Energy Policy 122 (2018) 203–213

Contents lists available at ScienceDirect

Energy Policy

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

Long-term U.S transportation electricity use considering the effect of autonomous-vehicles: Estimates & policy observations

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ARTICLE INFO

Keywords:
U.S transport electrification
Kaya identity
Light duty vehicle
Autonomous vehicle

ABSTRACT

In this paper, we model three layers of transportation disruption – first electrification, then autonomy, and finally sharing and pooling – in order to project transportation electricity demand and greenhouse gas emissions in the United States to 2050. Using an expanded kaya identity framework, we model vehicle stock, energy intensity, and vehicle miles traveled, progressively considering the effects of each of these three disruptions. We find that electricity use from light duty vehicle transport will likely be in the 570–1140 TWh range, 13–26%, respectively, of total electricity demand in 2050. Depending on the pace at which the electric sector decarbonizes, this increase in electric demand could correspond to a decrease in LDV greenhouse gas emissions of up to 80%. In the near term, rapid and complete transport electrification with a carbon-free grid should remain the cornerstones of transport decarbonization policy. However, long-term policy should also aim to mitigate autonomous vehicles' potential to increase driving mileage, urban and suburban sprawl, and traffic congestion while incentivizing potential energy efficiency improvements through both better system management and the lightweighting of an accident-free vehicle fleet.

1. Introduction

The transportation sector is now facing the same disruptions that have upended many other sectors of the economy. Platform and car-sharing companies such as Uber and Zipcar are threatening the vehicle ownership model that has stood for a century. Electric vehicles are the fastest-growing segment of the industry, with more than 50 models for sale in the U.S. today. Transportation may rapidly shift from human-piloted to driverless or autonomous vehicles (CAVs). While a range of opinions remain, most experts agree that CAV technology will be commercially available by the mid-2020s and commonplace in the 2030s (Lavasani et al., 2016; Niewenhuijsen, 2015; Arbib and Seba, 2017; U.S. Energy Information Administration, 2017). This technology is predicted to unleash dramatic changes in the ways personal vehicles are used.

This trifecta of disruptions, namely electrification, sharing, and autonomy, have become known in some transport circles as the "Three Revolutions." (Sperling, 2017, 2018) Together, the three are expected to have profound impacts across developed world economies, from the auto industry, to the labor force, to family lifestyles and more (Barclays, 2015; Clements and Kockelman, 2017; Albright and Stonebridge Group, 2016).

At the same time, the need for reducing greenhouse gases from transportation is beyond dispute. In 2016, U.S. GHG emissions from transport for the first time became the largest single component of total U.S. GHG emissions (U.S. Energy Information Administration, 2017; EPA Greenhouse Gas Inventory, 2017). U.S. withdrawal from its Paris commitment makes it essential that states and cities adopt policies that put transport emissions on a firm trajectory to mid-century zero.

The purpose of this paper is to examine one important outcome from all of these forces: the electricity needed to power passenger electric fleets in the United States and the implications of this shift for greenhouse gas emissions. The amount of electricity used along this path is a function of billions of individual trip and vehicle purchase decisions, all influenced in turn by myriad economic, demographic, policy, and technological factors. Our goal is to establish realistic bounds on the aggregate increase in electricity required to power light-duty vehicle (LDV) fleets between now and 2050 through a carefully structured set of assumptions and calculations. LDVs account for 90% of motor vehicle travel in the United States (Federal Highway Association, 2017).

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https://doi.org/10.1016/j.enpol.2018.07.033
Received 9 February 2018; Received in revised form 7 June 2018; Accepted 14 July 2018

1.1. Background

Many researchers have examined electricity use for light duty electric vehicles (EVs), often in combination with general forecasts of EV adoption and broader questions of transport energy use during a disruptive period. Generally, these estimates are either short term in nature or are conducted for a specific metropolitan area. Forecasts of metropolitan area EV use are exemplified by Gucwa (2014) for the San Francisco area, Zhao and Kockelman (2017) for Austin, Texas, and Childress et al. (2015) for Portland, OR.

Of the long-term forecasts, the enormous changes engulfing the sector typically give rise to a scenario approach, where transport energy use varies by such a wide margin that it is difficult to extract much in the way of policy or planning guidance (World Energy Council, 2011). For instance, both Brown et al. (2014) and MacKenzie et al. (2014) estimate long-term energy use in the United States – but only by scenario. BGR's three scenarios span long-term outcomes from − 95% to + 173% of current energy use – an extraordinarily large range of outcomes. MacKenzie, Wadud, and Leiby's four scenarios cover an only slightly smaller expanse; from − 40% of current energy to about + 140%. Stevens, et al. (2016) derive the widest estimates of all, partly because their purpose is to search for upper and lower bounds. Expressed as gallons of gasoline, their scenarios range from 37 to 303 billion gallons of gasoline per year, a factor of ten difference.

A handful of studies examine more precise long-term transport electricity demand. One such study is the Electric Power Research Institute/Natural Resources Defense Council environmental assessment of electric transport. This three-volume work predicts 450 TWh of LDV electric demand in 2050 in the United States, a figure not far from one of our cases (Electric Power Research Institute and Natural Resources Defense Council, 2015). Another estimate comes from the Brattle Group's recent report on Electrification, which estimates a rough bound of 2100 TWh of electricity use if all U.S. vehicle transport is electrified, a 56% increase over 2015 sales (Weiss et al., 2016). Unfortunately, these studies do not appear to account for disruptions caused by CAVs and vehicle sharing.

As a result of this literature review, we find that the existing work covers either too wide a range to guide many policy decisions or ignores some of the key disruptions on the horizon within the transportation sector. This paper aims to fill these gaps.

2. Methods

2.1. The kaya identity framework

Transport energy and emissions are often forecasted by (1) estimating the vehicle-miles that will be traveled (VMT) using well-established models benchmarked from prior changes in travel on these modes over decades; and (2) multiplying VMT times the energy use per vehicle-mile, which can be forecasted by analyzing current efficiencies, fuel economy rules, fleet composition shifts, and technical change.[1] This relationship, known as a Kaya identity, is often written in its aggregate form as:

$$v^*e = \Phi_l \tag{1}$$

Where total VMT is denoted by v, average energy intensity in kilowatt-hours per mile is denoted by *e,* and Φ_l is the total energy use for LDV transport (Kaya, 1990). This approach is useful when models predicting aggregate total travel are stable enough to perform well over long forecast periods and fleetwide average energy intensity can also be projected with confidence. Unfortunately, few of the conditions that make this *aggregate* approach useful hold today. Traditional forecasts of aggregate VMT began losing accuracy following the Great Recession of 2008, well before the sharing and autonomy disruptions had much of an effect. Autonomy is expected to greatly disrupt these forecasts, possibly along with new preferences for walkable urbanism, ride-sharing, and other changes.

