

# Private versus Shared, Automated Electric Vehicles for U.S. Personal Mobility: Energy Use, Greenhouse Gas Emissions, Grid Integration, and Cost Impacts

Colin J. R. Sheppard,\* Alan T. Jenn, Jeffery B. Greenblatt, Gordon S. Bauer, and Brian F. Gerke



Cite This: <https://dx.doi.org/10.1021/acs.est.0c06655>



Read Online

ACCESS |



Metrics & More

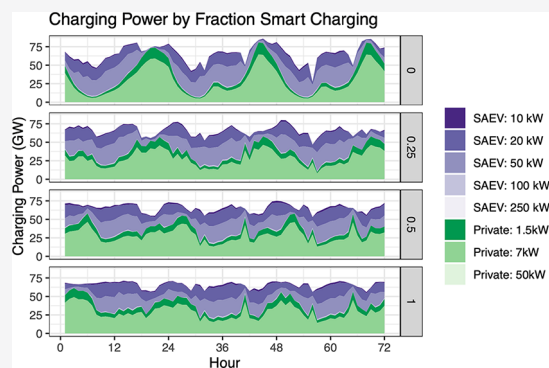


Article Recommendations



Supporting Information

**ABSTRACT:** Transportation is the fastest-growing source of greenhouse gas (GHG) emissions and energy consumption globally. While the convergence of shared mobility, vehicle automation, and electrification has the potential to drastically reduce transportation impacts, it requires careful integration with rapidly evolving electricity systems. Here, we examine these interactions using a U.S.-wide simulation framework encompassing private electric vehicles (EVs), shared automated EVs (SAEVs), charging infrastructure, controlled EV charging, and a grid economic dispatch model to simulate personal mobility exclusively using EVs. We find that private EVs with uncontrolled charging would reduce GHG emissions by 46% compared to gasoline vehicles. Private EVs with fleetwide controlled charging would achieve a 49% reduction in emissions from baseline and reduce peak charging demand by 53% from the uncontrolled scenario. We also find that an SAEV



fleet 9% the size of today's active vehicle fleet can satisfy trip demand with only 2.6 million chargers (0.2 per EV). Such an SAEV fleet would achieve a 70% reduction in GHG emissions at 41% of the lifecycle cost as a private EV fleet with controlled charging. The emissions and cost advantage of SAEVs is primarily due to reduced vehicle manufacturing compared with private EVs.

## INTRODUCTION

The transportation sector represents the fastest-growing segment of the world's GHG emissions, accounting for 23% of global energy-related carbon dioxide emissions in 2014,<sup>1</sup> with car sales set to more than double by 2050.<sup>2</sup> In the U.S., transportation has become the single greatest source of emissions, accounting for almost one-third of carbon dioxide emissions nationwide.<sup>3</sup> EVs have grown to more than 5 million (M) vehicles worldwide in 2019,<sup>4</sup> driven in part by rapidly falling battery costs,<sup>5</sup> but represent a tiny fraction of personal mobility. Prior research has proven the capability of EVs to meet the travel needs of the majority of drivers in the U.S.<sup>6,7</sup> Coupled with clean electricity, EVs have the potential to dramatically reduce the GHG intensity of private transportation.<sup>8,9</sup> However, adoption of EVs has been limited by factors including a sparse charging network, slow charging, short vehicle range, and higher capital costs compared to other types of vehicles.<sup>10–13</sup>

The global proliferation of ride-hailing, micromobility, and other shared mobility services alongside the prospect of widespread vehicle automation<sup>14</sup> has the potential to transform the transportation sector. Indeed, automated vehicles are already serving U.S. passengers without a backup human driver.<sup>15</sup> There is growing consensus that, without sharing rides (i.e., more than one party or passenger per vehicle), vehicle automation could lead to increases in vehicle miles

traveled, congestion, energy consumption, and emissions.<sup>16–19</sup> However, synergy between sharing, automation, and electrification<sup>17,20</sup> could result in deep reductions in GHG emissions.<sup>14</sup>

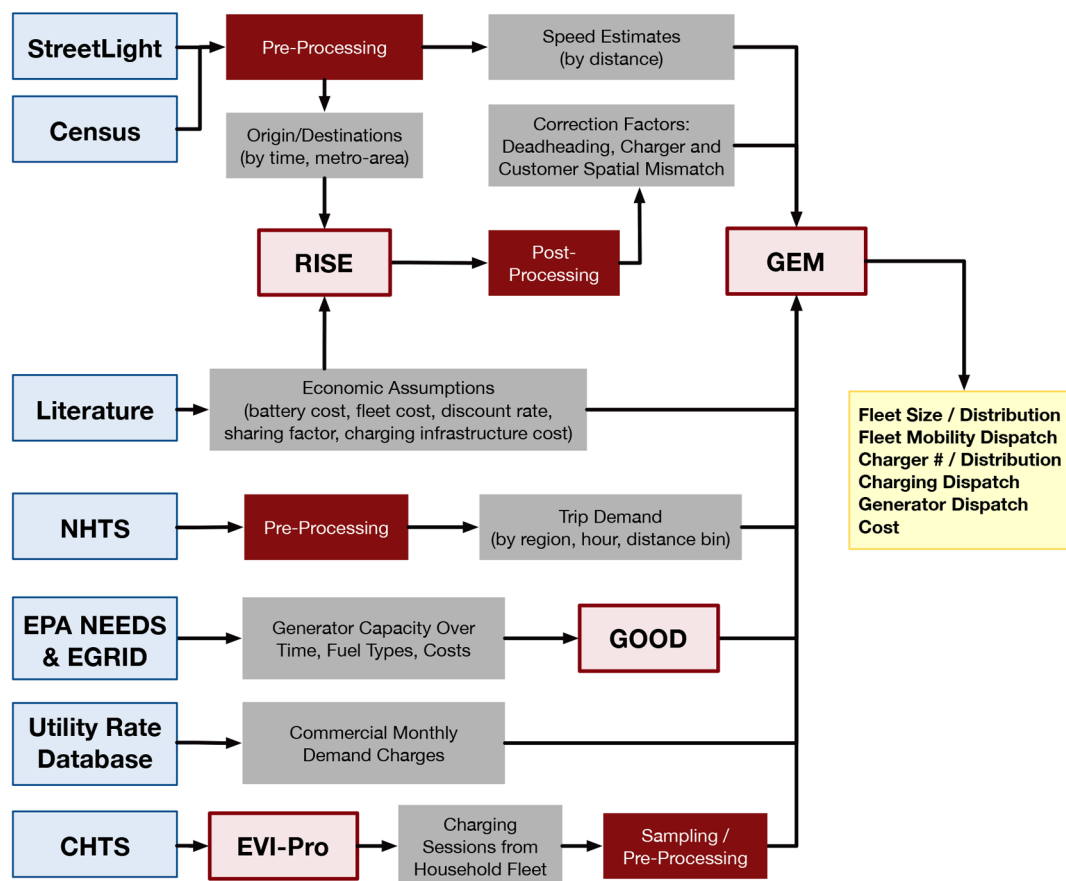
Centrally managed SAEVs could offer services similar to those provided by current ride-hailing companies, but at much lower cost and GHG intensity.<sup>21</sup> Because each SAEV only needs enough battery range for the trip requested and charging can be split over many short periods between trips, shared mobility could reduce requirements for battery range. This shift could overcome barriers of slow charging speeds and high capital costs while reducing GHG emissions.<sup>14,22,23</sup>

Public charging infrastructure is critical to accelerating EV adoption.<sup>24–26</sup> However, the business case for private sector investment in chargers is weak in the context of personally owned EVs.<sup>27</sup> EV charging also introduces significant new loads to electricity systems already challenged both by peak electricity demand and increasing levels of intermittent renewable generation.<sup>28,29</sup>

**Received:** October 12, 2020

**Revised:** January 29, 2021

**Accepted:** February 1, 2021



**Figure 1.** Sources of data (blue), data processing (dark red), models (light red), intermediate data (gray), and model outputs (yellow) in the overall modeling and processing workflow.

