ENERGY IMPLICATIONS OF SELF-DRIVING VEHICLES

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ABSTRACT

While lowering driving burdens and crash counts, self-driving or fully automated vehicles (AVs) will increase vehicle-miles traveled (VMT) and congestion in most settings. This is due to the potential for non-drivers to travel independently, empty vehicles repositioning themselves, and more low-density land development away from city centers. At the same time, automation may enable lower-cost demand-responsive ride-pooling in all-electric shared AVs (SAEVs), as a new and attractive form of transit, while reducing demand for climate-damaging air travel. No matter which AV-adoption path is taken, AV use will impact every nation's energy use and emissions. This chapter anticipates the energy implications of AVs as well as those of communicating or connected AVs (CAVs) in order to provide policy recommendations under different use and technology scenarios. CAVs will increase energy use if they are personally owned, since they will greatly increase VMT, and also if they serve as single-passenger taxis. If they emphasize pooled-ride services and operate on electricity from renewable-energy sources, they are expected to lower energy use and emissions. Recognizing all vectors of impact, a net energy reduction of 11% to 55% versus the U.S.'s current ground-transportation conditions is estimated here, depending on CAVs' drivetrain electrification. This work rank-orders the variable energy impacts of different behavioral changes and technologies and recommends adopting CAVs with electric drivetrains for shared-ride services in right-sized vehicles to delivers more sustainable transportation systems in the United States and abroad, even as VMT and congestion risks rise.

KEYWORDS

Energy consumption; Connected and autonomous vehicles; Fully automated vehicle; Self-driving vehicle; Electric vehicle; Ride-pooling

INTRODUCTION

Early-stage fully-automated or "autonomous" vehicles (AVs) have been providing commercial ride-hailing services to the public since 2020, in parts of the US and China. In the United States, Waymo continues expanding its driverless ride-hailing services to cities like Nashville and Miami, Dallas and San Antonio, in partnership with Uber, Lyft and others. Waymo's shared, automated all-electric vehicles (SAEVs) are serving hundreds of thousands of paid, private (not pooled) rides a week, in geofenced service areas across Austin and Phoenix, the San Francisco Bay Area, Los Angeles, and Atlanta. Zoox has been testing robotaxis in Los Vegas and San Francisco, Tesla Robotaxis have been deployed in Austin, and Baidu's Apollo Go fleet has accrued over 100-million "rider-only" (i.e., no safety driver present) miles across various Chinese cities (Broekman, 2025). These deployments largely mirror the private ride-hailing services such cities already offer, with no pooling of independent travel parties for a more cost-effective and seat-filling dynamic ride-sharing (DRS) service. Zoox aims to offer pooled (not private) service in its two-facing-two vehicles in 2027, and others may follow suit, delivering a form of demand-responsive, cost-effective jitney service with the potential to lower energy use, VMT, and network congestion - while improving access for all travelers. While no fully-automated vehicles are being sold to the general public, and AV-fleet managers have staff on hand for riders' and emergency personnel's calls for help, such vehicles will emerge, as Tesla, Mercedes-Benz, and many others improve their automated driver assistance systems (ADAS), sold directly to private owners.

Nearly all new vehicles log their positions (along with other information) and share that information with their manufacturers, making them a type of connected vehicle (CV). And all new vehicles may one day be required to continuously relay a basic safety message (BSM) regarding their position and speed to one another (and to roadside devices) as nations seek to make driving less dangerous. Such developments suggest that CAVs' current and coming impacts are not hypothetical, with multiple, competing companies deploying automated fleets and shaping urban (and eventually exurban and rural) mobility. There is early evidence on how CAV services can influence travel behavior, transportation's energy use, and emissions.

Motorized vehicle automation is generally categorized from Level 0, No Automation, through Level 5, Full Automation under all conditions and circumstances (NHTSA, 2018). This chapter discusses the impacts of Level 4 and 5 vehicles only—those that do not require any human intervention. These AVs allow occupants (and any attendants or operators, who are no longer "drivers") to spend their travel time engaged in other activities, like conversation and work, sleep and entertainment. The AVs may be privately owned (as Tesla is focused on) or "shared" with others, via ridehailing SAV fleets. Rides in those SAVs may be private or pooled with strangers sharing similar routes at the same time of day.

Connecting AVs can improve safety and performance through active, high-frequency transmission of vehicle position, speed, direction, and acceleration. If deployed on a wide scale, such transportation options change not only travel patterns, but also the economic structure and siting decisions of many businesses, the shape of urban areas, human lifestyles, job opportunities, and freight movement, relative to background trends.

This chapter focuses on the energy implications of AV adoption, as privately owned AVs and as shared fleets of smartphone-hailed SAVs, via pooled or private rides, with and without communication between nearby vehicles and infrastructure (CAVs), with and without an electric drivetrain (EVs). Access to such vehicles can raise or lower energy demand and emissions. For example, smoother driving cycles (with less aggressive acceleration and braking) tend to lower energy use, but CAV access will result in more travel, increasing energy consumption – everything else constant. This chapter synthesizes existing research on and deployments of CAV technology to anticipate and inform our shared future. It uses scenario analysis for an evolving market and summarizes the possible outcomes of rising CAV use.