There is no silver bullet to address these difficulties, but we gain a little tractability with a conceptual framework based on an expanded identity of the following form. The disaggregated kaya identity we use is:

$$\sum_i [v_{i,t}{}^*k_{i,t}{}^*e_{i,t}] = \Phi_{l,t} \tag{2}$$

where the stock in year *t* of EVs of a motorized vehicle type *i* is denoted by $\kappa_{i,t}$, $v_{i,t}$ is the average miles traveled by that vehicle type in year *t*, and $e_{i,t}$ is the average electricity use of the vehicle type *i* per mile traveled during year *t*, which we refer to as electric intensity (EI). The motorized vehicle types *i,* examined in our analysis, include different forms of electric vehicles (EV) including battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), and autonomous electric vehicles (AEV). Intuitively, this expansion of the identity trades the problem of forecasting aggregate VMT and energy intensity for the problem of forecasting the number of electric vehicles in the fleet each year, the efficiency of that vintage of EV, and number of miles that vehicle is driven. The uncertainties and potential errors in this approach remain large, but at least they are disaggregated within a more flexible and transparent framework. For example, this framework allows us to treat electric non-autonomous and autonomous cars and light trucks all separately, adjusting use intensity for vehicle type as well as allowing the composition of the fleet to migrate from one type to another.

2.2. Modeling the disruptions by layer

We break through some of these forecasting difficulties using a very simple approach. We first posit a baseline in which none of the disruptions occur. The latest FHWA forecast of VMT projects 0.71%/yr growth for the next 30 years, just slightly higher than U.S. population growth (0.63%) (Federal Highway Association, 2017). In this baseline scenario, however, we generally adopt the view of Litman, Circella, et al., that per-capita LDV travel by Americans has hit its peak and is likely to decline (Litman, 2016, 2017; Circella et al., 2016). As our goal is to forecast only electric VMT (eVMT), we forecast the sales of EVs each year and multiply them by each vehicle's expected annual travel. We do not increase expected per-vehicle travel based on an exogenous trend, such as the FHWA's 0.71% increase in per-capita VMT.

Disruptions from electrification, the adoption of CAVs, pooling and sharing, and additional factors are then factored into our implicit baseline in additional “layers” of calculations. The first layer is electrification, an interim scenario in which the only major change is the availability of EVs as an alternative to CVs. We employ relatively conventional third-party forecasts of EV penetration that do not appear to reflect the full impacts of other coming changes in transportation trends. Within this first layer we also project the composition of the EV vehicle fleet and changes in EV energy intensity, in kWh/mile, (EI) due to technological improvements in EVs themselves. The next layer of our calculation modifies this interim case to reflect the onset of autonomous vehicles. Importantly, we define CAVs in this paper *only* as fully commercialized level 4 or 5 vehicles. Of equal importance, we assume these vehicles are connected to smart traffic management systems in all major urban areas by 2050.[2] In this layer, we first survey CAV penetration predictions and adopt a base CAV penetration estimate. We also consider whether AEVs are likely to have significantly different EI than non-AEVs, including whether CAV technology will change travel and road safety to the point where vehicles will downsize and downweight

[1] VMT are either forecast in the aggregate using reduced-form econometric equations or from vehicle forecasts.

[2] See Section 2.2.2 for further discussion of these assumptions.

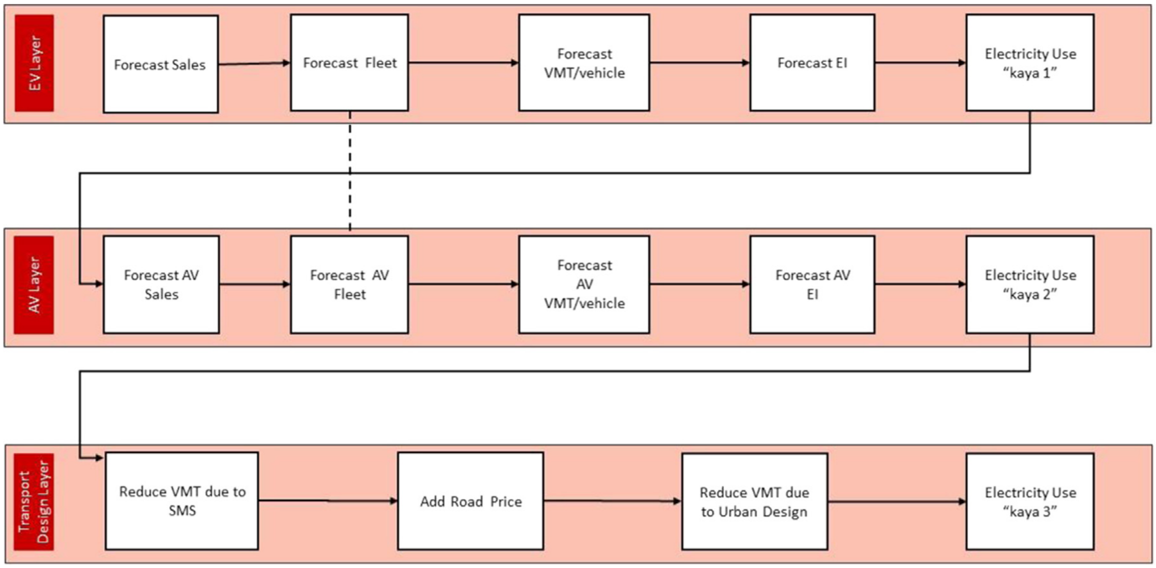

Fig. 1. Research approach.

significantly and thereby use less electricity per mile.

In the final layer, we add the potential impacts of the new pooled and shared modes, road pricing, and urban design. With the addition of our third layer the main part of our computational framework is complete. The scenarios emerging from this layer are intended to reflect the main impacts of all major disruptions on United States LDV electricity use through 2050. Our multilayer approach is summarized below in Fig. 1.

2.2.1. *Conventional EV ownership impact on electricity demand*

Many industry groups have projected U.S. electric vehicle sales, often without any visible adjustment either for the growth of autonomous driving or for new ownership models. For our analysis, we begin with these forecasts and employ a reduced form of the Bass Diffusion Model to model product growth rates. The specific quantitative formulation is shown below:

$$S_{(t)} = m\left(\frac{1- \quad e^{-(p+q)t}}{1+ \quad \frac{q}{p}e^{-(p+q)t}}\right) \tag{3}$$

Where, $S_{(t)}$ = percent of total sales in year t, m = final percent of total sales, p = coefficient of innovation, q = coefficient of imitation, t = year.

Our EV sales share forecasts, which range from 57% to 90% in 2050, are most accurately viewed as extensions of prominent industry forecasts out to the year 2050. We prepared these by first reviewing projections made by Green Tech Media, the US DOE's 2017 Annual Energy Outlook, EPRI & NRDC, BNEF, and the Institute for Electric Innovation (Gavrilovic, 2016; U.S. Energy Information Agency, 2017; EPRI and NRDC, 2015a, b; BNEF, 2017; Cooper and Schefter, 2017). Fig. 2 below shows our forecasted EV sales projections compared to prominent industry forecasts.