Many studies have assessed the benefits to electricity grids of controlled EV charging,<sup>30–33</sup> which can provide benefits of decarbonizing transportation and lowering costs of renewable integration and energy storage.<sup>34–37</sup> Preliminary investigations of the potential for SAEV-grid integration highlighted this potential.<sup>38,39</sup> However, only a handful of studies simulate EV-grid interactions at a national (or multinational) level in Australia<sup>40</sup> or western Europe.<sup>41–45</sup>

The current study expands upon prior work<sup>46</sup> using a hybrid modeling framework (Grid-integrated Electric Mobility or GEM) that combines individual vehicle trips, parametrized agent-based model outputs, a cost model for vehicles and charging behavior, and a national-level electricity production cost model. GEM co-optimizes the allocation of SAEV vehicles and charging infrastructure along with charge scheduling and economic dispatch of grid generators to find the minimal cost combination of vehicles, chargers, and operations to satisfy a given demand for trips. The result includes optimized EV fleets and associated charging infrastructure spanning both urban and rural areas, which serve the mobility needs of the entire U.S. population under various assumptions about automation, sharing, and charging strategies. We use GEM to explore how these parameters affect hourly electric load patterns, peak power demand, EV battery capacity, fleet size requirements, charger power levels and quantity, total cost of fleet ownership, renewables curtailment, and GHG emissions, in a future personal transportation system composed of any combination of privately owned EVs and centrally managed SAEVs.

Our goal is both to compare private and shared fleet electrification, as well as the interaction between these fleets and a future grid with higher penetrations of nondispatchable energy sources. The interactions between power generation on the grid and charging behavior of private and shared vehicles are complex. There are substantial cost savings that can be achieved by managing the charging patterns of EV fleets, but it would not be practical for these to come at the cost of decreased mobility. Therefore, our model must be capable of quantifying the temporal flexibility of charging the fleets in a manner that still satisfies mobility as well as resolve how this flexibility will align with low cost generation on the grid.

Furthermore, there is flexibility that can be added to the system by overbuilding, for example, by manufacturing more vehicles or increasing their range or adding more chargers or higher power charging. There are trade-offs inherent in the decision to build more flexibility into the system, they require upfront investment but yield operational benefits by accessing lower cost energy. Our methodological approach is to model all of these factors endogenously to capture these trade-offs in both the system design and operation.

## METHODS

We leverage previous work<sup>46</sup> where the authors developed an optimization model that examines SAEVs in the context of temporally varying electricity prices. In this study, we have extended the model to jointly optimize mobility (both SAEVs and private EVs), charging scheduling, and the power sector

for the entire U.S. by coupling our previous model to the Grid Operation Optimized Dispatch (GOOD) U.S.-wide electricity model.<sup>47</sup> This combined Grid-integrated Electric Mobility (GEM) model treats the size of the SAEV fleet and the amount of charging infrastructure as continuous decision variables (relaxing the problem from mixed-integer to quadratic), allowing for heterogeneous vehicle ranges and charger levels. The model minimizes operational costs by choosing the timing of fleet recharge while requiring that mobility demand be served, energy is conserved, and generation assets on the grid are dispatched in merit order. The future electricity capacity grid mix is an exogenous input into GEM and is based on NREL's Renewable Energy Futures study.<sup>48</sup> SAEV fleet planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time period.

In addition to extending the optimization model, we curated a set of empirically derived inputs and assumptions for the model application (details in subsequent sections and the Supporting Information). Several of our assumptions were also developed through detailed, agent-based simulation modeling using the Routing and Infrastructure for Shared Electric vehicles (RISE) model<sup>23</sup> and from simulations completed by the National Renewable Energy Laboratory using EVI-Pro.<sup>49</sup>

In Figure 1, we illustrate the source of all major model inputs and assumptions including intermediate modeling and analysis used in their derivation. Each model input is described in further detail below, beginning with the specification of the optimization model.

The GEM model is publicly available as open-source software under a permissive license.<sup>50</sup> Readers are encouraged to review the code-base, run their own simulation studies, and provide feedback or make contributions to the ongoing project. A snapshot of the exact code used to produce the results in this manuscript is also available.<sup>51</sup>

The dimensions of the model include time  $t$ , mobility region  $r$ , grid region  $i$ , vehicle battery size  $b$ , charger level  $l$ , trip distance  $d$ , and electricity generator  $g$ . The model is a quadratically constrained program and can be efficiently solved with a second-order cone programming solver.

**Objective Function.** The objective function minimizes the amortized daily cost of fleet and infrastructure capital, and fleet and electricity grid operations.

$$\min Z = \sum_r \left[ \sum_t (C_{tr}^d + C_{tr}^m) + nC_r^c + nC_r^v \right] + \sum_{g,t} (G_g C_g^g) + \sum_{i,t,i'} (T_{i,t,i'} C_{i,t,i'}^t) \quad (1)$$

where  $C_{tr}^d$  is the demand charge or capacity cost to use the grid and  $C_{tr}^m$  is vehicle maintenance cost in hour  $t$  and mobility region  $r$ ,  $C_r^c$  is the amortized daily charging infrastructure capital cost,  $C_r^v$  is the amortized daily fleet capital cost,  $n$  is the number of days in the simulation time horizon,  $G_g$  is the electricity produced by generator  $g$ ,  $C_g^g$  is the cost of producing a unit of energy by generator  $g$ ,  $T_{i,t,i'}$  is the electricity transmitted from grid region  $i$  to grid region  $i'$ , and  $C_{i,t,i'}^t$  is the marginal cost of transmission.

The system minimizes the objective function across a large number of decision variables: the energy to charge and consumed by vehicles at different points in time,  $P_{bitr}$  and  $E_{bitr}$

respectively; demand charge costs,  $C_{tr}^d$ ; vehicle maintenance costs,  $C_{tr}^m$ ; maximum power demand,  $P_r^{\max}$ ; size of the SAEV fleet and capital cost of the fleet,  $V_{br}^*$  and  $C_r^v$ ; the number of vehicles charging, moving and idle:  $V_{bditl}^c$ ,  $V_{bditr}^m$ , and  $V_{bitr}^i$  respectively; the number of chargers and capital cost of the infrastructure:  $N_{tr}$  and  $C_r^c$ ; demand allocation by battery type,  $D_{bditr}$ ; temporal power profile of private vehicles,  $P_{tr}^{\text{private}}$ ; generation by power plants,  $G_{gt}$ ; and transmission of power between regions,  $T_{iti'}$

The optimization is subject to a number of constraints that enforce realistic operations, as described in the Supporting Information.

**NHTS Data.** We applied the model at a national level based on estimates of hourly demand for private vehicle trips derived from the 2017 National Household Transportation Survey (NHTS).<sup>52</sup> NHTS respondents log trip distance, timing, and vehicle type for all household members on a specified day. The responses are weighted according to demographics to yield typical daily mobility profiles, by distance and trip start time. We computed these profiles by day type (weekday vs weekend), geographic region, and season, across the entire U.S.

To produce our trip-demand model inputs, we partitioned the country into 13 broad geographic regions, made up of the nine U.S. Census Divisions: New England (NE), Mid-Atlantic (MAT), South Atlantic (SAT), East-North-Central (ENC), West-North-Central (WNC), East-South-Central (ESC), West-South-Central (WSC), Mountain (MTN), and Pacific (PAC). In addition, the four largest states (California, Florida, New York, and Texas) are separated into their own individual regions. We refer to these regions as the Census-Division-Large-State (CDLS) partition. In addition, we subdivided the trips into "urban" and "rural" subregions (see Supporting Information for details). This yields a total of 26 regional data sets: 13 CDLS regions, each with urban and rural subregions.

Because mobility demand varies throughout the year, both in terms of the number of trips and their distribution by distance, it was important to capture seasonal variation in trip demand in addition to the hourly and regional distributions. We thus divided the data into four three-month blocks: December–February (winter), March–May (spring), June–August (summer), and September–November (autumn). The final output of this analysis was a set of hourly mobility-demand profiles, over the course of a typical day, subdivided by trip distance, day type, geographic region, and season.

**Correction Factors Using RISE.** Some of the parameters in the optimization model were determined using a spatially explicit, agent-based simulation tool. The parameters included deadheading ratios (the ratio of empty vehicle miles traveled to miles traveled with passengers), as well as oversizing requirements due to spatial mismatch (i.e., more chargers are needed in a region than the maximum coincident demand for charging; likewise extra battery capacity is required to access charging stations and for contingencies). To do this, we coupled trip data obtained from StreetLight Data with an agent-based fleet simulation framework called Routing and Infrastructure for Shared Electric vehicles (RISE) model, originally described in Bauer et al.<sup>23</sup> StreetLight Data is a company that aggregates data from cell phones and GPS devices to produce transportation metrics such as travel times and volume of travel. The resulting trip data sets spanned nine combined statistical areas (CSAs) throughout the U.S. covering distinct census divisions and population densities.