IMPACTS OF SELF-DRIVING VEHICLES

Widespread adoption of CAVs around the globe will take decades, which makes it challenging to anticipate energy and emissions impacts. This section estimates the range of each impact: some behavioral and technology responses 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, and social and economic interactions (see, e.g., Taiebat et al., 2018; Taiebat et al., 2019; Greenwald and Kornhauser, 2019; Wellik and Kockelman, 2020; Huang et al., 2020, 2025, and 2026; Fakhmoosavi et al., 2022). Understanding all possible CAV energy impacts requires a careful look into human behaviors and infrastructure systems, among other sectors. The estimates in this chapter cannot comprehensively predict the future, but they can be used as a starting point to anticipate likely impacts of CAV adoption.

This chapter classifies impacts into the following categories:

- Travel Demand Changes: including trip generation, destination, mode, and route choices, both local and long distance.
- Vehicle Operating Details: possible changes in acceleration and deceleration, driving cycles, and vehicle-following distances.
- Multi-Vehicle Interactions: interactions between and across CAVs and infrastructures; as well as shared fleets with and without pooled rides (i.e., dynamic ride-sharing (DRS) between strangers).
- Powertrain Energy Source: transition from gasoline-powered to electric drivetrains.

Travel Demand Changes Category

Better route choice

CAVs are likely to identify and selegct shorter and/or more efficient travel routes, using automated path (and lane) changes while en route, thanks to a highly connected environment, with multiple, constantly aware cameras and continuous consideration of BSMs. User-shared details (like one's own value of travel time or value of transfers and ride-pooling en route) will allow on-board processing units to pursue traveler-specific and fleet-aware objectives, such as finding paths with fewer stops and less empty travel (dead-heading) between ride-hailing customers or freight drop-offs and pickups.

CAV routing decisions affect individual trips and the wider network. At the individual level, riders may enjoy the best route required for their trip. At the system level, congestion levels may be lowered by distributing vehicles' assigned paths to minimize traffic jams and congestion delays. Past research (e.g., Gonder et al., 2016; Guo et al., 2013; Zeng et al., 2016; Zeng et al., 2017), indicates that energy consumption will fall by 5% to as much as 20% from routing improvements.

Newly induced trips from under-served populations

CAVs eliminate the burden of physically driving, so those unable to drive conventional vehicles can generally ride in CAVs. For example, the aged and people with certain disabilities are expected to benefit greatly from AV and SAV options (see, e.g., Lee and Kockelman, 2022). By 2030, around 74 million seniors are expected to be living in the United States, accounting for 26% of the U.S. population (Harper et al., 2016). Driver's licensing and conventional vehicles may become a thing of the past, much like horse-riding on public roadways. With more mode choices - on demand, to all destinations, and with self-driving technology improvements and smart, efficient routing for DRS making trips more affordable, underserved populations should be able to travel more easily than before. As trip rates rise (for currently under-served populations, including, for example, all teenagers), energy use and emissions are estimated to rise 10 to 14%, everything else constant (Harper et al., 2016).

Shared automated vehicles – empty driving

Shared automated vehicles (SAVs) are fully-automated vehicles shared among riders on demand. Since the late 20th Century, car-sharing has allowed users to access and drive conventional vehicles by the mile, minute, or hour in many U.S. cities (using Zipcar, Car2go, Enterprise and others). Ride-hailing is the use of a mobile device (typically a smartphone) to call what is essentially a taxi (rather than street-hailing a taxi in person). Ride-pooling (often called ride-sharing or DRS) involves multiple passengers sharing a vehicle at the same time, generally to depart from similar origins or arrive at similar destinations. UberX Share and LyftShare (previously called UberPool and LyftLine), along with apps like Hitch and BlaBlaCar (for longer-distance journeys), enable pooling between strangers, but such rides are presently rare in the U.S. (see, e.g., Paithankar et al., 2026).

SAV fleet managers can use fares and algorithms (and transit agency subsidies) that favor pooled rides, to reduce empty seats and VMT, possibly lowering network congestion and overall travel times. As this chapter goes to press, Waymo SAEVs are driving almost 50% empty in California (Abdelhalim, 2026), much like ride-hailed Uber and Lyft vehicles. They and others do not yet offer pooled rides or permit a rider in the front-left seat (where there is still a steering wheel and pedals). But policies and designs are evolving quickly, and Waymo's new Zeekr vans come with removable steering wheels (Business Insider, 2026). Zoox vehicles are designed for groups (in a 2-seats-facing-2-seats configuration), and cities, states and nations may soon cap empty SAV driving at 20% or less (by giving VMT credits for rides pooled between strangers).