Electricity consumption is driven by the total number of vehicles on the road, which is affected by car retirements as well as new car sales. To inform our estimate of electric vehicle stocks, we rely on the survival rates for conventional cars and light trucks provided by the Oak Ridge National Laboratory's (ORNL) Transportation Energy Data Book (Oak Ridge National Lab, 2016). Using these survival rates combined with trends for PHEV/BEV and light truck/car sales splits, we build a stock turnover model to capture the four types electric vehicles (i.e. PHEV car, PHEV truck, BEV car, BEV truck) to estimate the total electric vehicle stock (Inside EV website, 2017; Oak Ridge National Lab, 2016). In 2016, there was a 50/50 split of EVs purchased between PHEVs and

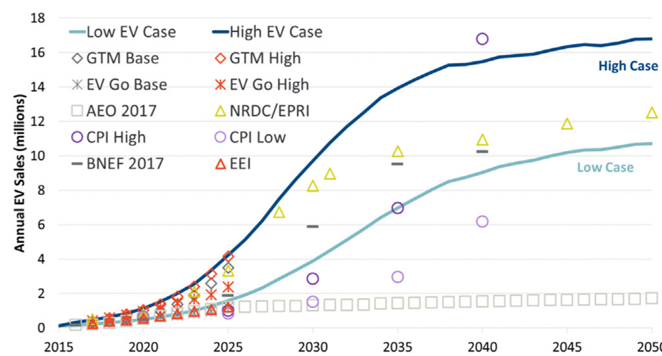

Fig. 2. U.S. EV sales projections.

BEVs. We assume that through 2050 the share of BEV adoption increases compared to the share of PHEVs, based on the Bank of America investment report that shows PHEV sales dropping to 30% by 2025. Following that trend, we decrease that share to 10% by 2050 (Ma et al., 2017) (Figs. 3 and 4).

We generate our eVMT estimates based on a 2015 Idaho National Labs (INL) survey that tracked the driving patterns of close to 15,000 PHEV and 7000 BEV owners from across the U.S.; we rely on the annual eVMT estimates that resulted from this survey to inform our initial-year eVMT assumptions (Carlson, 2015). We expect the annual miles driven per vehicle using electricity to increase as battery technology continues to improve and battery ranges increase. In order to capture the effect of battery improvement for the future years of our analysis, we fit a curve to projected battery energy density increases and use the percent increase over time to gross up the total electric vehicle miles for both PHEVs and BEVs until they equal the VMT for an internal combustion engine (ICE) vehicle. The VMT/vehicle changes asymmetrically year over year. The large jump from 2015 to 2025 is a result of the large increase in battery energy density that is expected to occur between those ten years (Fig. 4).

Our energy intensity numbers for the baseline case are derived from Argonne National Laboratory's Autonomie database and EPA's fueleconomy.gov (Autonomie, 2016). These data divide vehicles by size and type, allowing us to avoid confusing trends in fleet composition with trends in efficiency by vehicle type. Fig. 5 below shows the forecasted composite EI derived from the Autonomie report and used as our baseline estimates for EV efficiency.

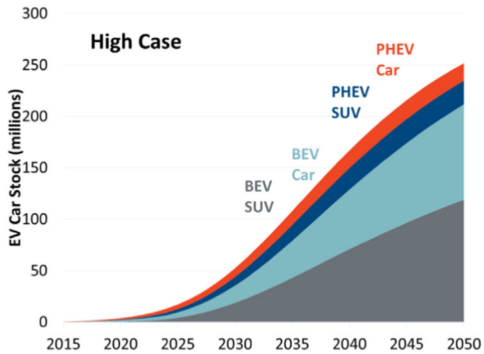

Fig. 3. U.S. Total stock of electric vehicles by type, conventional ownership and no autonomy.

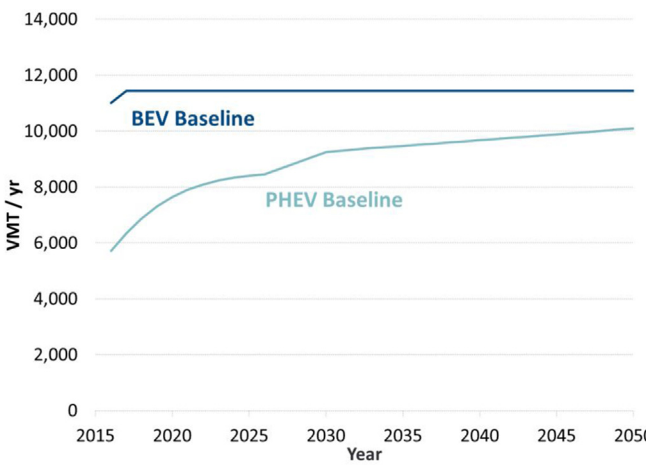

Fig. 4. Forecast eVMT/yr for baseline case.

2.2.2. Autonomous vehicle impacts on electricity demand

There is a wide range of opinions as to when level 4 or 5 autonomous vehicles will become ubiquitous. Some predict that shared CAVs will handle 95% of all passenger-miles by 2030 (Arbib and Seba, 2017) while others predict 100% level 5 autonomy will not occur until 2070 or later (Litman, 2017; Niewenhuijsen, 2015). Researchers also predict a wide range of scenarios or narratives as to how the CAV market will unfold (Shladover, 2015; Niewenhuijsen, 2015; Lang, et al., 2016). Given these considerations, we adopt Lavasani et al. (2016) estimates of Bass or "S-curves" using parameters selected by comparing CAVs to other types of technologies (similar and dissimilar) for which there are full adoption histories. The results of Lavasani, Jin, and Du's base estimate is that cumulative CAV sales rise from 1.3 MM in 2030 (five years after introduction) to 70 MM by 2045 and saturation by 2060.

Next, we collated assumptions on CAV technology impact on VMT and EI of light duty vehicles. There is widespread agreement that vehicle autonomy will trigger significant changes in the travel patterns of many Americans. Some of these changes will reduce VMT, while others are expected to increase it significantly (Kockelman et al., 2017; Litman, 2017). We model three key categories of VMT effects:

- Increase Road Capacity: reductions in traffic congestion increases throughput of road infrastructure.
- Reduce Drive Time Cost: more convenient and affordable transportation, especially by giving people opportunity to engage with other activities while driving (e.g. work, sleep, or entertainment).
- Increased Mobility Access: underserved populations (i.e. under age 16, senior citizens, persons with disabilities) have greater opportunity to travel.

Many researchers have estimated some or all of these travel impacts. While all of the numbers we present are expressed as percentage increases in either VMT or EI due to one isolated factor, the entries reflect vastly different techniques, assumptions, and annual values found in the literature that serve as the basis for the percentage result shown (Kim et al., 2015; Stevens et al., 2016; Zhao and Kockelman, 2017; Chidress et al., 2015; Sivak and Schoettle, 2015; Harper et al., 2016). Table 1 provides the finalized assumptions for our assumed VMT effects due to CAVs. Due to the wide range of estimates found describing VMT impacts, we adopted a low and mid case as a sensitivity.