For full details of the preprocessing methodology, see the [Supporting Information](#).

Simulations were conducted for each city with 20k, 40k, 100k, 200k, 400k, and 800k trips, and with both 15 kW and 50 kW charging power. Locations of chargers were determined by *k*-means clustering of trip origins and destinations, which was determined to work as effectively as the siting algorithm described in Bauer et al.<sup>23</sup>

The model proceeds chronologically over 1 day of data, repeating until the fleet's aggregate battery capacity at the end of the day is within 5% of that at the beginning of the day. In each minute, trips are assigned to the nearest vehicle, and idle vehicles are routed to charge or rebalanced in anticipation of future demand (see reference for details). Travel times and distances between each taxi and trip or charging point are imputed by drawing random values from the corresponding distribution obtained from StreetLight Data. To ensure a reasonable relationship between time, distance, and speed for each trip, distances are resorted in order to best match the relationship between draws for duration and speed. If a trip can only be served by a vehicle with insufficient battery capacity, the vehicle's range is increased by 50-mi increments until capacity is adequate. If no vehicle can serve a trip within a 10 min wait time, a new vehicle is added to the fleet. Thus, both battery range and fleet size increase organically over the course of the simulation, providing estimates of the minimum values required to serve demand. Vehicles serving trips that end outside the CSA are removed from the fleet; trips starting outside the CSA are served by new vehicles that are then added to the fleet.

For each simulation, we recorded the empty distance and time traveled to each passenger pick-up and charging event to determine the average empty-to-occupied trip ratios for each city, often referred to as the "deadheading" ratio. As shown in [Figure 3](#) in the [Supporting Information](#), we found that deadheading ratios increase roughly with the square root of area per trip. Given that vehicle speeds are different when empty and when serving trips, we estimated separate ratios for time spent empty and energy consumed while empty. These results were used to correlate key system deadheading ratios and oversizing requirements to travel demand spatial density, which were then extrapolated to each region in GEM. The extrapolated values for the six parameters are listed in a table in the [Supporting Information](#).

**Private EV Fleet.** Electric load from private EVs and its associated flexibility is an exogenous input to GEM. We prepared these load profiles by analysis of simulated individual charging sessions from the EVI-Pro infrastructure planning model. This tool, developed by the California Energy Commission and the National Renewable Energy Laboratory, is based on travel diaries from the California Household Travel Survey and can simulate the mobility and charging behavior of vehicles over a variety of electric vehicle types, charging infrastructure levels, and assumptions about traveler preferences (e.g., preferences for home charging vs workplace charging). Each run of EVI-Pro produced daily charging sessions covering approximately 50 000 travelers. Using a sampling tool developed by the Schatz Energy Research Center at Humboldt State University, we constructed regional fleets of private EVs that match the size of the simulated private fleets in GEM, as well as the average daily mileage of these fleets consistent with the NHTS data.

The individual charging sessions contained plug-in, charging completion, and plug-out times. Using the virtual battery approach,<sup>53</sup> we aggregated these sessions into constraints that represented the maximum and minimum power and energy that must be delivered to the private fleet in each hour of the day. The constraints were constructed so that, if satisfied, it was possible to meet the energy demands of every individual charging session by the plug-out time. Finally, we parametrized the creation of the constraints to assess the impact of partial flexibility in the private charging demand. In other words, if the flexibility parameter was set to 0%, then uncontrolled charging was assumed and the lower cumulative energy bound (eq 22 in [Supporting Information](#)) was equal to the upper cumulative energy bound (eq 23 in [Supporting Information](#)). If flexibility was set to 100%, then we assumed all charging sessions could be delayed to the maximum possible moment while still delivering the original energy to the fleet. Any value between 0% and 100% was a direct scaling of the degree of flexibility between the two extremes; quantitatively, this meant the lower cumulative energy bound is proportionally closer to the upper bound than the 100% scenario.

**Electricity Grid Modeling.** The electricity grid model in GEM is developed based on an economic dispatch model known as the Grid Operation Optimized Dispatch (GOOD) model.<sup>47</sup> The GOOD model simulates the operation of power generators across the country by dispatching specific generation assets to meet demand load, the order of which is determined by a "bidding" process, where the lowest cost generation on the margin is the next to participate in providing power. The model also includes transmission between regions on a substate basis, which is then aggregated up to the CDLS regions used in GEM. Within a region, generators are aggregated by their fuel type, variable costs, and CO<sub>2</sub> emissions rates.

The data regarding the generators to model the electricity grid are combined from the EPA NEEDS (v5.15) and eGrid 2016 databases. These contain a large number of attributes for every generator, including capacity, fuel costs, operations and maintenance (O&M) costs, emissions rates, and heat rates. These attributes allow us to characterize the operations of each generator in the dispatch model. We employ representative hourly profiles across a full year for wind and solar resources disaggregated by the substate regions and aggregated by the weighted capacity in each region. These data are not averaged solar and wind profiles, which would smooth out intermittency. The transmission between each region has an associated capacity (not always bidirectional) that includes wheeling costs in certain pairwise regions. The dispatch model has been validated against generation and emissions from the power sector in 2018.<sup>47</sup>

While the mobility side of GEM provides an endogenous "input" into the electricity grid side of the optimization via the electricity demand associated with vehicle charging, this is in addition to an exogenously specified baseline demand from all other non-EV loads. This baseline is obtained from EPA NEEDS (v5.15) and contains electricity load demand on an hourly basis throughout the year in all substate regions across the U.S. Once again, these loads are aggregated to the CDLS regions used in GEM. The economic dispatch portion of GEM simultaneously fulfills charging demand from the baseline load and from the EV charging load; it is therefore able to influence the mobility-system decision making process

under the assumption that the costs associated with charging would be real-time costs. To the extent that the system can reduce costs by promoting charging at certain times of the day, GEM considers this decision among the suite of cost trade-offs contained in the optimization formulation.

**Key Assumptions.** In Table 1, we list key assumptions used for the Base scenario of the optimization model.

**Table 1. Key Modeling Assumptions Used to Define the Base Scenario**

input	symbol	values
charger types and power	$\gamma_l$	L010 = 10 kW
		L020 = 20 kW
		L050 = 50 kW
		L100 = 100 kW
		L250 = 250 kW
charger capital cost	$\phi_l^c$	L010 = \$5k
		L020 = \$11k
		L050 = \$31k
		L100 = \$77k
		L250 = \$305k
charger lifetime	$L^c$	10 years
charger distribution factor	$\delta_l$	1.0 for all types
demand charge price	$\beta_r$	\$7.7/kW/month
annual discount rate	$r$	0.05
sharing factor	$\sigma_d$	1.5
vehicle capital cost	$\phi^v$	\$30 000 (includes cost of automation)
vehicle daily fixed O&M	$\phi_{om}^v$	\$1.64
vehicle per-mile O&M	$\beta_v$	\$0.09
battery capital cost	$\phi^b$	\$150/kWh
vehicle/battery lifetime	$L^v$	2 years
	$L^b$	
battery capacity	$B_b$	75 mi range = 19.7 kWh,
		150 mi range = 41.1 kWh
		225 mi range = 64.4 kWh
		300 mi range = 89.4 kWh
		400 mi range = 124.0 kWh
conversion efficiency	$\eta_b$	75 mi range = 310 Wh/mi
		150 mi range = 324 Wh/mi
		225 mi range = 338 Wh/mi
		300 mi range = 351 Wh/mi
		400 mi range = 353 Wh/mi
speed by distance bins	$\nu_{dtr}$	0–2 mi = 18 mph
		2–5 mi = 22 mph
		5–10 mi = 32 mph
		10–20 mi = 38 mph
		20–30 mi = 40 mph
		30–50 mi = 45 mph
		50–100 mi = 48 mph
		100–300 mi = 48 mph

## RESULTS

Our results reveal the tremendous impact that vehicle electrification can have on the transportation system. Private EVs with uncontrolled charging would reduce GHG emissions by 46% from a baseline of 1134 million metric tons CO<sub>2</sub>-equivalent (MtCO<sub>2eq</sub>) per year associated with a fleet of personally owned gasoline-fueled vehicles<sup>54</sup> (including vehicle manufacturing emissions). Private EVs with fleetwide controlled charging would achieve a 49% reduction in emissions from baseline and reduce peak charging demand

by 53% from the uncontrolled scenario, achieving a 38% reduction in total cost of ownership from a gasoline baseline.

