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Evaluating the emission benefits of shared autonomous electric vehicle fleets: A case study in California

Yanning Li *, Xinwei Li, Alan Jenn

University of California, Davis, Institute of Transportation Studies, 1590 Tilia St, Davis, CA 95616, United States

HIGHLIGHTS

- We evaluate the emissions from SAEVs with a grid operation model.
- SAEV charging demand is simulated using real-world data from TNCs.
- In the Californian grid, SAEVs are more than 5 times less CO_2 intensive than ICVs.
- Emission benefits of SAEVs increase with the expansion of renewable generation.
- Synergizing SAEV charging with grid operation yields substantial emission benefits.

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ABSTRACT

The transportation sector is a major source of greenhouse gas (GHG) emissions. Shared autonomous electric vehicles (SAEVs) have the potential to mitigate emissions, but the effect can be highly dependent on the growth and operation of the SAEV fleet as well as its interaction with the evolving power system. In this study, we simulate travel and charging behaviors of SAEVs based on empirical data of ride-hail service operations, and integrate SAEV charging with the Grid Optimized Operation Dispatch (GOOD) model, taking into account the expansion of renewable generation and charger capacity over time. Emissions from SAEVs are compared across different market adoption levels, occupancy rates, and charging strategies. We find that under the Californian power grid, SAEVs are generally more than 5 times less carbon intensive than modern day ICVs on a per mile basis. The extent of aligning charging schedule with renewable generation is an essential determinant of the economic and emission impact from an SAEV fleet. At higher levels of renewable penetration, synergizing SAEV charging with grid operation can be the most impactful means to reduce emissions from an SAEV fleet, generating up to 95% less emissions than other charging strategies. We also examine the introduction of a carbon tax and find that it can further amplify the advantage of smart charging by approximately 1.5 times in the cost-effectiveness of emission mitigation.

1. Introduction

The transportation sector has been a major source of greenhouse gas (GHG) emissions. In 2019, 37.5% of the total CO_2 emission in the US are from transportation, in which passenger cars contributed 40.5% [1]. The state of California, which is one of the largest automobile markets in the US, produced about 166 million metric tons (MMT) of CO_2 equivalent from its transportation sector in 2019 [2]. California has been setting stringent goals to combat the rise in GHG emissions. The state has already accomplished the goal of reducing statewide GHG emissions to 1990 levels by 2020, which was set by the California Global Warming Solutions Act of 2006 (Assembly Bill 32). Senate Bill 32 then expanded the standard to a 40% GHG reduction of 1990 levels by 2030 [3]. Under this goal, California Air Resources Board (CARB) strengthened the Low Carbon Fuel Standard (LCFS) towards reducing the carbon intensity of transportation fuel pool by at least 20% by 2030 [4]. To realize a low carbon future, the transportation sector will need to undergo a profound transformation towards a more sustainable and efficient system. The emerging trends of vehicle electrification, shared mobility, and autonomous vehicles (AVs) have the potential to transform the transportation sector.

A vast number of studies have proven potential emission benefits

* Corresponding author.
E-mail addresses: yspli@ucdavis.edu (Y. Li), xwli@ucdavis.edu (X. Li), ajenn@ucdavis.edu (A. Jenn).

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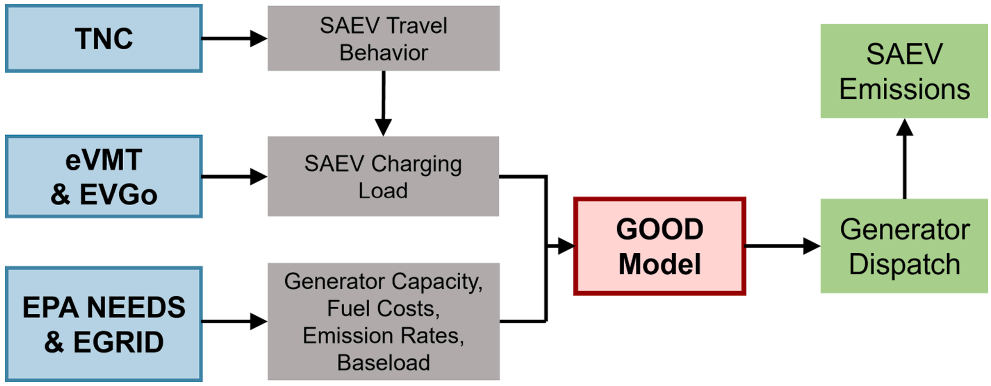