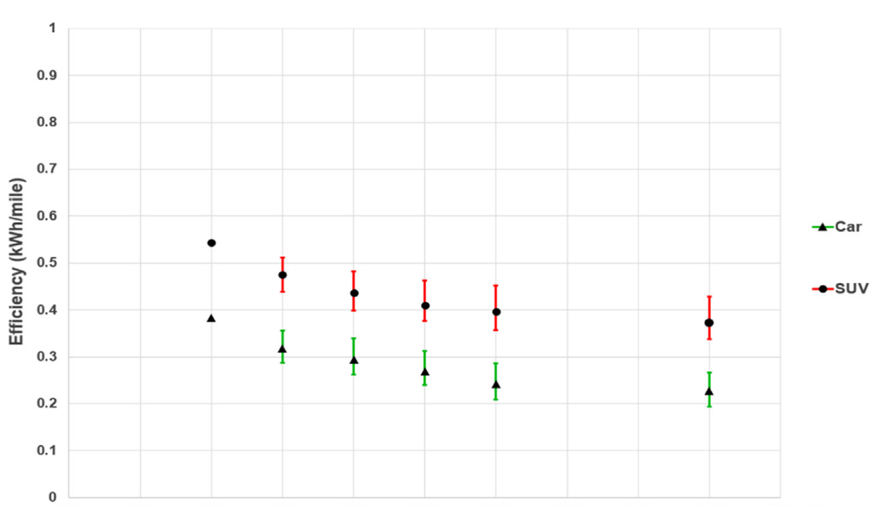

Fig. 5. Forecasted composite EI.

Table 1
Assumed VMT Effects of CAVs.

AV VMT effects	Low		Mid	
	VMT Change	Phase-In	VMT Change	Phase-In
Road Capacity Effect	0%	N/A	+ 5%	Linear from 2025 to 2050
Lower Time Cost for Driver (Intra- and Intercity)	+ 15%	Starting 2030	+ 20%	Starting 2025
Increased Access	+ 8%	Linear from 2030 to 2050	+ 15%	Linear from 2025 to 2050
Total	+ 23%	N/A	+ 40%	N/A

In addition to VMT impacts, autonomy is predicted to affect the amount of electricity used per mile of travel by any given vehicle type. There are a variety of reasons why electricity use per mile is predicted to differ. Although the effects are sometimes categorized and often named differently, five multi-faceted and somewhat overlapping categories stand out in the literature:

- Traffic Smoothing: reducing braking and acceleration in urban areas at low as well as high average speeds.
- Intersection Management: reducing braking, acceleration, and stops due to better intersection management; can be considered a sub-element of traffic smoothing.
- Higher Average Speeds: faster travel on uncongested highways at speeds where aerodynamic drag takes a measurable energy toll.
- Platooning: multiple cars or trucks driving close enough together at high speeds to reduce drag on the vehicles following the leader.
- Rightsizing/Performance: designing and manufacturing CAVs that have smaller powertrains and therefore smaller batteries than conventional counterparts.
- Lightweighting: designing and manufacturing CAVs that have lower weights due to the absence of conventional vehicle safety equipment and therefore higher efficiencies.

To model this layer, we integrate the CAV sales adoptions into our original projection of EV sales by assuming that every CAV purchased is an EV and that the total sales of EVs, whether CAVs or CVs, does not change between our conventional layer and our autonomy layer. Our assumption that CAVs are 100% electric biases electricity consumption upward, allowing us to assume that our ultimate calculation represents an upward bound for electricity consumption. Then, we re-compute the electricity consumption of the fleet by utilizing the expanded Kaya identity explained above, taking into account the different VMT and EI numbers of CAVs.

As distinct from some of the CAV effects on VMT, autonomy's EI effects appear to be sensitive to the fraction of CAVs in the fleet in their locality. When examining CAV EI effects, we must therefore be attentive to at least these three parameters: the point at which CAVs are concentrated enough to begin to change EI; the terminal level of EI changes when CAVs saturate; and the shape of the curve between them. Our approach to these parameters is mainly to ignore the first two points and use the literature to give us a final level of EI effect at CAV saturation. Rather than try to estimate the first two parameters, we simply linearly phase in effects from the inception of commercial CAVs in 2025. While this may not reflect the trajectory of EI effects, our primary focus is the end point. Table 2 provides the finalized assumptions for our assumed EI effects due to CAVs.

2.2.3. Additional considerations

To inform our sensitivity analyses, we consider additional factors that will influence future LDV travel in especially unpredictable ways: (1) Ride Pooling and Ride Sharing (2) Road Infrastructure Costs, including CAV-specific infrastructure, and (3) the redesign of urban areas to reduce the need for personal vehicle travel. While each of these factors may be reflected to a degree in our baseline view of flat per-capita VMT growth (which is also related to changes in our electric and autonomous layers), their impacts are especially uncertain. Accordingly, before finalizing our projections we consider whether we can learn enough to modify our electricity demand estimates or at least determine the likelihood of significant upside or downside potential.

Table 2
Assumed EI Effects of CAVs.

Effect	Impact	Timing
Traffic Smoothing	− 15%	50% reduction in technology improvements in EI for the first 10 years, then linear phase-in from 2035
Intersection Management	− 4%	Linear phase-in for urban EVs starting in 2035 and fully implemented by 2055
Higher Average Speed	+ 8%	Linear phase-in from 2030 to 2035
Platooning	− 2.5%	Linear phase-in from 2030 to 2035
Rightsizing/Weight Reduction	− 50%	Phased in linearly at 1% per year or 1.5% per year starting in 2040

2.2.3.1. Pooling and sharing. This layer considers the impacts of the many emerging shared and pooled transport modes, including various forms of what are being called “mobility networks.” It is important to bear in mind that sharing the use of a vehicle by dividing its exclusive use between two families in succession is very different than two riders who are strangers “sharing” a single ride between two points. We refer to the latter as pooling rather than sharing. As in previous sections, the ultimate objective of this section is to attempt to bound the impact of pre- and post-autonomy sharing and pooling on VMT and EI by mode and time frame. The impacts we seek are changes to VMT and EI by mode from the estimates already adopted in Layers 1 and 2.

The implementation of this layer is complex due to the lack of data availability as well as the uncertain nature of how these new mobility technologies will interact with the layers previously introduced. Once commercial autonomy arrives, most analysts predict that conventional carsharing will decline as customers shift to on-demand autonomous taxis; those who continue to share cars will share mutually- or fleet-owned CAVs. Carpooling, which is already a pre-CAV mode with modest and declining U.S. use, will lose its drivers and thereby ostensibly become cheaper and more heavily used, including as part of multi-modal mobility networks.

Considering impacts of these travel modes on EI, Greenblatt and Saxena (2015) estimate that adding a second person to a single-occupant average vehicle increases the vehicles energy consumption by 0.6%, without assuming any vehicle size changes. While shared/pooled vehicles could be designed differently, in ways that either reduce or increase efficiency, we have found no evidence to suggest this should occur. Considering these findings, we assume that the EI impact of sharing and pooling alone is unlikely to be large and therefore do not include it in our analysis.

In regards to VMT impacts, the current literature has not yet reached agreement on whether demand ride services will act as a VMT-additive or VMT-subtractive force. A Committee for Review of Innovative Urban Mobility Services was recently convened by the National Academy of Science. After examining the available evidence on the effect of ridesharing on VMT, the Committee decided that “it is too early to determine which of these competing forces will predominate, and effects are likely to play out in different ways depending on local circumstances,” (Transportation Research Board, 2015). Considering this finding and after reviewing the literature, we depend upon a simple back of the envelope calculation to bound the changes in electricity demand from these modes, rather than explicitly modeling the disaggregated Kaya identity.