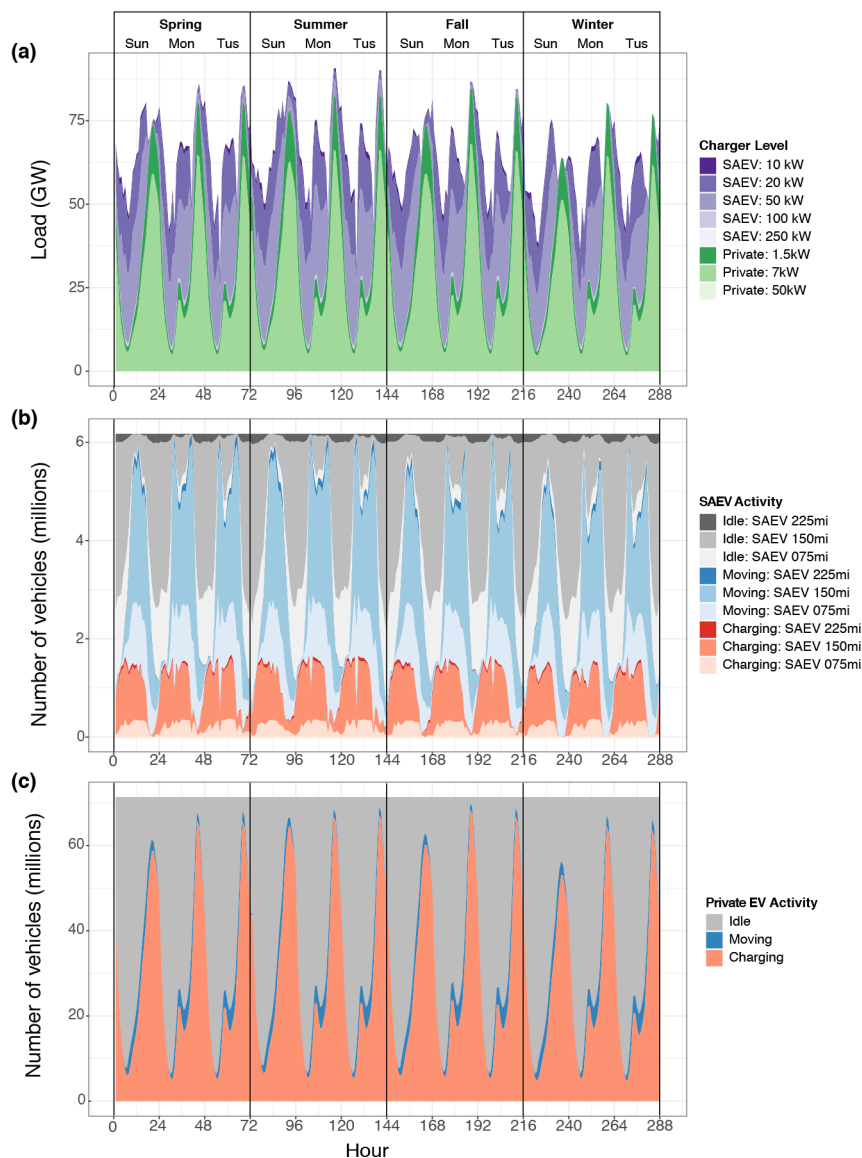
If SAEVs serve all mobility currently served by light-duty vehicles, GHG emissions would be reduced by 70% from a gasoline baseline. Moreover, the total cost of ownership (\$1.570 trillion/year or \$4800 per capita) would decrease 74%, and peak electricity demand from an SAEV fleet would be 47% lower than the peak from a private EV fleet with uncontrolled charging. In other words, over 80 GW of generation capacity (or demand-side flexibility)—greater than half of current standalone U.S. natural gas combustion turbine capacity<sup>55</sup>—would not be needed to support full electrification.

We present our results as functions of two key parameters that are observed to have the largest impacts: the fraction of trips served by SAEVs, denoted by  $S$  (with the remaining fraction served by private EVs) and the fraction of private EVs that engage in controlled charging, denoted by  $C$ . Note that simulations assumed all SAEV charging was controlled based on the presumption that all aspects of automated fleet operations will likely be centrally managed.

**Time Series of EV Charging and Vehicle State.** Figure 2 depicts a reference scenario, where half of nationwide light-duty mobility is served by SAEVs ( $S = 50\%$ ) and the other half is served by privately owned EVs with no controlled charging ( $C = 0\%$ ). Panel a shows charging load versus time over 12 representative days consisting of 1 weekend day and two weekdays from each of four months spaced throughout the year to reflect seasonal variability. In this scenario, we see large differences between the temporal patterns of SAEV and private EV charging. While private EV charging load peaks sharply in the evening, with a much smaller secondary peak in late morning (on weekdays) and the lowest demand in early morning, SAEV charging loads are spread over many more hours of the day, with a broad peak during daytime hours and almost no charging during the private EV evening peak. To satisfy demand, private EV charging is composed of 20% level 1 (1.5 kW) and 80% level 2 (6.7 kW), whereas the cost-minimizing SAEV charging profile is fulfilled by 4% 10 kW, 38% 20 kW, and 56% 50 kW charging, with less than 3% fulfilled by faster levels (100–250 kW).

Panel b shows vehicle activity (charging, moving, or idle) disaggregated by battery range for SAEVs, and panel c shows aggregate vehicle status for private EVs. Note that we have not included trips of distances greater than 300 mi. in this study, as such trips are exceedingly rare, making up <0.1% of all trips. Our model also neglects complications from trips that are longer in distance than the highest range vehicle (225 mi.). Trips longer than 225 miles make up 0.17% of all trips. In reality some number of longer range vehicles would be necessary, or vehicles would need to recharge en-route to serve all trips.

Panels b and c indicate that there are over ten times more private vehicles than SAEVs; overall, SAEVs are moving 38% and charging 17% of the time, whereas private EVs are moving 4% and charging 40% of the time. The private EVs follow a typical uncontrolled load shape, with a very high peak in the evening associated with plug-in events happening after the evening commute. There is an analogous smaller peak in the midmorning on weekdays as drivers arrive to work and use workplace charging. We see that very few SAEVs are idle between early morning and early evening, with the highest fraction of moving vehicles after daytime charging ends

