
Multi-vehicle Operation	V2V & Platooning	Vehicle-to-vehicle connectivity & platooning	-2% to -19%
	Shared AVs & Ride-Sharing	Fuel savings from vehicle right-sizing & dynamic ride-sharing (DRS)	-5% to -12%
	V2I & Smart Intersections	Vehicle-to-infrastructure connectivity & smart intersection	-6% to -30%
Powertrain Energy Source	Plug-in Electric & Hybrid Electric Vehicles	Drivetrain shifts from gasoline to electricity	-30% to -70%

However, when classified by category level, changes can be observed more directly. Fig. 1 shows the most optimistic and most pessimistic change in energy impact for each category. The Travel Demand Changes and Driving Details categories are more likely to add energy use than other two impact categories. If an individual vehicle's driving performance is improved, it is reasonable to assume that the vehicle will consume more energy than before. Similarly, passengers and travelers will have different travel patterns than before, leading to more trips over longer travel distances. Thus, it is reasonable to expect that CAVs' impacts on travel demand and driving details will use more energy, excepting the route-choice and drive-cycle impacts, which carry energy savings.

In the Multi-vehicle Operations category, energy savings is expected, thanks to connections and communications among vehicles and infrastructure systems that are rarely available with conventional vehicles. Enhanced communications abilities are expected to improve interactions, delivering more fuel-efficient driving (between vehicles, when approaching signal lights or merge points, and when selecting destinations and routes, for example). Table 1's Powertrain Energy Source category is highly related to energy consumption, thanks to drivetrain electrification, which is likely to be CAV's greatest energy saving opportunity.

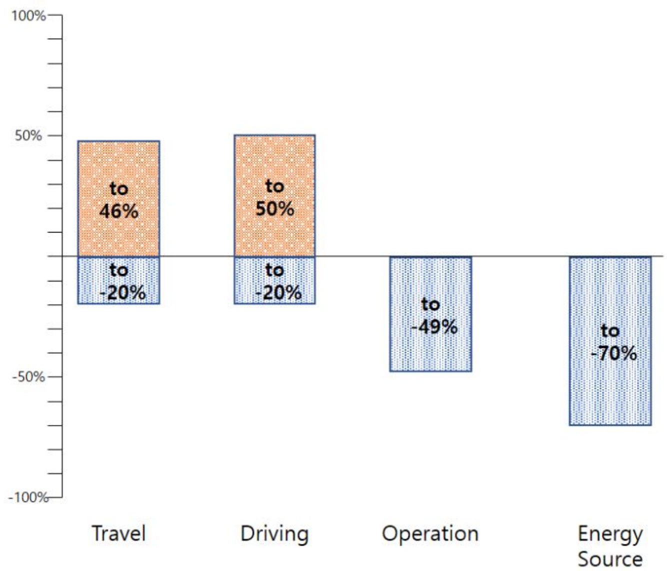

FIGURE 1. Predicted Changes in Light-duty Vehicle Energy Use (Across Table 1 Categories)

SCENARIO ANALYSIS

Due to the uncertainty surrounding CAV implementation, it is difficult to predict the exact outcome caused by adoption of CAVs. Each impact may cancel out the other, or the range of change might be greater than what is expected by the literature. To overcome this uncertainty, this paper conducted a scenario analysis to anticipate various scenarios that can be observed in the future. The change in energy consumption is analyzed with respect to the market penetration rate (MPR) of self-driving vehicles. Since electrification of powertrains has shown the largest impact on energy use, its impacts are analyzed separately by including and excluding its impact in the model.

Energy Consumption with respect to Penetration Rate

Random sampling analysis was undertaken to overcome the uncertainty of future predictions. Considering all the impacts except the impact from energy source change, random samples of each impact's change in energy consumption were generated. Assuming uniform distributions for each impact's range of values, expected energy-use changes were simulated via Monte Carlo methods. Some impacts may be correlated (like adoption of SAVs and DRS) and actual distributions probably are not uniform, but this analysis assumes independence across impacts and flat density functions for transparency and ease. Powertrain electrification impacts are excluded initially here, in order to first focus on CAV system impacts. Assuming 100% CAV MPR, 1,000 random values were sampled in every impact category (excluding electrification, initially). Fig. 2 shows the outcomes of this random sampling process.

Assuming a 100% current energy consumption value, lower values imply energy savings, while larger suggest increased energy use. Fig. 2 shows that most 100% MPR results reduce US energy use by light-duty vehicles (per capita), with an average reduction of 11%. Thus, energy savings (per person, in the realm of personal travel) are expected with full adoption of CAVs in the United States.

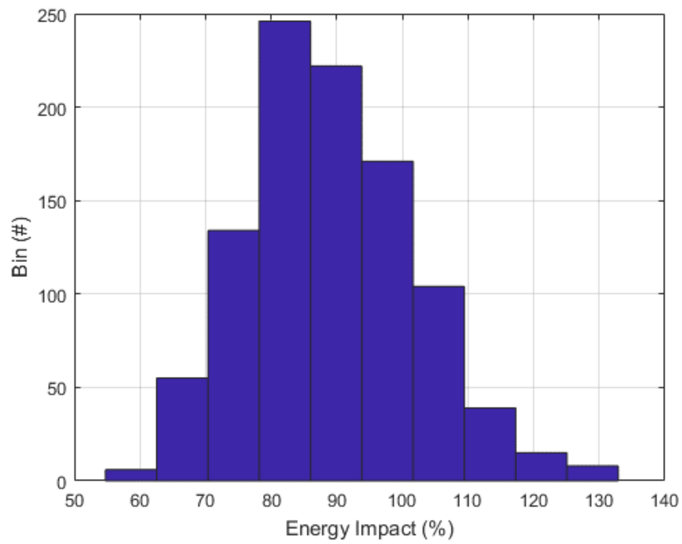

FIGURE 2. Energy Impacts from Random Sampling of Table 1 Impacts, Assuming 100% Penetration Rate of CAVs