Table 3
Summary of Case Assumptions.

Variable name	Description	Stress case	Policy case
EV Sales	The rate of EV sales, or more completely, the growth of LDV EVs in the fleet;	High EV (90% by 2050)	
Energy Intensity	The level at which EVs increase their energy efficiency;	0–20%	15–40%
Cheap EV	The extent of the mileage effect from lower EV operating costs;	10%	0%
CAV Entry Year	The year in which commercial fully-autonomous CAV sales begin;	2025	2030
CAV VMT Effects	The overall (net) long-term effect of CAVs on VMT (due to a number of effects, each with their own ranges and uncertainties), and how in the aggregate this phases; this is aggregated with "Cheap EV" for a total high factor of 50%	40%	23%
CAV Sales	The rate of CAV sales, or more completely, the growth of LDV CAVs in the fleet;	75% by 2050	
CAV EI	The overall (net) long-term effect of CAVs on realized kWh used per mile from various effects, and how this phases in (Sum of effects of traffic smoothing, intersection management, faster travel, and platooning)	− 13.5%	− 21.5%
Rightsizing/weight reduction	Whether and when CAVs allow a further substantial gain in EI due to lightweighting and/or rightsizing, implemented as a per-year increase starting in 2040;	− 1%	− 1.5%
Pooling/Shared VMT Reduction	Whether Pooling, Sharing, or Seamless Mobility Systems will reduce future VMT as well as shift it to higher-density modes;	0	− 2%
Urban Design	Whether redesign of our urban areas reduces VMT;	0	− 2%
Road Pricing	The form in which road pricing is adopted over the next decade or two;	$.022	$.024
Road Pricing Addition Through 2050	The increase in real road pricing cost by the year 2050	$0	$.024
Elasticity	The sensitivity of driving in EVs and electric CAVs to road prices.	− 0.2	− 0.2

More specifically, we are unconvinced that ride sharing or pooling will take hold without a concerted policy push towards seamless mobility systems (SMS). In order to get an upper bound on the reductions in electricity demand that this SMS growth would enable, we first assume that, in the absence of strong SMS policies, transit ridership remains flat at 60 billion PMT. We also simplify the calculation by assuming that SMS systems shift average LDV auto miles to transit miles, ignoring the first and last mile LDV use (or, equivalently, assuming its EI equals transit EI per PM). Finally, we assume that the electricity used for transit is zero, so that a shift of one passenger from an electric LDV to an SMS saves 100% of the electricity used by the LDV but does not increase electricity use for transit.

The result of this simple calculation shows that a doubling of transit ridership growth rates, which would yield 150 billion transit PMT (triple 2015 levels) would save less than 30 billion kWh (TWh) at 0.33 kWh/mile, a little under 1% of current U.S. electricity use. Quadrupling the growth rate to yield a 300% increase by 2050 would save 60 TWh, about 2%. To incorporate this into our model we assume on the low end there is no VMT impact due to these modes, and on the high end, a 2% nationwide reduction in VMT, accounting for both rural and urban areas (Henao, 2017; Rodier et al., 2016; Transportation Research Board, 2015; Circella et al., 2016).

2.2.3.2. Road infrastructure pricing. The cost of new and maintained roadway and related infrastructure, and the means of paying for it, are gigantic questions overhanging the future of U.S. transportation (U.S. U.S. National Economic Council, 2014). We do not think it is practical to attempt a detailed analysis of the wide range of possible road pricing outcomes and the range of their impacts on VMT and EI. However, we believe we can get a rough, order-of-magnitude range by examining two simple pricing scenarios: a flat 2.2 2017 cents per mile charge and a larger 2.4 cents per mile ($.60/gal @ 25 mpg) escalating to double its level in real terms by 2050. The first level of charges is similar to the GAO's estimate of the level needed to maintain current roads, indexed for inflation (U.S. Government Accountability Office, 2012). The second level of change corresponds to a recommendation by several environmental groups (Cambridge Systematics, 2009).

Based on a review of the literature, we employ a long-run road usage charge elasticity of − 0.2 as our base elasticity and later explore sensitivities with a level of − 0.35 (Deakin et al., 1996; Small and Van Dender, 2007; Binny et al., 2011). The result is a 10–42% reduction in VMT in the year 2050 when the full effects of our four VMT fee scenarios are applied.

2.2.3.3. The built environment. Finally, we explore the extent to which additional alterations in the built environment could affect trends of vehicle miles traveled. The potential to moderate personal vehicle travel demand by changing the built environment is one of the most heavily-researched subject in urban planning, often motivated by the desire to reduce the negative environmental and health impacts of travel (Ewing et al., 2015; Boarnet and Crane, 2001). The literature evaluating the extent to which a difference in built environment affects overall vehicle miles traveled estimates that anywhere from a 0.3–14% reduction in VMT could be achieved (Ewing et al., 2008; Cambridge Systematics, 2009; Outwater et al., 2014). Due to the vast heterogeneity between planning agencies and departments across the US, we are skeptical of the high end potential reduction as it assumes relatively similar and stable reductions due to such built environment changes. We therefore assume that the VMT result of a concerted nation-wide effort towards compact urban design policies would only save an additional 2% of VMT by 2050, the second highest estimate of VMT reduction found in the literature (Outwater et al., 2014; Cambridge Systematics, 2009).

2.3. Scenarios

We create two scenarios by adjusting the key assumptions described previously in a way that we think are near the edges of the probability space in which the true future outcome resides. Table 3 below summarizes these two scenarios labeled Stress Case and Policy Case.

We label the first scenario our "Stress Case" because it contains what we subjectively view as a combination of future events that represent the highest electricity use scenario that could realistically occur: high EV sales; early CAV entry; high ultimate increases in VMT from EV price reductions and CAV time reductions; no reduction in VMT from pooling; base case improvements in energy intensity for EIs generally and small (1%/year) additional lightweighting efficiencies for CAVs; road charges equal to current average total levels, escalating with inflation (applying uniformly to all EVs and CAVs); and relatively low travel sensitivity to road pricing. We do not believe it likely that all of these factors will jointly occur, making this something of an upper bound. With the possible exception of extreme VMT increases from autonomy, we would be surprised if any of these factors had larger positive effects on electricity use than we project, and we have made consistently conservative assumptions regarding the factors that reduce electricity demand. In addition, we assume all CAVs are electric, an assumption biasing our results upwards.

At the other end of the spectrum, we design a strong environmental policy scenario, or "Policy Case." This case assumes that federal, state, and/or local policies cause nearly every variable that leads to lower travel and/or higher efficiency to change to what we believe is realistically possible. This includes unspecified travel demand management policies that reduce the increase in VMT from lower EV costs to zero and the increased VMT from CAVs to 23%, after which we further reduce driving from the response to road pricing for all vehicles that begins at 2.4c/mile in 2025 and increases to double that level in real terms by 2050. In addition, we apply a 2% VMT reduction for pooling and sharing, assume high efficiency gains for EVs, assume CAV lightweighting begins in 2040 at 1.5%/year, and assume urban redesign further reduces travel 2% by 2050. Under current political conditions it is quite unlikely that all of this will occur, but technology breakthroughs or a stronger public support for climate policies as climate change worsens in the coming decades makes this a worthwhile bookend to our forecasts.