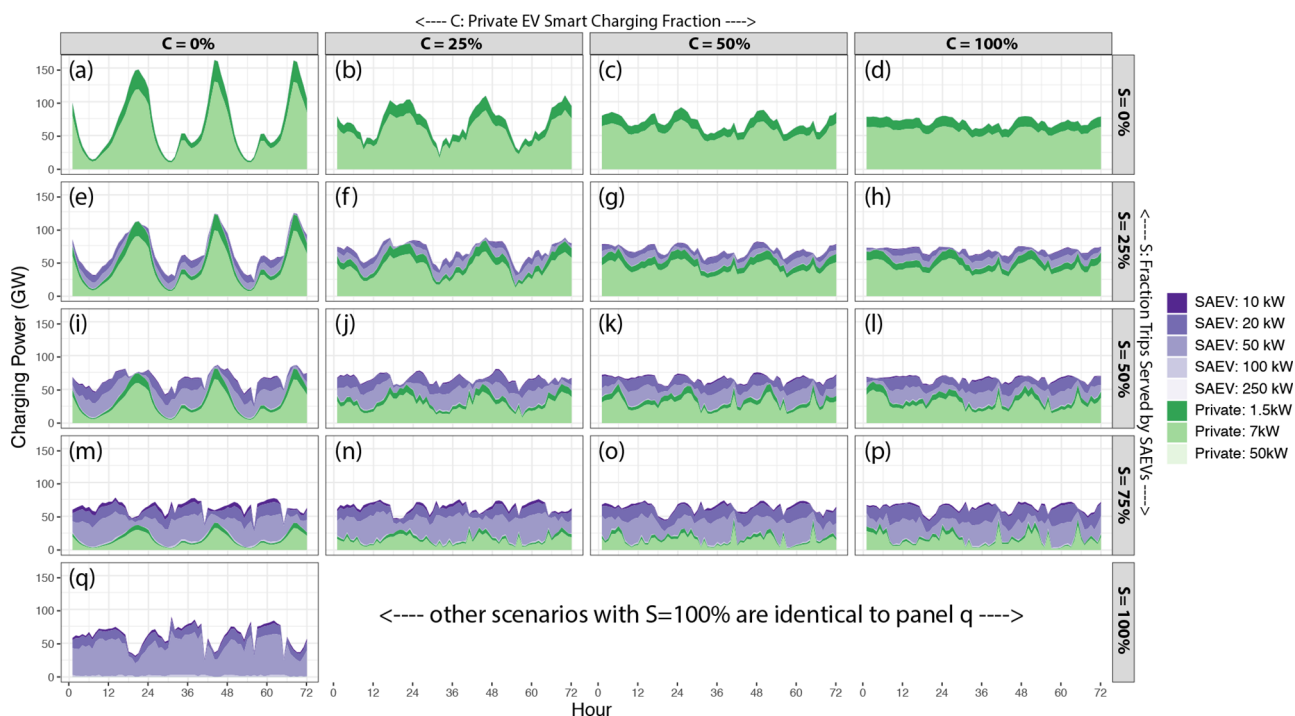


**Figure 2.** Reference scenario for  $S = 50\%$  and  $C = 0\%$  (half of all trips are satisfied by SAEVs, and half by private EVs with uncontrolled charging), showing (a) charging load by power level, (b) EV state (charging, moving, or idle) by battery range for SAEVs, and (c) EV state (charging, moving, or idle) for private EVs. The scenario was run over 12 days: three consecutive days—Sunday, Monday, and Tuesday—in each season.

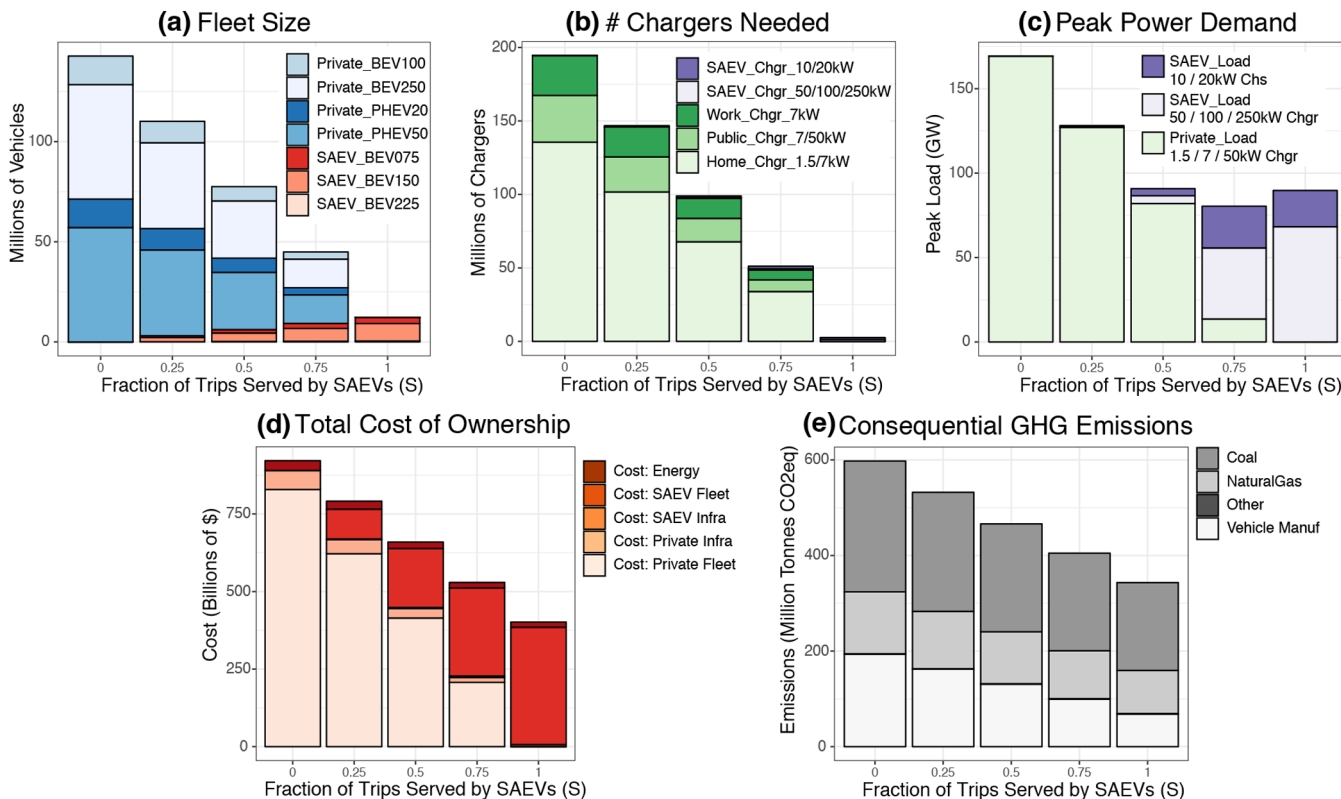
around 4 p.m. SAEV movement drops to nearly zero after midnight, followed by a resumption of charging activity. However, at most 27% of total SAEVs (1.7 M out of 6.2 M) are charging at any given time, indicating there is sufficient charging capacity to allow the majority of vehicles to be available. The two peak moving periods on weekdays correspond to the morning and evening commutes. During the evening peak period, the SAEV fleet is nearly fully utilized, aside from a small fraction of vehicles that are charging (more SAEVs are charging during the morning than the evening commute peak).

The temporal charging load patterns change dramatically as  $S$  and  $C$  change. Figure 3 shows 3 days of charging load from each of a set of model scenarios, where  $S$  and  $C$  each range from 0% to 100%. The highest peak loads are found in the upper left panel (a) due to exclusively uncontrolled private EV charging, with a peak of 162 GW, slightly more than the current total U.S. capacity for standalone natural gas

combustion turbines.<sup>55</sup> As either  $S$  or  $C$  increases, peak loads diminish, approaching a minimum level of 71 GW in panels l and p, where load is nearly evenly spread throughout the day. With no shared vehicles (panels a–d), charging load profiles are smoothed as  $C$  increases from 0% to 100%, leading to an increase in the load factor from EVs (the maximum power divided by the average power), which steadily increases from 41% to 85%. Over the course of a year, electricity demand from vehicle charging is ~540 TWh or nearly 80% of total renewable generation including hydro-power and accounts for 13.5% of total projected electricity demand including EVs. In panel l, the 71 GW peak constitutes a little over 11% of the peak demand in the U.S. (~620 GW), though these peaks are not coincident. In panel q, when  $S = 100\%$ , the peak load is 45% lower than that of the panel a peak and is spread over many more hours, peaking approximately at midday with a sharp minimum in late afternoon coinciding with a peak in vehicle travel. Of note,



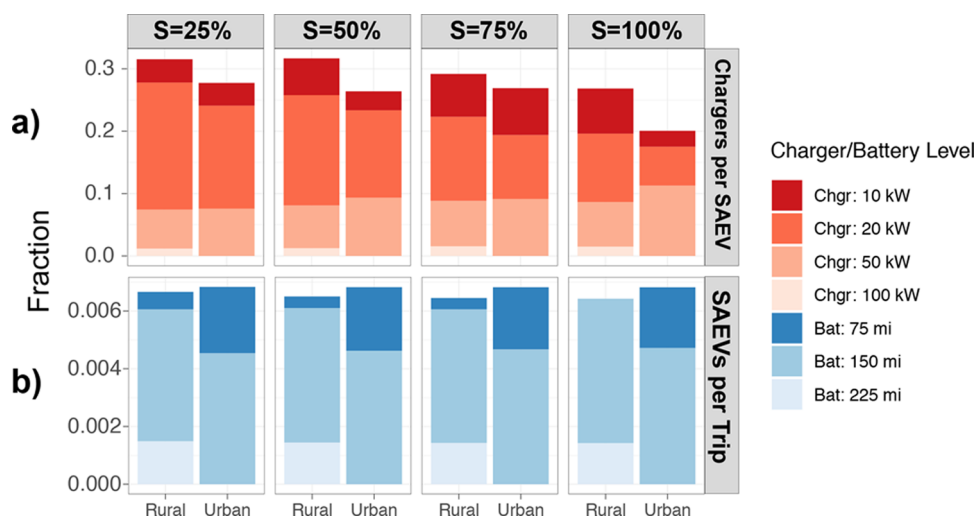
**Figure 3.** Three days (1 weekend day, followed by two weekdays) of simulated EV charging load as functions of SAEV trip fraction ( $S$ ) and private EV controlled charging fraction ( $C$ ), disaggregated by charger level, for both private EVs and SAEVs. Each panel is labeled by the value for  $S$  and  $C$  used in the simulation. Panels a–d:  $S = 0\%$ ,  $C = 0$ – $100\%$ . Panels e–h:  $S = 25\%$ ,  $C = 0$ – $100\%$ . Panels i–l:  $S = 50\%$ ,  $C = 0$ – $100\%$ . Panels m–p:  $S = 75\%$ ,  $C = 0$ – $100\%$ . Panel q:  $S = 100\%$  (value of  $C$  is irrelevant as there are no private EVs).