It is inevitable that a certain proportion of SAVs' VMT will be without passengers (e.g., driving to refuel/recharge and/or clean SAVs) and minimizing such distances is important for transport system efficiency and sustainability. Fagnant et al.'s (2014) early, grid-based, limited-geofence (10 miles x 10 miles) simulations estimated life-cycle energy savings of -12%, using conventional sedans (and reduced parking infrastructure), relative to typical U.S. household vehicle (and parking) investments. Later, more realistic demand and network simulations for Austin, Texas (see, e.g., Loeb et al., 2018; Loeb et al., 2019) estimated +6% to +14% VMT increases, assuming some ride-pooling.

This chapter assumes a net increase in energy use of +6 to +14% from empty-AV driving, with cities and states not allowing empty travel by privately owned AVs (since no one is available to "rescue" the AV is something goes wrong) and not allowing more than 20% empty travel by SAV fleet operators (by giving VMT credits for pooled rides between strangers). Unfortunately, settings without such regulations could experience nearly a doubling in VMT and associated energy use (Harb et al., 2018), since many households and firms could shift to owning fewer vehicles to accomplish all trips (dead-heading between one family member's destination, and then next member's origin, for example) and "cruising" empty to find lower-cost parking in central business districts, for example. Empty driving will need to be actively regulated to avoid local gridlock, unnecessary crash risks, and greater global climate damages.

Longer-distance travel

As the "driving" task disappears, drivers can focus on work and converse with others, use their phones and tablets, and sleep en route. The value of travel time will fall for those who were previously tasked with driving/operating the vehicle (Zhong et al., 2020), and riders will be less reluctant to spend more time in cars and trucks, covering greater distances (Fakhrmoosavi et al. 2024). This chapter assumes CAV occupants will often travel longer distances than drivers of conventional vehicles, for both intra- and inter-regional trip-making.

Access to AVs will affect competing travel modes, like transit and air travel. Americans rarely travel by airlines, but over 40% of their person-miles traveled (PMT) are for trips of 50-miles or more one-way (Fakhrmoosavi et al., 2024). In a Michigan case study, LaMondia et al. (2016) estimated that AVs would capture 37% of conventional vehicle trips for travel distances between 50 and 100 miles. For trips shorter than 500 miles, AVs drew roughly 30% of travelers from conventional vehicles and airlines. For trips over 500 miles (one-way), AVs attracted 20–24% of personal-vehicle travelers, and roughly 15% of air travelers. Using the FHWA's rJourney data set (synthetic U.S. person-trips of 50+ miles), Perrine et al. (2020) estimated that widespread adoption of self-driving vehicles would reduce total long-distance PMT by 7% and domestic airline revenues by 47%, while personal-vehicle travel distances would rise 9.6% (as travelers shift to ground-based automobile travel). Fakhrmoosavi et al. (2024) estimated 35% more driving for trips over 75-miles (one-way) and 21% fewer passenger-miles by aircraft.

Use of a AVs to travel 500 miles or further (in private vehicles as well as self-driving luxury buses with reclining chairs, food service, an attendant, and bathrooms, for example) is expected to rise, increasing energy consumption by ground transport. But top speeds are expected to remain around 80 mi/hr on public roadways, so air travel will remain the dominant mode for person-trips of 1,000 miles or more (Perrine et al., 2016; LaMondia et al., 2019; Fakhrmoosavi et al., 2024). Based on these past travel demand modeling results, a 6% to 18% rise in U.S. long-distance, ground-based passenger-travel energy consumption is assumed here.

It is useful to note that long-distance trucking is also expected to rise, thanks to fully automated ATrucks enabling operators/attendants to rest, work on other tasks, effectively reducing door-to-door times on longer/overnight trips and per-ton-mile costs. Huang et al.'s (2024) U.S.-wide freight study estimated a 50% ton-miles market share for ATrucks (across nearly all inter-county distances), and an 11% overall increase in U.S. highway-based freight movements (in value and ton-miles), thanks to ATrucks. And Huang et al.'s (2020) Texas Triangle simulations of freight and passenger transport suggest a dramatic 47% increase in that mega-region's VMT (delivering very serious congestion delays in many settings, at peak times of day), with the greatest distance increases evident in suburbs-to-central-city trip-making, along with dramatic 82% reductions in passenger flights between Houston, Austin, San Antonio and Dallas airports.

Vehicle Operating 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. The driving skills of communicating/connected AVs will exceed those of most conventional (human-operated) vehicles. For instance, CAVs are expected to be able to drive at faster speeds with closer spacing to just-ahead/downstream vehicles while improving safety.

Everything else constant, higher traffic densities and/or speeds should allow highways and intersections to serve more vehicles, thereby raising network capacities (especially along freeways, where stop signs, 90-degree turns, and driveways with slow-moving vehicles are not present). Faster travel speeds would lower travel times, improving traffic conditions (assuming no added flows/demands to consume the added capacity) but consume more energy (due to added drag forces, at speeds above 40 mph, for example). Based on a review of the literature (Lee et al., 2018; Brown et al., 2014), this chapter assumes a 7 to 30% increase in energy consumption as a result of higher travel speeds, relative to current conditions.