3. Results

3.1. Conventional ownership pre-autonomy results

In our baseline (i.e. first "layer") results, we project U.S. 2050 electricity demand of 890 TWh and 510 TWh with our high and low EV stock assumptions, respectively. These figures represent roughly 23% and 13%, of the current U.S. electricity demand of 3900 TWh and 20% and 11%, respectively, of EIA's projected 2050 electricity consumption of 4500 TWh. As a sensitivity, we test EV drivers' response to reduced operating costs of EVs compared to CVs (Kim et al., 2015). Through common fuel price elasticity effects, we model this increased VMT to take effect on all BEVs in 2025 and reach 10% added VMT by 2040. With this added effect, the projected electricity demand is 970 and 560 TWh, comprising 22% and 12% of 2050 demand, respectively. Table 4 below summarizes these findings.

On top of our interim electricity projections, it is important to note that the energy intensity of EVs does not decrease as dramatically as may be expected due to the projected improvement in battery technology. While it is true that our energy intensity improves year over year, the make-up of our electric vehicle stock also changes towards light trucks and SUVs which have considerably higher energy intensity than sedans. In effect, we find that the combination of these two trends basically cancel each other out, and the fleet's energy intensity over time remains relatively stable and even may increase in the short term – unless and until autonomy allows for radical change in vehicle design, or Americans lose their preference for large vehicles.

3.2. Results from the full kaya model

We estimate U.S. 2050 LDV electricity use to approximately be 1140 TWh and 570 TWh, in the Stress and Policy Cases, respectively. As these cases are intended to approximate upper and lower likely boundaries, the results are surprisingly close together. Whereas the earlier literature surveys described in the introduction found upper and lower bounds differing by as much as a factor of ten, our calculations suggest that the difference between our likely boundary cases is only about 700 TWh, 17% of today's electricity use. To put this range of electricity demand in perspective, the U.S. generated 4085 TWh of electrical energy in 2016. Absent increases from electric transport and the conversion of other end uses such as heat from carbon fuels to electricity, the approximate level of growth in electricity sales in the U.S. is roughly zero (0.8%/year in EIA's latest forecast, including EVs). Even in our stress case, adding 1000 TWh to U.S. supplies in the next 32 years would add about 0.6% to annual electricity sales growth.

In Fig. 6a and b, we deconstruct 2050 LDV electricity use in our Stress and Policy Cases, respectively. Starting from the left, the first bar in Fig. 6a is a contrived starting point that shows the energy that would be used by our projected 2050 EV fleet if those vehicles were unchanged in their annual average travel from today and they used today's average electricity per mile. The second bar on the chart, EV VMT, shows the added electricity from the presumed increase in travel induced by lower EV operating costs. Of course, this increased travel applies only to each EV as it enters the fleet. Similarly, the third bar shows the increased energy from the substantial added CAV travel in this scenario, applied to each CAV as it enters the fleet.

These are the main factors driving electricity use up; the remaining factors have the opposing effect. The fourth bar, EV EI, shows the reduction in electricity use attributable to the low case improvements in EI efficiency through 2050 forecasted by the National Academy of Engineering. The fifth bar, CAV EI, shows our highly conservative estimates of efficiency improvements specifically enabled by CAVs, such as platooning. The final bar shows the very modest effects of charging all vehicles a current 2.2 cents per mile for road use, indexed to inflation at an assumed long-run VMT price elasticity of − 0.2. The chart shows that even the modest low-end efficiency gains projected for EVs and CAVs wipe out the rather significant increases in per-vehicle VMT by 2050, whereas road pricing has a relatively small effect at this case's assumed level and elasticity.

The decomposition of the Policy Scenario in Fig. 6b suggests an even greater importance for potential efficiency improvements. The leftmost base bar on this figure is conceptually the same as the base bar in Fig. 6a, that is, the projected 2050 EV and CAV fleet in 2050 operating at today's mileage and efficiency levels (the size of the two base bars differ by a few TWh due to some small technical features of the scenarios). In this scenario, we also assume that policies discourage EV drivers from taking advantage of the lower opportunity costs of driving EVs, so only one factor, increased VMT from CAV entry (second bar on the chart), increases electricity use above the base bar level. Having started commercial sales five years later, the 2050 CAV fleet is only 128 MM vehicles (50% below the Stress Case CAV level), and these vehicles

Table 4
Estimated LDV Electricity Consumption in the U.S. – Baseline Case.

EV sales	Year	Total Number of EV in service	Portion stock electric (%)	Fleet average eVMT/ vehicle (per yr)	Fleet average efficiency (kWh/mile)	Total TWh (TWh)	Total TWh with price effect (TWh)
High EV	2015	410,000	0%	7180	0.32	1	1
	2025	17,000,000	7%	10,100	0.34	59	59
	2030	52,000,000	20%	10,700	0.33	190	190
	2040	170,000,000	60%	11,000	0.32	590	650
	2050	250,000,000	85%	11,200	0.31	890	970
Low EV	2015	410,000	0%	7180	0.32	1	1
	2025	7100,000	3%	10,100	0.34	24	24
	2030	21,000,000	8%	10,700	0.33	74	76
	2040	82,000,000	29%	11,000	0.32	290	320
	2050	150,000,000	50%	11,200	0.31	510	560

Note: No ownership model changes or autonomous vehicle impacts.

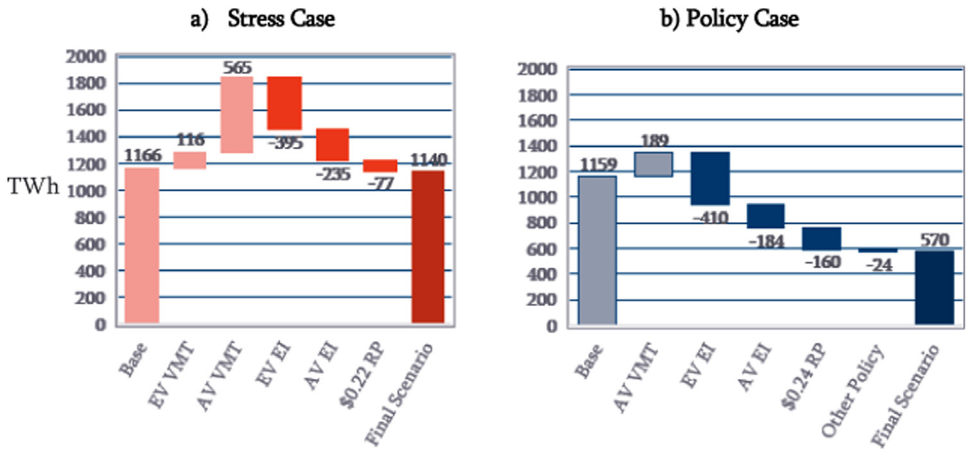

Fig. 6. Components of Estimated Total U.S. Electric Use by LDVs in 2050 (TWh).

are driven only 23% more (rather than 40%), so it is no surprise that the incremental electricity demand from this factor is 189 TWh, versus over 565 TWh in the Stress Case.