**Figure 4.** (a) Fleet size, (b) numbers of chargers, (c) peak power demand, (d) total cost of ownership, and (e) consequential GHG emissions vs fraction of SAEV trips ( $S$ ) with  $C = 0\%$ .

scenario  $S = 100\%$  does not result in the smoothest load, a result that is explained further in the discussion of Figure 4c.

**Annual Average Results.** Figure 4 shows results for key outputs averaged over time and geography, displayed across



**Figure 5.** (a) Optimal fleet size (in vehicles per trip) and (b) charging infrastructure requirements (in chargers per vehicle) disaggregated by urban and rural regions for  $C = 0\%$  and with  $S$  ranging from 25% to 100%.

the full range of  $S$ , for  $C = 0\%$  (uncontrolled private EV charging). This slice focuses on the impact of SAEVs because they show the greatest variation in outcomes. In the [Supporting Information](#), we present results analogous to [Figure 4](#) but for a private EV fleet (with  $S = 0\%$ ), varying  $C$  across its range to show how controlled EV charging influences system outcomes.

[Figure 4a](#) shows the fleet size, which decreases by an order of magnitude from  $\sim 145$  M vehicles in the  $S = 0\%$  case (these 145 M vehicles are “active” vehicles used on a typical weekday, and represent  $\sim 56\%$  of the current stock of U.S. light-duty vehicles<sup>54</sup>) to  $\sim 12$  M vehicles in the  $S = 100\%$  case. This occurs because the utilization per SAEV is about 12 times higher than a private EV, due both to increased time spent moving, the number of passengers per trip, and faster recharging times. On average across the scenarios, the cost-minimizing SAEV fleet is composed of 27% vehicles with a range of 75 miles, 69% with 150 miles, and 4% with 225 miles. Private EV ranges were a scenario assumption, not a result of the optimization, so their distribution reflects a projection that average range will increase steadily but modestly over time.

[Figure 4b](#) shows the number of chargers needed. As with fleet size, there are far more chargers when  $S = 0\%$  (195M) than  $S = 100\%$  (2.6M), reflecting much higher utilization among SAEV chargers. These chargers consist of roughly half lower power levels ( $\leq 20$  kW) and half 50 kW DC fast chargers, with about 1% of the network consisting of faster 100 and 250 kW chargers.

Peak power, shown in [Figure 4c](#), also decreases substantially as  $S$  increases: Peak demand is 161 GW at  $S = 0\%$  and almost half this ( $\sim 89$  GW) when  $S = 100\%$ . The dramatic increase in SAEV contribution to peak power between  $S = 50\%$  and  $75\%$  is due to the fact that when  $S = 50\%$  the SAEV loads can still “valley fill” within the private EV load (see [Figure 3](#), panel i vs m), whereas when  $S = 75\%$  the SAEV load becomes dominant throughout the day. The increase in peak demand from  $S = 75\%$  to  $100\%$  is driven by an increase in cost minimization opportunities through charge scheduling available to a full SAEV fleet that are not possible when some private EVs are still engaging in uncontrolled charging.

Similar to peak power, the total cost of ownership for the EV fleet shown in [Figure 4d](#) decreases by 56% as  $S$  increases

from 0% to 100%. Across this range, both energy and charger costs are minor components of total cost, which is dominated by vehicle purchase cost. However, because of the higher utilization and smaller average battery sizes of SAEV fleets, total vehicle cost for  $S = 100\%$  is roughly half that of the  $S = 0\%$  scenario.

[Figure 4e](#) shows the consequential GHG emissions of charging the EV fleet. Emissions fall from  $\sim 600$  MtCO<sub>2eq</sub> in the  $S = 0\%$  case to  $\sim 340$  MtCO<sub>2eq</sub> in the  $S = 100\%$  case. By comparison, emissions from a gasoline vehicle fleet including manufacturing is 1134 MtCO<sub>2eq</sub>. The optimization does not directly minimize emissions (they are not in the objective function) but an overall positive correlation between cost and emissions leads to a reduction in fossil GHG emissions arising from greater use of controlled charging. In addition SAEVs consume less total energy and the vehicle manufacturing emissions are lower because of the smaller (even though more rapidly overturning) SAEV fleet. The result is a 43% reduction in GHG emissions between the  $S = 0\%$  and 100% cases or a 70% reduction in emissions from a gasoline-fueled baseline.

**Urban versus Rural Fleets.** To build intuition for how key model results are interrelated and to examine how infrastructure and fleet requirements might differ between regions, we compare simulation outputs between urban and rural geographies. [Figure 5](#) shows national-level SAEV results disaggregated by urban versus a rural region across the range  $S = 25$ –100% for two parameters of interest: chargers per vehicle (disaggregated by charging speed) and vehicles per trip (disaggregated by battery size). These two parameters were chosen because they showed the largest differences between urban and rural regions and trends versus  $S$ .

We found that rural regions required a higher fraction of chargers per vehicle than urban regions but that both fractions decreased as  $S$  approached 100%, suggesting higher utilization in a larger network. Moreover, rural regions required more 10–20 kW, as well as 100 kW chargers than urban regions, which required more 50 kW chargers. These differences became more pronounced as  $S$  progressed from 25% to 100%. The 100 kW chargers accounted for between 10% and 14% of energy consumption among rural vehicles, which in aggregate accounted for about 2% of total vehicle energy consumption and miles traveled.



The total ratio of vehicles per trip is slightly lower in rural versus urban regions, indicating higher utilization, a consequence of longer-range vehicles and more, faster chargers which combine to reduce vehicle time spent out of service. The vehicles per trip ratio is largely invariant as  $S$  increases in both regions. By contrast, the distributions of battery capacities are quite distinct: there are many more longer-range (225-mi.) vehicles in rural regions as compared to urban, which have many more 75-mi. range vehicles and virtually no 225-mi. range vehicles; the fraction of medium range (150-mi.) vehicles are mostly equivalent in both regions. Interestingly, as  $S$  increases from 25% to 100%, rural regions shift away from the small number of 75-mi. vehicles toward 150-mi. vehicles, with the fraction of 225-mi. vehicles remaining almost the same. A similar, though harder to discern, trend appeared in urban regions. The increased trip densities at higher values of  $S$  favor longer range vehicles (which are more expensive and have lower energy efficiency), which enable the lower charger densities discussed in panel a.

**Geographic Differences in Electricity Mix and GHG Emissions.** There was very little difference in most key variables by geographic region, with the exception of electric generation mix and GHG emissions. Because of much more coal use in certain regions and much more renewable generation in others, we expected large differences in both of these outputs.

**Additional Sensitivity Runs.** The results presented above represent two of seven parameters that we systematically varied. In the [Supporting Information](#), we present the results of varying other important parameters: the sharing factor, vehicle capital cost, battery capital cost, battery lifetime, and vehicle energy conversion efficiency.

## DISCUSSION

Our results paint a very different picture of the future transportation system from the one we see today. Private EVs with 100% controlled charging could reduce GHG emissions by 53% compared to gasoline vehicles and reduce the total cost of ownership by 38%. In addition, they are able to reduce peak demand from charging by 53% from uncontrolled EVs, which is 6 percentage point greater reduction than a system composed entirely of SAEVs.