Smoother driving cycles

While higher speeds add drag force, CAVs should have smoother driving cycles (relative to human-driven vehicles). By knowing (and preparing for) downstream traffic conditions (and by listening to downstream signal timing plans), stop-and-go driving is smoothed. Driving by computer or wire also ensures smoother acceleration, cruising, and deceleration behaviors, requiring less energy, especially when driven in an intentionally eco-friendly way (Liu et al., 2017; Barth et al., 2009). This chapter estimates 10 to 20% energy savings from smoother driving cycles, relative to conventional (uniformed and relatively noisy or jerky) human driving.

Computer and sensor power demands

The computers, cameras, and other sensors used in automated vehicles deliver better performance and an improved driving experience for passengers when compared to vehicles without automation. But they require added energy, much like an automobile's air conditioner (A/C). Farrington and Rugh (2000) noted that a sedan's steady-state A/C requires about 1,000 W of energy (vs. 500 W an idling vehicle), lowering an EV's range by about 15%. After simulating thousands of trips using battery-only EV (BEV) and conventional (internal combustion engine, ICE) drivetrains, He et al. (2023) concluded that automation power demand below 1,000 W is needed for CAVs' eco-driving energy benefits to outweigh the added automation load, especially at lower speeds. A 2,000 W CAV-computing system notably increases energy use in all-electric AVs driven at low speeds (with standard EV sedans consuming about 250 Watt-hours per mile, or 6,250 W of power at 25 mi/h and 15,000 W at 60 mi/h). At operating speeds above 40 mi/h, the CAV trips consumed the same amount of energy as non-automated vehicles. (This is especially true with conventional drivetrains because so much energy is lost or wasted as heat, while EVs are much more energy efficient.) More recently, Liu et al. (2025) reviewed 59 different studies of all-electric (CAVs), which suggest that full automation increases energy use by an average of 41%, and eco-driving strategies (including more informed car-following and lane-changing) roughly counteract that, via a 37% (average) savings.

Fortunately, most AVs and CAVs are expected to have all-electric drivetrains since direct current is needed for sensors and computing (at 1000 to 2000 W), and all-electric drivetrains are simpler to construct and manage than hybrid systems (or conventional systems with big batteries). Thanks to long-term reduction in battery prices, and large-scale EV production at Tesla Gigafactories and in China, EVs have also become cost-competitive (and often less expensive than) conventional drivetrain cars. This chapter assumes CAV systems will add 1,000 W of auxiliary load, at least long-term, which is more than running a high-performance desktop computer (with CPU and GPU), and will raise average energy consumption by 4 to 15%, all else constant.

Multi-vehicle Interactions Category

Vehicle-to-vehicle (V2V) communications 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 speed synchronization and closer spacing among vehicles, which should eventually lead to platooning of vehicles. Platooning can improve string stability (Li et al., 2017; Talebpour et al., 2016) and increase roadway capacity (Zhao et al., 2013), since vehicles will be driving with reduced acceleration noise and maintaining closer spacing. 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). Such factors should deliver lower energy use and emissions, as compared to vehicles without V2V platooning.

Many V2V investigations suggests energy and emissions savings between 7% and 35% (see, e.g., Li et al., 2017; Talebpour et al., 2016; Zhao et al., 2013; Gonder et al., 2012; Li et al., 2015; Alsabaan et al., 2013). But such research emphasizes cruising along lengthy highway corridors, while much driving occurs on urban roadways, with significant mixing and friction en route, due to driveways and signal lights, turning and merging. In the U.S., highway driving is 33% (interstate highways plus expressways, only) to 55% (when including major arterial roads) of all VMT (Wadud et al., 2016). Thus, this chapter assumes that V2V energy and emissions savings will vary from -2% (= -7% x 33%) to at most -19% (= -35% x 55%), as compared to conventional driving. It will be many years and perhaps decades before many or most vehicles can platoon en route along such corridors.

Vehicle-to-infrastructure (V2I) communication and smart intersections

Vehicle-to-infrastructure communication, or V2I, refers to a communication protocol between vehicles and nearby infrastructure, instead of communication between vehicles. V2I can affect many settings – like intersections and bridges, tight curves and parking lots. This section focuses on the energy and emissions impacts of connected, smart intersection management, with and without traffic signals. Connected intersections may issue orders for AV approach speeds and lane assignments, in order to maximize node capacities, minimize network delays, lower emissions and crash counts, and help traffic adjust to downstream conditions (see, e.g., Lee et al., 2012; Niu et al., 2013a and 2013b; Qian et al., 2011; Rakha et al., 2011; Sanchez et al., 2006). In the long term, automated intersection management (AIM) may one day be implemented without traffic signals (Carlino et al., 2013; Fajardo et al., 2011; Sharon et al., 2017), while ensuring that AV trajectories do not collide and stopping is minimized.