Extreme Electrification Effects with respect to CAVs' Penetration Rate

The penetration of CAVs is expected to occur gradually, rather than abruptly. Thus, energy impacts are expected to emerge rather gradually, alongside CAVs' market penetration. To anticipate these energy impacts over time (as share of CAVs or "CAV%" rises), a scenario analysis was conducted, based on Eq. 1:

$$\text{Energy (\%)} = \text{CAV\%} \times (\text{All Effects}) + (100 - \text{CAV\%}) \times 100 \qquad (1)$$

CAV impacts are derived by taking the average random-sample result at each penetration rate, using Eq. 1's weighted average approach. To quantify powertrain–electrification impacts, two different results are provided: One includes EVs' impacts, while the other neglects any added electrification.

Fig. 3 shows the average energy results of these calculations, along with standard deviation bands, and the most optimistic and pessimistic results. As CAV MPR rises, so does the standard deviation. This can be explained by the uncertainty of predicting the future, and therefore a larger error can be observed for future predictions. While the most pessimistic result shows an increase in energy use and the most optimistic result shows energy savings, the average value predicts that decreased energy impact with respect to the increase of MPR is more likely. It is likely that emissions will fall as well, since many emission species are reasonably proportional to energy expended in ground transportation.

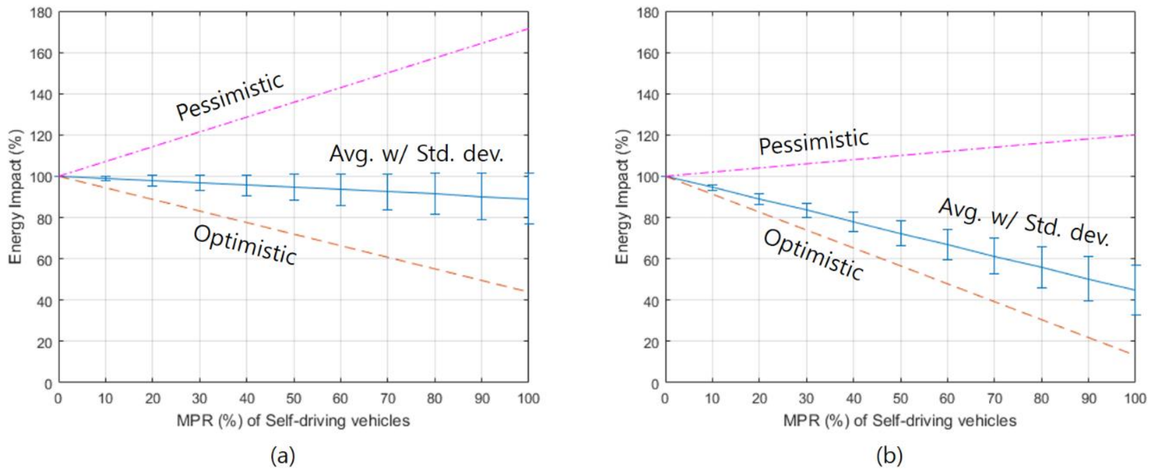

FIGURE 3. Estimated Energy Impacts of CAVs Without (a) and With (b) Electric Vehicles

The extreme effects from electrification of the powertrain is analyzed in both 0% and 100% rate of electric vehicles (EVs) on the road. A decrease in energy consumption is expected without any EVs (Fig. 3a), but the amount of decrease increases when 100% of vehicles on the road as EVs (Fig. 3b). The average decrease in energy consumption without EVs is approximately 11%, while it reaches a 55% decrease when all the CAVs are EVs. The range between pessimistic and optimistic estimates decreases when EVs are included in the model, indicating a more accurate prediction can be made. In conclusion, adoption of CAVs is expected to lower energy consumption slightly, without electric drivetrains. And adoption of electric CAVs (both plug-ins and hybrids) is expected to decrease energy usage substantially.

CONCLUSION AND POLICY IMPLICATIONS

This paper anticipates the many possible outcomes from CAV adoption in an already-motorized country, like the U.S. Added driving, on-board sensors and computers, and higher travel speeds are expected to increase transport's energy use, while shared, right-sized vehicles, drivetrain electrification, and other behaviors reduce it. There are a variety of possibilities, resulting in a wide range of uncertain implications. Via an extensive literature synthesis, this paper defined impact types and their ranges. Scenario analysis and Monte Carlo sampling deliver a stronger sense of how these vectors of change come together. Fortunately, the industry's natural move toward electrified drivetrains is expected to deliver a 44% energy savings, more than offsetting added VMT's energy demands. Adoption of electric trucks (presumably for intra-regional travel) and rising availability of fast-charging technology can also lower the transport sector's energy demands. Even without electrification, this paper's estimates – seeking to reflect all possible CAV futures -- suggest a slight reduction in average energy demands.

However, under Paris Agreement targets (UNFCCC, 2015), the U.S. and other motorized nations are unlikely to meet their net greenhouse gas emission reduction targets. For the US, those were to be 26-28 % below 2005 levels in 2025. Unfortunately, none of the CAV implications, CAV market penetration scenarios, and electrification scenarios presented in this paper can satisfy this target. One possible solution is to increase renewable energy's share in U.S. power generation, so that electric CAVs can be charged with clean energy. The nation's current renewable energy share is 17.1% (US EIA, 2019), while the total electricity demand is estimated to increase by 20% to 38% in 2050 (Mai et al., 2018). More behavioral, political, and technical changes are needed to help transportation deliver its fair share of GHG savings.

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