Conversely, the factors that reduce electricity use are larger in this scenario. Lower EV EI reduces demand by 410 TWh, enough to offset not only this scenario's increases from CAV travel, but almost enough to offset the much higher CAV VMT increases in the Stress case. Paradoxically, CAV EI savings are lower in this case than in the Stress Case, partly because we change the per-vehicle CAV EI very little between these two scenarios and partly because the lower penetration of CAVs in this scenario allows for lower CAV-induced efficiencies. Road pricing that increases slowly in real terms has a larger effect than in the Stress Case; at the same assumed elasticity of − 0.2 the effect is just over 20% of ultimate total demand.

3.3. Robustness

Fig. 7 shows 2050 total LDV electricity use in a series of sensitivity calculations. In order of appearance, the sensitivity scenarios examine the start date for CAV sales, high vs. low EV sales, road pricing elasticities and a revised scenario ("EV mandate") in which all new internal combustion ICE auto sales are halted after 2040. As expected, the table shows that EV sales are a very important driver of electricity demand, swinging 2050 demand by about 200 TWh in the policy scenario and

Fig. 7. Sensitivity Calculations (U.S. Electricity for LDVs in TWh).

300 TWh in the Stress scenario. While this is a very significant difference, it again highlights the fact that the ballpark in which 2050 LDV electricity demand will play is somewhere in the vicinity of 500–1200 TWh. The remaining sensitivities do not change the character of the main scenarios, including the case in which ICE sales stop in 2040; this scenario adds only about 50 TWh (5%) to 2050 electricity use.

3.4. Implications for greenhouse gas emissions

To evaluate the implications of our scenarios on greenhouse gas emissions, we relied on emissions modeling performed by the U.S. Energy Information Agency, which projects emissions factors for standard internal combustion engines as well as of the whole electric sector through 2050. These factors, combined with our stock modeling of the LDV sector, are combined to calculate a baseline estimate of greenhouse gas emissions for the LDV sector. We then calculate an alternative estimate of GHG emissions for the LDV sector based on an optimistic policy case where emissions from the electric sector decrease linearly to 95% of 2015 electric sector emissions by 2050. This assumption is not our attempt at a best guess case of what is likely to happen. Rather, it provides a lower bound to the greenhouse gas impact of the EV scenarios we present above. Furthermore, we estimate an upper bound of GHG emissions by assuming no EVs are adopted and LDV GHG emissions result entirely from ICE vehicles burning gasoline.

It is important to note that we only consider the GHG emissions that result from the fuel used to power the LDVs (i.e. the burning of gasoline for ICE vehicles and the overall emissions rate of the electric sector for EVs). While we are aware that various upstream processes also emit significant GHGs (e.g. raw materials processing and car manufacturing), it was beyond the scope of this paper. Future work should address these questions with life-cycle assessment methods.

The upper bound U.S. LDV fuel-related transport sector emissions are calculated to be 755 MMT in 2050. In the four EV scenarios we discuss above, our 2050 baseline calculation of GHG emissions ranges from 571 MMT in the Baseline Low EV case to 333 MMT in the Policy Case with autonomous vehicles, a 24% and 56% reduction, respectively, from the no EV world. When using the decarbonized electric sector emissions factor, these results drop to 166 MMT in the Stress case to 151 MMT in the Policy Case with autonomous vehicles, an 78% and 80% reduction, respectively, from the no EV world. Fig. 8 below summarizes these findings.

Unsurprisingly, EV adoption with or without corresponding reductions in the electric sector emissions leads to substantially less GHG emissions. Still, even in the optimistic decarbonized electric sector case, LDV transport emissions are non-zero, though substantially reduced. This result is due to the fact that the entire LDV fleet is not converted to electricity and it will likely be difficult to eliminate all GHG from the electric sector. It is also interesting to note the minimal differences between the High EV (Base), Stress, and Policy cases, which suggests that High EV adoption and decarbonization are the main drivers of future transport emissions.

Another relevant point of comparison is determining the carbon emissions resulting from our scenarios if the electric sector maintains the current carbon emissions factor, as opposed to either the EIA projected trajectory for emissions or the decarbonized electricity sector cases. With this assumption, our stress case with autonomous vehicle case sees minimal reductions in GHG emissions as compared to the no EV case. The significant increase in VMT in this scenario results in substantially more electricity consumption and thereby a higher emissions estimate. If the electric sector doesn't decarbonize, this scenario would result in 724 MMT of carbon emissions, which is still a 4% reduction from the no EV case if automated vehicles substantially increase VMT. While unlikely, this case is informative when considering the effects of aggressive electric vehicle adoption without corresponding policy of electric sector decarbonization, and it also serves to demonstrate that even in a worst-case power system scenario, electrifying the transportation sector would still see benefits for greenhouse gas emissions over ICE vehicles.

4. Concluding observations and policy implications

Based on our findings, electric and autonomous passenger vehicles will represent a large and important new demand driver for the electricity sector, but not one that should be difficult to supply. In 2015, the U.S. electric industry added 18,754 MW of all types of generation, a level quite representative of the last 20 years. At a 50% average load factor, this generation would supply 82 TWh, about of tenth of what LDVs will need by 2050, but added in just one year. Wind and solar 2015 additions alone will supply about 36 TWh of electricity; if this level remained unchanged for the next 32 years these sources would provide 1150 TWh of additional electricity in 2050, coincidentally roughly equal to our Stress case. Of course, electricity demand will grow as other sectors such as buildings and industry are electrified, but that does not negate our point that potential electricity demand from transportation falls within reasonable bounds of electricity grid expansion.

More importantly for the impact of electricity on greenhouse gas emissions, the U.S. DOE reports that it expects wind and solar (collectively "variable renewable electricity") will double their total current

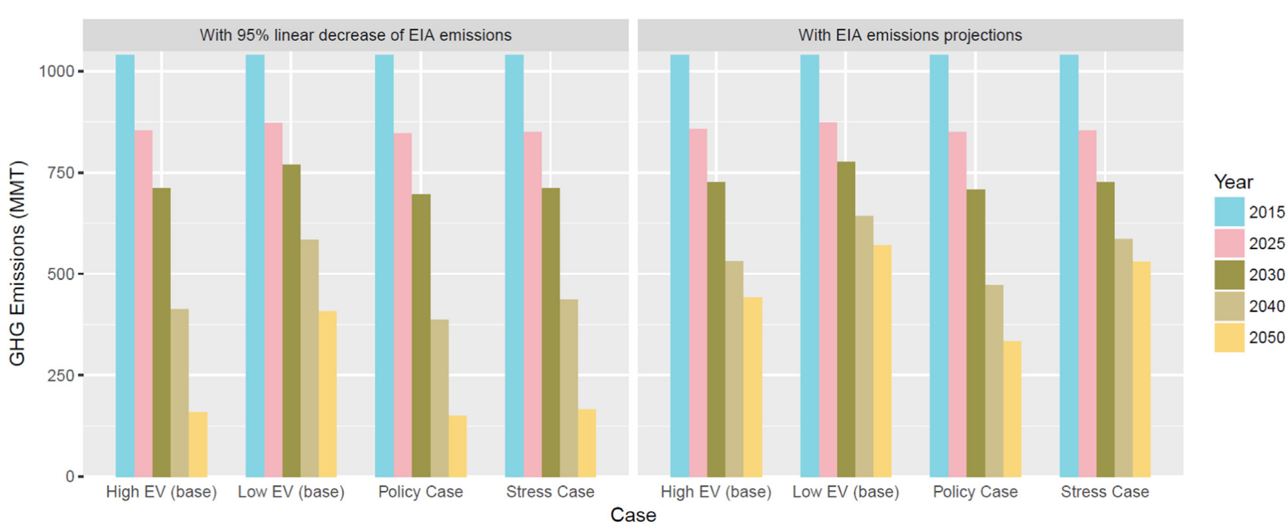

Fig. 8. U.S LDV greenhouse gas emissions across our scenarios.