V2I energy savings estimates for intersection applications vary across studies, ranging 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). Like the V2V estimates described above, this range of reductions is modified here, using U.S. non-highway VMT, which lies between 45% and 67%. Thus, vehicles' energy savings from V2I implementation is assumed to vary from -6% (= -13% x 45%) to at most -30% (= -44% x 67%) overall, when compared to conventional intersection management, long term. In reality, it may be very difficult to automate most intersections at most times of day, since pedestrians, cyclists, and those on scooters (and motorcycles, perhaps) will not be automated. The presence of such travelers at intersections and along local roadways, and the uncertainty of their choices, will limit opportunities for non-stop, smooth, highly-informed travel by AVs.

Shared automated vehicles – right-sizing and ride-pooling

As discussed earlier, driving by empty SAVs requires energy. But a single SAV serves about 10 times as many (intra-regional) trips as a conventional vehicle (Fagnant and Kockelman, 2018; Chen and Kockelman, 2016; Su et al. 2025), or 30 trips per day instead of 3, providing dramatic savings in (off-street) parking spaces needed (Fagnant et al., 2014). SAV-fleet vehicle-miles traveled (VMT) will exceed the VMT of conventional vehicles for such trips due to empty driving between travel parties, unless rides are pooled. Regular pooling or DRS can quickly offset the added VMT, and even reduce overall VMT for a given set of trips, if they were previously driven, rather than accomplished by transit, carpool, or active modes (Martinez and Crist, 2015; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2022). Paithankar et al. (2026) simulated 17% lower Austin, Texas SAV-fleet VMT under a 40% fare savings for those who choose ride-pooling, and the fleet's empty-VMT share fell from 32% to 25%.

Many recent simulations rely on range-constrained (e.g., 180- to 300-mile-range) right-sized SAEVs (4-person vehicles, achieving roughly 3 miles per kWh of battery energy), with proactive relocation (moving idle SAEVs to neighborhood with higher expected demand) and regular vehicle cleaning and battery recharging. These very detailed SAEV-fleet simulations result in roughly 25-37% empty driving (Dean, et al. 2022; Su, et al. 2026), but may lower energy use and emissions, depending on SAV ride-pooling rates and which household vehicles would have been owned and operated in lieu of the SAEVs (with presumably no empty driving permitted allowed of household AVs).

Onat et al. (2023) estimated that vehicle automation reduces greenhouse gas (GHG) emissions by 17% per mile (an average across 12 vehicle models), while increasing manufacturing/embodied emissions (a growing share of vehicles' lifecycle emissions) by as much as 40%. Roca-Puigrós et al.'s (2023) comparisons of shared mobility systems to privately owned and operated AVs anticipate much benefit from the former. SAEV fleets have the potential to lower U.S. transportation energy use while serving the same number and type of person-trips, thanks to vehicle right-sizing, popularity (and possible subsidy) of pooled rides/DRS, all-electric drivetrains, and reduced crash rates (and associated losses) (Gawron et al., 2018). Policymaking and personal preferences will prove critical in the shape and scale of things to come. This chapter assumes a -5% to -12% energy savings from SAV right-sizing and ride-pooling. But savings could be much bigger if Americans stop buying large household vehicles and shift to using pooled (with strangers) rides in SAEV fleets, including demand-responsive right-sized automated-transit systems.

Powertrain Energy Source Category

Electric and hybrid electric vehicles

As technologies advance, EV costs fall, energy- and carbon-saving regulations strengthen, and public concern about climate change grows, the share of vehicles equipped with electric motors will continue to rise. CAV deployments accelerate adoption of electric powertrains, by requiring more direct-current (DC) electronics onboard (for sensors and computing). Various forecasts and simulations suggest that electric powertrains will dominate U.S. and global fleets by 2050 (e.g., Quarles 2018; Loeb et al., 2018 and 2019; Chen and Kockelman 2016; Roca-Puigròs et al., 2023; Hoehne et al., 2023). CAVs' ability to reposition and recharge themselves (using inductive or robotic chargers) eliminates the need for human interaction, which is particularly advantageous for SAEV fleets (since they are typically empty when sent to recharge). Battery-only EVs have no tailpipe emissions, and studies estimate their use lowers vehicle lifetime energy consumption by 30 to 70% (Hawkins et al., 2013; Al-Samari et al., 2017; Pitanuwat et al., 2015). But it is the upstream feedstocks used for electric power production, along with mining for batteries and other materials, that will most affect emissions and planetary damages (Vilaca et al., 2022).

Summary

In summary, CAVs are very attractive to travelers (and freight carriers) for a variety of reasons, but may use more energy than conventional (human-driven) vehicles for a variety of reasons (including more sensors and VMT). If AVs are deployed with thoughtful control and communications (for eco-driving and crash avoidance), their widespread adoption may save the U.S. transportation sector some energy (while generating more roadway congestion, everything else constant). Considering all the likely changes, a shift to electric drivetrains is expected to have the biggest impact on U.S. vehicles' energy use. And that shift is expected regardless of CAV and SAV adoption. The results of this literature review are summarized in Table 13.1, assuming an already highly motorized country, like the U.S.