Fig. 1. Data sources (blue), intermediate data (gray), model (red), and outputs (green) in the general research framework.

from replacing conventional internal combustion vehicles (ICVs) with electric vehicles (EVs). Some studies focus on the direct emissions from the use phase of EVs [5-12], while others calculate the full life cycle emissions [13-18]. EVs have experienced a strong growth in sales over the past decade, with global EV stock reaching 10 million in 2020 [19]. Many policies are encouraging an acceleration in this trend, for example, the Zero Emission Vehicle (ZEV) program in California aims at 5 million EVs on the road by 2030 in California [20]. The International Energy Agency (IEA) projects that the number of EVs on the road may reach as high as 300 million globally by 2030 [19], which could generate a large burden of charging load on the power system. Therefore, the integration of the transportation and energy sectors is essential. Maximizing environmental benefits depends not only on the speed of EV uptake, but also the decarbonization of the power system [12], as well as realizing the potential of managed charging that could avoid additional capacity expansion of the grid, and enhance power system flexibility to better utilize and offset the growth of intermittent renewable generation. Many studies seek to incorporate the scheduling of EV charging into power system operation model, and conclude that more significant benefits can be achieved by adapting EV charging according to grid conditions [5-10].

The market of shared mobility has been rapidly growing in recent years, which generally includes car sharing (such as ZipCar and Car2Go) and on-demand ride hailing (such as Uber and Lyft), with these new mobility services provided by transportation network companies (TNCs). Previous researches suggest that shared mobility could potentially reduce car ownership, since a smaller fleet size is needed to meet the same amount of travel demand as private cars [21-23]. This could in turn relieve traffic congestion [24] and reduce GHG emissions [21,22,25].

In addition to some of the recent shifts in transportation through electrification and new mobility services, automakers like Tesla, Waymo, and Cruise have recently been conducting trials of automated vehicles and are planning to commercialize them in the future [26]. AVs are expected to improve traffic efficiency via increasing speed and reducing travel time [27,28], increase safety by avoiding crashes [29], and save energy consumption [30]. However, some studies argue that the net energy consumption from AVs could be even higher than traditional vehicles because the drop in marginal cost of driving and travel time cost can cause a rebound effect and thus induce even more travel demand. Discussions have been going on about the relative magnitude of reduced vehicle miles traveled (VMT) versus the induced travel, and indicates that the energy and environmental outcomes from AVs alone can be very uncertain [24,31-33].

Vehicle electrification, shared mobility, and autonomous vehicle complement each other in many ways. The high capital cost of EVs and AVs can be more easily amortized if adopted in shared mobility, due to the higher utilization of capital assets [33]. The increased travel intensity of ride sharing could further increase the emission savings of EVs on a per vehicle basis [34]. And electrifying AVs could make AVs' emission benefits more promising [27,28,35]. In return, autonomizing shared EV fleets could make it easier to conduct centralized optimization of charging and routing [36]. Thus, shared autonomous electric vehicles (SAEVs), as a synergy of the three technologies, could achieve more significant environmental and energy benefits over conventional private ICV, compared with application of each technology separately.

Only a handful of studies have assessed the environmental impacts of SAEVs. Greenblatt and Saxena compared the use phase emissions and costs of SAEVs with private ICVs [37]. Gawron et al. conducted life cycle analysis (LCA) for SAEV [38]. Even fewer studies explore the impacts of a full SAEV fleet. Majority of them assume that electricity generation are not affected by the operation of SAEVs. For example, Zhang et al. estimated SAEV travel demand by simulating each individual's mode choice based on a utility maximizing evolutionary algorithm, and calculated corresponding emissions with average hourly emission rate from California Independent System Operator (CAISO) [39]. Iacobucci et al. proposed SAEV charging optimization algorithms according to renewable generation in a microgrid [40] and according to hourly price of electricity [41], with the power generation dispatch as a static input in both studies. Loeb and Kockelman [42], Iacobucci et al. [36], Liao et al. [43], and Yi and Smart [44] used agent based traffic simulation to investigate routing and charging algorithms for SAEVs, and the environmental impact of the proposed strategies were also estimated with past data on grid emission factor. Other studies address the interaction between SAEV charging and grid operation, but tend to simplify the projections on SAEV travel demand and grid development. For example, Jones and Leibowicz adopted an aggregated model to incorporate the SAEV uptake and charging into grid operation, with a simplified SAEV travel demand assumption scaled up from private vehicle travel demand [45]. Sheppard et al. conducted similar research integrating aggregate mobility and grid models, but based on the current generation capacity mix, rather than an outlook into a potentially cleaner power system in the future [46]. Furthermore, these studies may overestimate SAEV charging flexibility without considering charging capacity limit in their models, and lack discussion on more possibilities of charging strategies.