output of about 300 TWh between now and 2030 under a "no clean power plan" scenario, and with no other changes in federal or state carbon or renewables policy. Most of this doubling will occur by 2024, when current tax credits expire, and under traditionally conservative EIA cost estimates for wind and solar (U.S. DOE, 2017). One additional doubling in the 20 years between 2030 and 2050 would equal nearly all LDV electricity use, and it is highly likely that the rate of wind and solar growth will far exceed one doubling in 20 years. We do not mean to imply that the growth of electric transport poses no issues whatsoever for the U.S. power sector. We acknowledge that our focus in the above analysis is on the energy requirement resulting from electrified vehicles. While the concern over electric capacity might be small, balancing the hour-by-hour electric generation and demand remains a challenge. Much research is ongoing that aims to understand the impact of EV charging on the electrical grid. Though beyond the scope of this paper, a number of solutions have been proposed: grid-scale storage (Castillo and Gayme, 2014), V2G charging management (Mwasilu et al., 2014), and dynamic power pricing (Luo et al., 2018). Furthermore, a future with AV fleets may allow for the co-optimization of providing transportation services with the provision of electricity resources (Bauer et al., 2018). The size of EV loads poses enormously important challenges for the redesign and management of a larger, two-way distribution system with intelligent charging, reformed rate structures, and new distribution regulation and business models.

Furthermore, as new supplies are created, the overall power grid must make a transition to carbon-free operation in what some researchers note is shorter period than all other similar energy transitions have occurred (Smil, 2016). This is evidenced by the fact that, once electrified, the largest driver of reducing emissions in the transport sector is the decarbonization of electricity. If the only policy objective is reduced greenhouse gas emissions, it is important to note that there is little absolute difference in GHG emissions between our baseline high EV, stress, and policy cases.

Yet significant differences in our cases do emerge as the sector takes into account that the transition to low-carbon electricity generation must occur in the context of higher demands for power grid resilience against ever-strengthening climate extremes, cybersecurity threats, and changes to the industry structure. In addition to GHG policy considerations, transportation managers will also need to grapple with congestion management, city and urban design, safety measures, mobility for underserved populations, and public health concerns, among a host of additional issues. By any measure, this is a turbulent landscape. Our only point is that, as the industry copes with its many challenges, supplying LDVs in the aggregate with carbon-free power looks manageable, and indeed provides the industry with significant added revenues that will undoubtedly prove useful.

In regards to policy, in spite of the massive uncertainties surrounding the future of transport, only a few dimensions of the coming disruptions seem amenable to policy measures large enough to influence power demand by large amounts. First among these is any policies that shift LDV transport away from ICEs in any mode (but especially in LDVs) while at the same time aggressively pursuing electric sector decarbonization goals. On this point there is a somewhat unusual confluence of support from clean energy and climate policy advocates and the great majority of the electric power industry.

Beyond electrification of LDVs per se, the policy approaches to reducing carbon in the transportation sector seem to divide into these categories:

(A) shift drivers – and later, single occupants of CAVs – out of SOVs and into either pooled rides or, much better, integrated multimodal on-demand mobility systems, via any number of policy tools;
(B) encourage or require electric LDVs to become more efficient more quickly than otherwise, much as CAFE and ZEV standards have forced ICE fleet efficiency gains;
(C) Harvest the vehicle and system efficiency improvements theoretically offered by CAVs as soon as possible after they are introduced.

In our framework, category A shifts travel to more efficient modes, and reduces VMT generally, while categories B and C reduce EI. In the realm of Category A, there are only a handful of well-known policies, albeit each with thousands of variations, that could make a big difference. Widespread (likely federal) road pricing changes could significantly affect LDV travel through own-price effects and also shift travel to more efficient modes. The fact that half of federal roadway spending is now made from general revenues amounts to an astonishingly large, under-recognized, and regressive subsidy to auto travel and its carbon emissions today, and to EV and CAV use tomorrow (Helveston, 2017).

The second category of policies, efficiency improvements, are a familiar refrain in U.S. transport policy. CAFE standards have demonstrated that the technical efficiency of autos can improve dramatically when stimulated by policies, albeit not without a hiccup now and then. Replicating this trajectory for EVs and CAVs has the potential to save trillions of dollars of power system costs as well as significant carbon in the years before full grid decarbonization.

While we focused our analysis on increasing electricity demand and greenhouse gas emissions from transportation in the United States, our analysis can be used to provide insight into other countries as well. Because our paper relies heavily on electric and autonomous vehicle adoption and a driving culture, the analysis best translates to advanced economies with significant VMT per capita, such as Canada and Australia. Countries with stronger climate change and urban sprawl policies, as in many European nations, will likely see a lower VMT increase from autonomy and in some cases a more rapid transition to electric vehicles.

Emerging economies are slowly making the transition to a more car-centric economy (Ecola and Wachs, 2012). On the one hand, these countries may see a delay in either electric car adoption, autonomous vehicle adoption, or both as the cost of the technology initially prohibits wide-spread adoption. On the other, concerted policy efforts may have a greater effect on both the rate of EV adoption (as in China) and VMT changes (Cui, 2018).

The realm of potential transportation futures is still highly uncertain. Researchers have just begun to estimate the true impacts of automation and transportation as a service on transportation energy demand. Given the significant implications of electric and automated vehicles on greenhouse gas emissions, infrastructure development, and social systems, there is an obvious need for further work. Future work should aim to condense the available evidence of the impact of these emerging travel modes while understanding their adoption trajectory. The results of such work could then be integrated into our modeling framework. Research that would inform such work is currently ongoing or has yet to be done.

Acknowledgements

The authors would like to thank John Paul Helveston and Henry Kelly for their insights and reviews of earlier drafts of this manuscript. Ryan Hopping, Bai Li and Xuehui Sophia Xiong provided excellent editorial and research assistance. We gratefully acknowledge financial support from the Hewlett Foundation (2016-5132), the Energy Foundation, and Boston University. We also thank a long list of experts who provided data and insights that were integral to this paper; please see a full list of acknowledgements on our website at bu.edu/ise.

Author disclosures

In addition to his Boston University duties, Peter Fox-Penner serves as chief strategy officer for Energy Impact Partners, which owns interests in storage and EV infrastructure firms, among others (see www.

energyimpactpartners.com). In addition, he is on the Advisory Board of EOS Energy Storage. Jennifer Hatch and Will Gorman have no financial interests in the transport or power sectors.

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