Table 13.1 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 AVs – Empty Driving	SAVs traveling empty to next passenger	+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 Cycles	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 Interactions	V2V & Platooning	Vehicle-to-vehicle connectivity & platooning	-2% to -19%
	V2I & Smart Intersections	Vehicle-to-infrastructure connectivity & smart intersection	-6% to -30%
	Shared AVs – Right-Sizing & Ride-Sharing	Fuel savings from vehicle right-sizing & dynamic ride-sharing (DRS)	-5% to -12%
Powertrain Energy Source	Plug-in Electric Vehicles	Drivetrain shifts from gasoline to electricity	-30% to -70%

When classified by category level, changes can be observed more directly. Figure 13.1 shows the largest energy increases and reductions for each category. It is also shown that the Travel Demand Changes and Driving Details categories are more likely to increase energy use relative to the other two impact categories. 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 Interactions category, energy savings are projected, largely due 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, due to drivetrain and powertrain electrification.

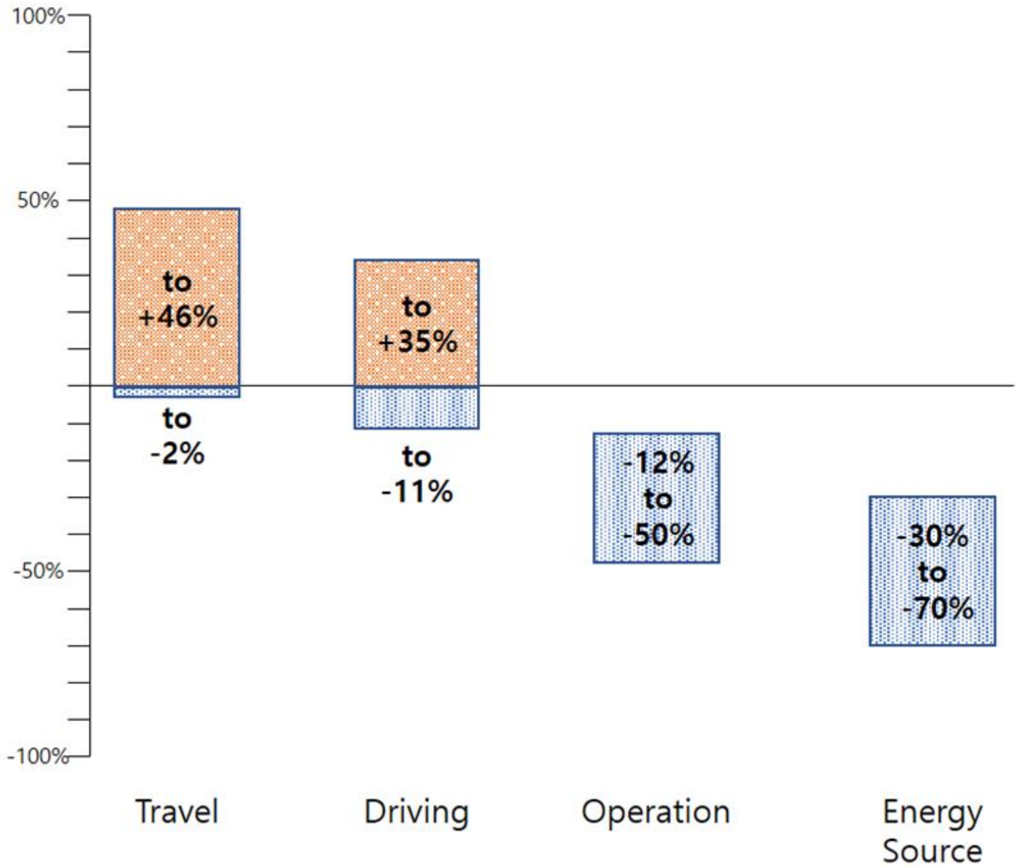


Figure 13.1 Predicted Changes in light-duty vehicle energy use (across Table 13.1 categories)

SCENARIO ANALYSIS

Due to the uncertainty surrounding CAV implementation, it is difficult to predict the near-term and long-term energy effects of widespread CAV adoption. Various impacts may cancel one another, and the range of changes may exceed what is expected by the literature. To reflect such uncertainty, this work uses scenario analysis to explore a range of potential future outcomes. Energy consumption changes are analyzed with respect to the market penetration rate (MPR) of self-driving vehicles. Since powertrain electrification delivers the greatest overall impacts, it is analyzed separately, by including and excluding its impact in the model.