When all trips taken in light-duty vehicles are provided by SAEVs, personal mobility can be fulfilled with 12 M vehicles, 9% of the active vehicles required when they are privately owned, and with only 2.6 M chargers (0.2 per EV). From an economic standpoint, sharing and automation provide tremendous benefits, enabling a 74% reduction in total fleet cost compared to gasoline vehicles today. The operation of SAEVs and controlled charging of individual vehicles are able to reduce peak charging load by 47% from what would otherwise be present when  $S = 0\%$  and  $C = 0\%$ . This can significantly improve both the efficiency and emissions rate of fossil generation (by shifting to lower GHG-emitting fossil generators) while simultaneously better utilizing solar and wind resources (due to flexibility in charging times), resulting in a reduction in solar curtailment by about one-third.

One of the driving forces behind our results is that vehicle autonomy enables significantly higher utilization of any given vehicle. Private EVs remain unused most of the time because most people's mobility needs can be satisfied in just a small fraction of the day. For SAEVs, vehicles can fulfill multiple individuals' travel needs throughout the day, remaining highly

utilized for many hours, yet with ample time available to relocate to new passengers or to recharge. Shared ride-hailing trips, therefore, permit many fewer vehicles to serve the same number of total trips and enable more efficient pooling, further reducing fleet size, numbers of chargers, energy use, cost, and GHG emissions.

Users of a fleet of SAEVs make no major sacrifices in their mobility needs. All trips are still served, though the particular attributes of trips might change. For example, on-demand mobility entails a wait time, pooled rides could take longer than driving oneself; but these increases could be offset by eliminating the time spent searching for and accessing parking. The net effect of these differences could be positive or negative depending on the individual circumstances of each trip, but every trip is still completed in the same hour of each of day.

While rural regions require longer-range battery capacities than urban regions, we find that only 4% of the total fleet must have a range of 225 miles to satisfy all trips. By comparison, urban regions are able to serve all trips with a mixture of 75- and 150-mi. range vehicles, and virtually no longer-range vehicles. It is possible that the actual fleet would need some longer-range vehicles to serve demand during emergency situations and holiday travel, but in most cases these peaks in demand likely could be satisfied by shuffling vehicles between regions.

While our results are specific to the U.S., they may be generalizable to other regions with comparable levels of private vehicle utilization, average driving distances, and grids that are transitioning to renewable electricity, such as Western Europe and, increasingly, China. More densely populated regions will likely see higher levels of vehicle occupancy and lower deadheading ratios, resulting in even greater impacts. We believe that this study provides strong evidence of the value of SAEV fleets to decarbonize personal transportation without compromising individual mobility needs. While a fully private EV fleet with uncontrolled charging would reduce national GHG emissions by 47% compared to a gasoline-fueled baseline, an additional 3 percentage points could be reduced by employing controlled charging and a further additional 20 percentage points could be reduced by serving all mobility with SAEVs for an overall 70% reduction from the gasoline baseline. If the cost of fossil generation were higher or additional low-GHG electricity sources (e.g., from renewables) became available, this reduction could approach 100%.

## ASSOCIATED CONTENT

### Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.0c06655>.

Model specification, NHTS data, correction factors using RISE, EVI-Pro, additional metrics, geographic analysis, sensitivity runs, and references (PDF)

## AUTHOR INFORMATION

### Corresponding Author

Colin J. R. Sheppard – Lawrence Berkeley National Laboratory, Berkeley, California 94720-8099, United States; Marain Inc., <https://www.marain.ai/>; [orcid.org/0000-0001-5891-388X](https://orcid.org/0000-0001-5891-388X); Email: [colin@marain.com](mailto:colin@marain.com)

## Authors

Alan T. Jenn – University of California, Davis, California 95616, United States; Lawrence Berkeley National Laboratory, Berkeley, California 94720-8099, United States; [orcid.org/0000-0003-4232-0697](https://orcid.org/0000-0003-4232-0697)

Jeffery B. Greenblatt – Lawrence Berkeley National Laboratory, Berkeley, California 94720-8099, United States; Emerging Futures, Inc., Portland, Oregon 97201, United States

Gordon S. Bauer – The International Council on Clean Transportation, <https://theicct.org/>; [orcid.org/0000-0002-1756-5919](https://orcid.org/0000-0002-1756-5919)

Brian F. Gerke – Lawrence Berkeley National Laboratory, Berkeley, California 94720-8099, United States

Complete contact information is available at:  
<https://pubs.acs.org/10.1021/acs.est.0c06655>

## Notes

The authors declare no competing financial interest.

## ACKNOWLEDGMENTS

Modeled output of private EV charging from Eric Wood, Matteo Muratori (National Renewable Energy Laboratory). Private EV sampling tool by Jerome Carman, Peter Alstone (Humboldt State University). StreetLight Data provided GPS input data for the RISE model. This article and the work described were sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Vehicle Technologies Analysis Program. The following DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Rachael Nealer, Jake Ward, Katherine McMahan, Kelly Fleming, and Heather Croteau. The authors also acknowledge Tom Wenzel of Lawrence Berkeley National Laboratory for critical feedback on this manuscript. This work was funded by the U.S. Department of Energy Vehicle Technologies Office under Lawrence Berkeley National Laboratory Agreement No. 32048. Lawrence Berkeley National Laboratory is supported by the Office of Science of the United States Department of Energy and operated under Contract Grant No. DE-AC02-05CH11231.

## REFERENCES

- (1) World Energy Outlook 2016, 2016. <https://www.iea.org/reports/world-energy-outlook-2016>.
- (2) Hao, H.; Geng, Y.; Sarkis, J. Carbon footprint of global passenger cars: Scenarios through 2050. *Energy* **2016**, *101*, 121–131.
- (3) U.S. Environmental Protection Agency. *Green Vehicle Guide: Fast Facts on Transportation Greenhouse Gas Emissions*, 2019. <https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions>.
- (4) IEA. *Global EV Outlook 2019: Scaling-up the transition to electric mobility*, 2019. <https://webstore.iea.org/global-ev-outlook-2019>.
- (5) Bloomberg New Energy Finance. *Electric Vehicle Outlook*, 2019. <https://about.bnef.com/electric-vehicle-outlook/>.
- (6) Needell, Z.; McNERney, J.; Chang, M.; Trancik, J. Potential for widespread electrification of personal vehicle travel in the United States. *Nature Energy* **2016**, *1*, 16112.
- (7) Saxena, S.; MacDonald, J.; Moura, S. Charging ahead on the transition to electric vehicles with standard wall outlets. *Appl. Energy* **2015**, *157*, 720–728.
- (8) Hawkins, T.; Gausen, O.; Stromman, A. Environmental impacts of hybrid and electric vehicles, a review. *Int. J. Life Cycle Assess.* **2012**, *17*, 997–1014.
- (9) Cai, H.; Xu, M. Greenhouse Gas Implications of Fleet Electrification Based on Big Data-Informed Individual Travel Patterns. *Environ. Sci. Technol.* **2013**, *47*, 9035–9043.
- (10) Green, E.; Skerlos, S.; Winebrake, J. Increasing electric vehicle policy efficiency and effectiveness by reducing mainstream market bias. *Energy Policy* **2014**, *65*, 562–566.
- (11) King, C.; Griggs, W.; Wirth, F.; Quinn, K.; Shorten, R. Alleviating a form of electric vehicle range anxiety through on-demand vehicle access. *Int. J. Control* **2015**, *88*, 717–728.
- (12) Barbour, N.; Menon, N.; Zhang, Y.; Mannering, F. Shared automated vehicles: A statistical analysis of consumer use likelihoods and concerns. *Transport Policy* **2019**, *80*, 86–93.
- (13) Merfeld, K.; Wilhelms, M.-P.; Henkel, S.; Kreutzer, K. Carsharing with shared autonomous vehicles: Uncovering drivers, barriers and future developments—A four-stage Delphi study. *Technological Forecasting and Social Change* **2019**, *144*, 66–81.
- (14) Greenblatt, J.; Saxena, S. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change* **2015**, *5* (9), 860–865.
- (15) Associated Press. Waymo: Phoenix begins Testing Self-Driving Vans on Public Roads. *CBS News*, 2018. <https://www.cbsnews.com/news/waymo-phoenix-tests-self-driving-vans-on-public-roads/>.
- (16) Litman, T. *Autonomous Vehicle Implementation Predictions*; Victoria Transport Policy Institute, 2017.
- (17) Fulton, L. M. Three Revolutions in Urban Passenger Travel. *Joule* **2018**, *2*, 575–578.
- (18) Zhang, W.; Guhathakurta, S.; Khalil, E. B. The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. *Transportation Research Part C: Emerging Technologies* **2018**, *90*, 156–165.
- (19) Henao, A.; Marshall, W. E. The impact of ride-hailing on vehicle miles traveled. *Transportation* **2019**, *46*, 2173–2194.
- (20) Sperling, D. *Three Revolution: Steering Automated, Shared, and Electric Vehicles to a Better Future*; Island Press, 2018.
- (21) Chen, T. D.; Kockelman, K. M.; Hanna, J. P. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transportation Research Part A: Policy and Practice* **2016**, *94*, 243–254.
- (22) Luk, J. M.; Kim, H. C.; De Kleine, R.; Wallington, T. J.; MacLean, H. L. Review of the Fuel Saving, Life Cycle GHG Emission, and Ownership Cost Impacts of Lightweighting Vehicles with Different Powertrains. *Environ. Sci. Technol.* **2017**, *51*, 8215–8228.
- (23) Bauer, G. S.; Greenblatt, J. B.; Gerke, B. F. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. *Environ. Sci. Technol.* **2018**, *52*, 4920–4928.
- (24) Franke, T.; Krems, J. F. Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour* **2013**, *21*, 75–89.
- (25) Franke, T.; Gunther, M.; Trantow, M.; Krems, J. F. Does this range suit me? Range satisfaction of battery electric vehicle users. *Applied Ergonomics* **2017**, *65*, 191–199.
- (26) Wolbertus, R.; Kroesen, M.; van den Hoed, R.; Chorus, C. G. Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment* **2018**, *62*, 283–297.
- (27) Melaina, M.; Muratori, M.; McLaren, J.; Schwabe, P. Investing in Alternative Fuel Infrastructure: Insights for California from Stakeholder Interviews: Preprint. *National Renewable Energy Laboratory Publications*, 2017, NREL/CP-5400-67617. <https://www.nrel.gov/docs/fy17osti/67617.pdf>
- (28) Nelson, J. H.; Wisland, L. M. *Achieving 50% Renewable Electricity in California: The Role of Non-Fossil Flexibility in a Cleaner Electricity Grid*; Union of Concerned Scientists, 2015.