To address the research gaps mentioned above, this work performs an attributional investigation into the emissions from an SAEV fleet, by integrating the SAEV charging demand and charger capacity expansion into a grid dispatch simulation, while optimizing future renewable capacity expansion in the grid in line with the aggressive climate policy in California. We incorporate unique datasets of real TNC trips and EV charging activities to simulate the travel demand and charging load of the SAEV fleet. Emission outcomes are analyzed with respect to different market penetration levels, charging strategies, vehicle occupancy rates, and carbon policies, with annual projections from 2022 to 2030.

The rest of the paper is organized as follows: Section 2 explains the methodology and data sources used in this research. Section 3 presents and discusses the SAEV emission results from the power system

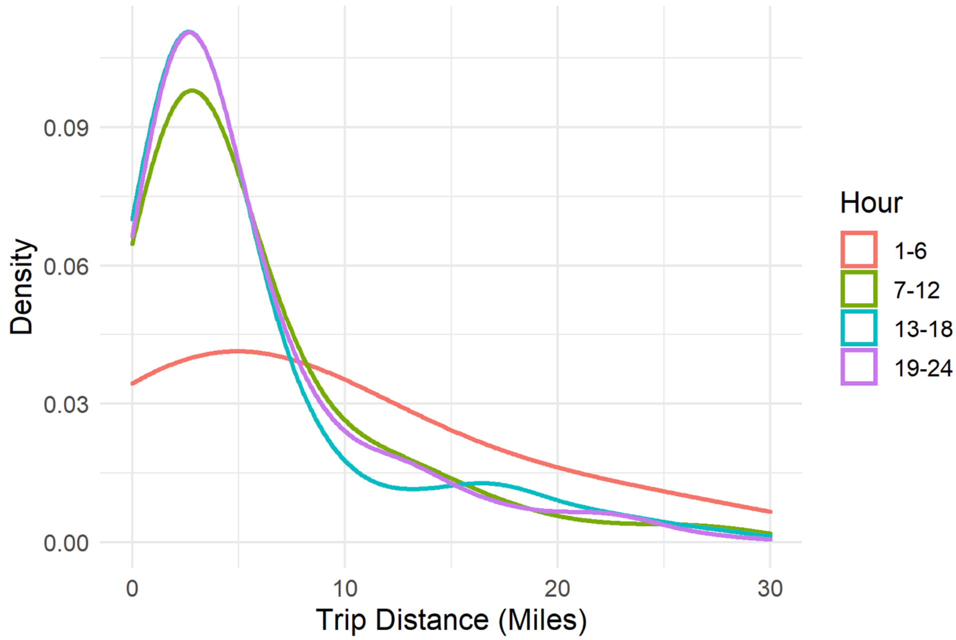

Fig. 2. Trip distance distributions of TNC vehicles every 6 h derived from empirical ride-hailing datasets.

simulation. In Section 4, we conclude the major implications and outlook of our work.

2. Data and methods

The general framework of our research can be seen in Fig. 1. First, the travel behavior of SAEVs is simulated based on empirical data from TNCs, under different assumptions of the adoption level and occupancy rate of the SAEVs (Section 2.1). Then the travel demand simulated is used to estimate electricity charging demand and generate hourly charging profiles under various charging strategies (Section 2.2). The SAEV charging load is then fed into a power system simulation model, along with baseload demand data and installed generation capacity information within the Western Interconnect (WECC). The dispatch model calculates the optimal generation profiles, which are used to estimate the emissions caused by the SAEV charging demand (Section 2.3).

2.1. Vehicle travel patterns

Accurate simulation of daily travel patterns of an SAEV fleet is fundamental to estimate their electricity consumption. Since there are no empirical datasets that currently exist for this new type of service, existing ride hailing services could be the best analogue. In this study, we assume that SAEVs operate in the same manner as existing TNC services when providing trips. We employ a unique dataset of both Uber and Lyft in period 3 operation (driving a passenger from an origin to destination) that provides the distribution of distance travelled per trip and the frequency of travel demand within each hour of a day. The probability density function of the trip distances in different hours is visualized in Fig. 2.