Energy Consumption with respect to Penetration Rate

Excluding the impact from energy source changes, random samples were generated to represent the variation in energy consumption associated with each remaining impact. Assuming uniform distributions for each impact's range of values, expected energy-use changes were simulated using Monte Carlo methods. Some impacts may be correlated (such as adoption of SAVs and DRS) and actual distributions probably are not uniform, but this analysis assumes independence and flat density functions for transparency and ease. Powertrain electrification impacts are excluded initially here, in order to first focus on CAV system impacts, and to recognize the fact that the U.S. vehicle fleet is likely to eventually electrify even without CAV technologies. Assuming 100% CAV MPR, 1,000 random values were sampled in every impact category (excluding electrification, initially). And Fig. 13.2 shows the outcomes of this random sampling process.

Assuming a 100% current energy consumption value, lower values imply energy savings, while larger ones suggest increased energy use. Figure 13.2 shows that most 100% market penetration results reduce light-duty vehicle energy use (per capita), with an average reduction of 11%. Thus, mild energy savings (per person, in the realm of personal travel) are expected with full adoption of CAVs in the United States, on average – regardless of drivetrain type.

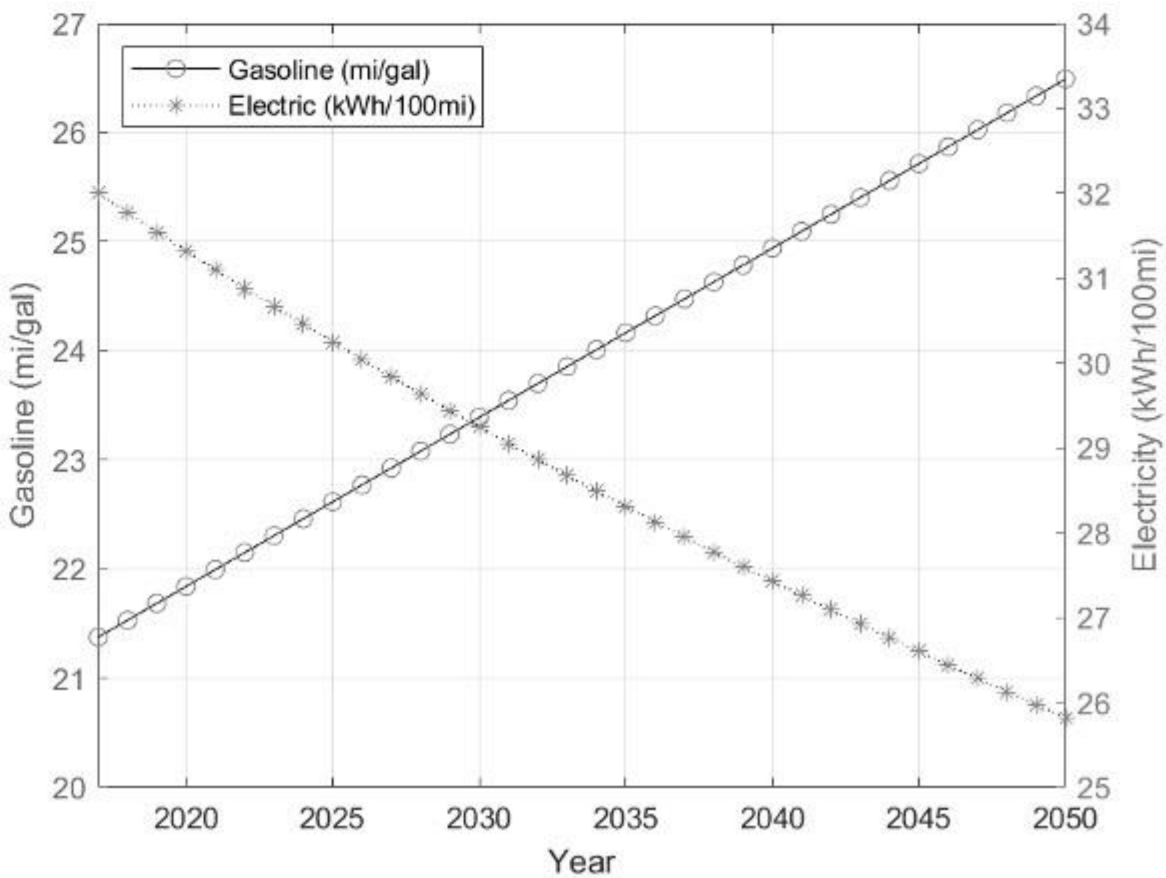


Figure 13.2 Energy Impacts from Random Sampling of Table 1 Impacts, Assuming 100% Penetration Rate of CAVs