- (29) Alstone, P.; Potter, J.; Piette, M.; Schwartz, P.; Berger, M.; Dunn, L.; Smith, S.; Sohn, M.; Aghajanzadeh, A.; Stensson, S.; Szinai, J.; Walter, T.; McKenzie, L.; Lavin, L.; Schneiderman, B.; Mileva, A.; Cutter, E.; Olson, A.; Bode, J.; Ciccone, A.; Jain, A. *Final Report on Phase 2 Results, 2015 California Demand Response Potential Study: Charting California's Demand Response Future*; Lawrence Berkeley National Laboratory, 2016.
- (30) Richardson, D. B. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renewable Sustainable Energy Rev.* **2013**, *19*, 247–254.
- (31) Foley, A.; Tyther, B.; Calnan, P.; O Gallachoir, B. Impacts of Electric Vehicle charging under electricity market operations. *Appl. Energy* **2013**, *101*, 93–102.
- (32) Sheppard, C.; Szinai, J.; Abhyankar, N.; Gopal, A. *Grid Impacts of Electric Vehicles and Managed Charging in California: Linking Agent-Based Electric Vehicle Charging with Power System Dispatch Models*; Sustainable Energy Systems Group, Sustainable Energy Department, Energy Analysis and Environmental Impacts Division, International Energy Studies Group, International Energy Analysis Department, 2019.
- (33) Szinai, J. K.; Sheppard, C. J. R.; Abhyankar, N.; Gopal, A. R. Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management. *Energy Policy* **2020**, *136*, 111051.
- (34) Lopes, J.; Soares, F.; Almeida, P. Integration of electric vehicles in the electric power system. *Proc. IEEE* **2011**, *99*, 168–183.
- (35) Tarroja, B.; et al. Assessing the stationary energy storage equivalency of vehicle-to-grid charging battery electric vehicles. *Energy* **2016**, *106*, 673–690.
- (36) Forrest, K.; et al. Charging a renewable future: The impact of electric vehicle charging intelligence on energy storage requirements to meet renewable portfolio standards. *J. Power Sources* **2016**, *336*, 63–74.
- (37) Coignard, J.; Saxena, S.; Greenblatt, J.; Wang, D. Clean Vehicles as an Enabler for a Clean Electricity Grid. *Environ. Res. Lett.* **2018**, *13*, 054031.
- (38) Iacobucci, R.; McLellan, B.; Tezuka, T. Modeling shared autonomous electric vehicles: Potential for transport and power grid integration. *Energy* **2018**, *158*, 148–163.
- (39) Jones, E. C.; Leibowicz, B. D. Contributions of shared autonomous vehicles to climate change mitigation. *Transportation Research Part D: Transport and Environment* **2019**, *72*, 279–298.
- (40) Li, M.; Lenzen, M.; Wang, D.; Nansai, K. GIS-based modelling of electric-vehicle-grid integration in a 100% renewable electricity grid. *Appl. Energy* **2020**, *262*, 114577.
- (41) Hedegaard, K.; Ravn, H.; Juul, N.; Meibom, P. Effects of electric vehicles on power systems in Northern Europe. *Energy* **2012**, *48*, 356–368.
- (42) Haque, A. N. M. M.; Ibn Saif, A. U. N.; Nguyen, P. H.; Torbaghan, S. S. Exploration of dispatch model integrating wind generators and electric vehicles. *Appl. Energy* **2016**, *183*, 1441–1451.
- (43) Hanemann, P.; Behnert, M.; Bruckner, T. Effects of electric vehicle charging strategies on the German power system. *Appl. Energy* **2017**, *203*, 608–622.
- (44) Taljegard, M.; Göransson, L.; Odenberger, M.; Johnsson, F. Impacts of electric vehicles on the electricity generation portfolio - A Scandinavian-German case study. *Appl. Energy* **2019**, *235*, 1637–1650.
- (45) Limmer, S.; Rodemann, T. Peak load reduction through dynamic pricing for electric vehicle charging. *International Journal of Electrical Power & Energy Systems* **2019**, *113*, 117–128.
- (46) Sheppard, C.; Jenn, A.; Bauer, G.; Gerke, B.; Greenblatt, J.; Gopal, A. A joint optimization scheme for the planning and operations of a regional electrified fleets of ride hailing vehicles serving mobility on demand. *Transportation Research Record: Journal of the Transportation Research Board* **2019**, *2673* (6), 579–597.
- (47) Jenn, A.; Clark-Sutton, K.; Gallaher, M. P.; Petrusa, J. Environmental impacts of extreme fast charging. *Environ. Res. Lett.* **2020**, *15*, 094060.
- (48) Hand, M. M.; Baldwin, S.; DeMeo, E.; Reilly, J. M.; Mai, T.; Arent, D.; Porro, G.; Meshek, M.; Sandor, D. *Renewable Electricity Futures Study*; National Renewable Energy Laboratory, 2012.
- (49) Wood, E. W.; Rames, C. L.; Muratori, M.; Srinivasa Raghavan, S.; Young, S. E. *Charging Electric Vehicles in Smart Cities: An EVI-Pro Analysis of Columbus*; NREL: OH, 2018.
- (50) Sheppard, C.; Jenn, A. Grid-integrated Electric Mobility (GEM) Model. *GitHub*, 2021. <https://github.com/LBNL-UCB-STI/gem>.
- (51) Sheppard, C.; Jenn, A.; Bauer, G.; Greenblatt, J.; Gerke, B. Grid-integrated Electric Mobility (GEM) Model – Manuscript 2021 Branch. *GitHub*, 2021. <https://github.com/LBNL-UCB-STI/gem/tree/manuscript-2021>.
- (52) U.S. Department of Transportation, Federal Highway Administration 2017 National Household Travel Survey, 2017. <https://nhts.ornl.gov>.
- (53) Xu, Z.; Su, W.; Hu, Z.; Song, Y.; Zhang, H. A Hierarchical Framework for Coordinated Charging of Plug-In Electric Vehicles in China. *IEEE Trans. Smart Grid* **2016**, *7*, 428–438.
- (54) U.S. Energy Information Administration. *Annual Energy Outlook*, 2019. <https://www.eia.gov/outlooks/aeo/>.
- (55) U.S. Energy Information Administration *Preliminary Monthly Electric Generator Inventory (based on Form EIA-860M as a supplement to Form EIA-860)*. <https://www.eia.gov/electricity/data/eia860M/> (accessed September 2020).