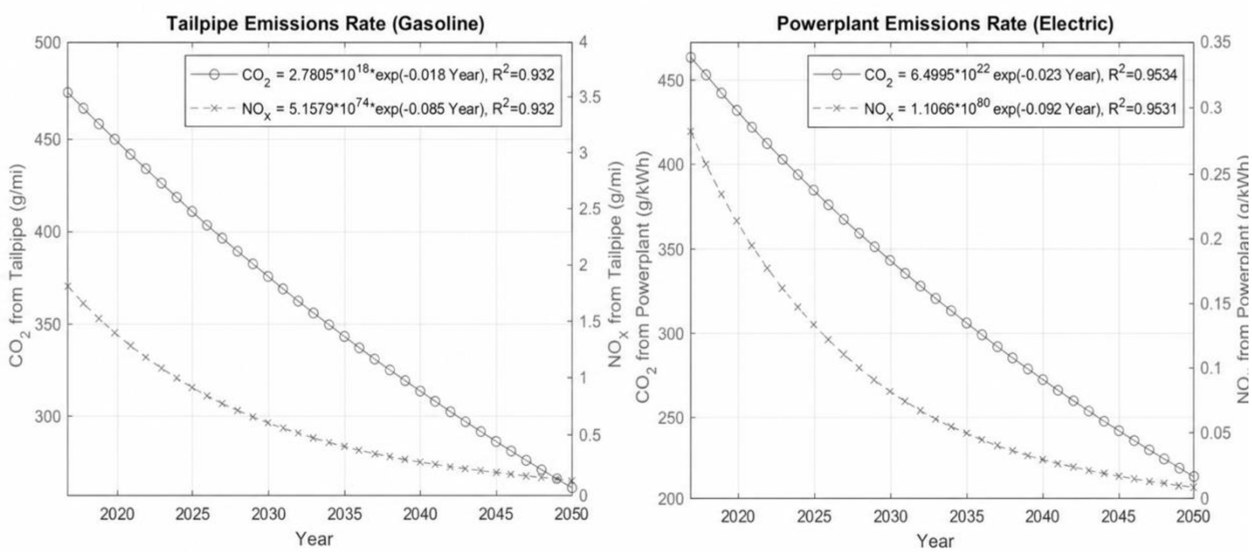
Extreme Electrification Effects with respect to CAVs' Penetration Rate

Vehicles are expensive assets, with relatively long lifetimes (e.g., 5 to 25 years, depending on annual mileage and crash frequencies), so market penetration of CAVs is expected to occur gradually, rather than abruptly. Thus, energy impacts are also expected to emerge gradually. To anticipate these energy impacts over time (as share of CAVs or "CAV%" rises), a scenario analysis was conducted, based on Eq. 1:

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

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. 13.3 shows the average energy results of these calculations, along with 1-standard deviation bands, and the most positive and negative results. As CAV MPR rises, so does the standard deviation band. This can be explained by the uncertainty of predicting the future, so a larger error is 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 values suggest net energy savings as MPR rises. It is likely that emissions will fall as well, since emission species are reasonably proportional to energy expended in ground transport (and U.S. power grid operators have been decommissioning coal-fired power plants, while shifting to lower-cost renewables with some battery storage systems).



(a) Gasoline Vehicle Emissions Rate (g/mi for CO_2 and NO_x) (b) Electric Vehicle Emissions Rate (g/kWh for CO_2 and NO_x)

Figure 13.3 Estimated energy impacts of CAVs without (a) and with (b) electric vehicles

The effects of powertrain electrification are analyzed here using both 0% and 100% battery-only EV penetration rates. A decrease in U.S. energy consumption is expected (but not guaranteed) without any EVs (Fig. 13.3a), and energy savings are certainly greater when 100% of CAVs are EVs (Fig. 13.3b). The average, simulated energy savings (within the U.S. transportation sector) falls from approximately -11% to -55% when all CAVs rely on electrified drivetrains (rather than petrol). But U.S. human-driven vehicles are expected to shift toward all-electric drivetrains even without automation and connectivity, so the -11% savings is the more realistic forecast, relative to background trends.

SUMMARY

This chapter anticipates the many possible outcomes from CAV adoption in an already highly motorized country, like the U.S. Added driving, on-board sensors and computers, and higher travel speeds are expected to increase transport energy use, while pooled rides in shared, right-sized vehicles, powertrain electrification, smoothed driving cycles, and other changes reduce it. There are a variety of possibilities, resulting in a wide range of uncertain implications. Through an extensive literature synthesis, this chapter defined impact types and their ranges. Scenario analysis and Monte Carlo sampling convey 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 chapter's estimates – seeking to reflect all possible CAV futures – suggest a slight reduction (-11%) in average energy demand by the U.S. transportation sector.

However, under Paris Agreement targets (UNFCCC, 2015), the U.S. and other motorized nations are unlikely to meet their net GHG reduction targets. For the U.S., the target was 26 to 28% below 2005 levels in 2025, and roughly 18% was achieved. Unfortunately, none of the CAV implications, market penetration and drivetrain electrification scenarios presented in this paper will achieve a net-zero GHG emissions target by 2050, without shifting the nation's fleet to 100% electric drivetrains manufactured and charged using 100% "clean energy" (via renewable and nuclear power sources, battery storage, recycled vehicle and battery materials, direct carbon capture, and clean mining operations). The nation's current renewable energy share is 26% (US EIA, 2026), and its total electricity demand is expected to rise substantially by 2050 (Mai et al., 2018; Batra et al., 2025). More behavioral, political, and technical changes are certainly needed to help U.S. transportation deliver its fair share of energy and emissions savings.

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