From this distribution, we bootstrap the travel distance of an average SAEV in each hour from each day, over the years from 2022 to 2030. Since these miles only account for operation when driving passengers, we then scale the miles by a deadheading factor of 38.5% [47] to include the additional miles travelled in periods 1 and 2 (driving in search of passengers and driving to pick-up matched passengers respectively).

We examine three different assumptions for the growth of the SAEV fleet based on different proportions of current Uber and Lyft market size, which is around 96,000 vehicles in the San Francisco Bay Area of California. Under medium adoption level, the SAEV fleet will be as large as 10% of current TNC market by 2030. And the low and high adoption levels correspond to 5% and 25% respectively. We assume a linear growth in the market adoption from 0% in 2021 to 2030.

According to the design of prospective autonomous vehicles providing shared rides, such as the Cruise Origin, we define scenarios across a range of assumptions of the average occupancy rate from 1 to 4 passengers per trip for the SAEV fleet. We assume that under a certain SAEV market adoption level, the total travel demand in passenger-miles is fixed. Therefore, the size of SAEV fleet is scaled down with the increase of vehicle occupancy rate, assuming that the average vehicle occupancy of a TNC vehicle is 1.55 in the original data [48].

The hourly travel distances of the average SAEV are then scaled up according to different SAEV fleet sizes defined by combinations of market adoption level and vehicle occupancy rate to obtain the daily travel patterns of the SAEV fleet.

2.2. Vehicle charging behavior

The daily energy demand of the SAEV fleet is estimated based on the travel demand from Section 2.1. Equation (1) shows how the energy conversion efficiency rate (kWh/mile) is calculated:

$$\eta = \frac{v^{*}\eta_0 + P_{draw}}{v} \tag{1}$$

where v is the average velocity of SAEVs, which is assumed to be 30 miles/hour [49]. η_0 is the average conversion efficiency of EV powertrain, which is assumed to be 0.3 kWh/mile [50]. P_{draw} is the average additional power draw that the SAEV consumes as it runs. The power draw is assumed to be 8.3 kW based on information from automaker stakeholders.

The aggregate daily energy demand of the SAEVs is then allocated into each hour of the day to form the hourly charging profiles. Different charging strategies are represented by the different hourly distributions of the charging load. In this work, 7 different charging strategies are defined.

- "*Nighttime Charging*", "*Daytime Workplace Charging*", and "*Daytime Public Charging*" strategies are based on charging patterns extracted from real-world charging data from the Electric Vehicle Miles Traveled (eVMT) project conducted by the Plug-In Hybrid & Electric

Fig. 3. SAEV hourly charging profiles of different charging strategies, in each day of 2030, with medium adoption level and occupancy rate of 1 passenger.

Vehicle Center at UC Davis. In the eVMT project, the day-to-day usage patterns and charging behavior of EVs are monitored over the period of a full year. A total of over 55,000 charging events are captured in the data [51-53].

- The strategy of "*Charging Inverse to Netload* '' is defined according to baseload demand data and renewable generation data from the grid simulation results, without including the SAEV charging load into the model. The netload patterns are extracted, standardized, and inversed to generate the charging probability pattern. Scheduling charging under this pattern is expected to help consume excess intermittent renewable generation and flatten the aggregate demand curve in the power system.
- The pattern of "*Charging Inverse to Ride Requests*" is based on TNC data. The number of ride requests in each hour is obtained, and this pattern is standardized and inverted to define the charging probability. Under this strategy, less charging activities are scheduled when there are more ride requests, which is expected to be beneficial for the ride hailing service provider.
- Lastly, the "*Uniform Charging*" adopts a flat charging pattern across the period of a day.

For these six charging strategies, after obtaining the standardized average charging pattern of a day as mentioned above, the day-to-day hourly charging probabilities are then generated by sampling from normal distributions. For each hour, the expectation of the normal distribution is the corresponding value in the average pattern, and the variance is derived from the real-world charging data of EVGo. To obtain these hourly variances, the charging data in California from 2014 to 2019 is normalized by day, and the variance of all the charging load in each hour is calculated respectively. The daily charging probability patterns are then multiplied with the daily energy needed to form daily charging profiles. An example of the charging load profiles of these six charging strategies are depicted in Fig. 3. These charging profiles are part of the demand side input into the power system operation model.

The final charging strategy is "*Smart Charging*", which assumes flexibility in charging schedule, making sure that all the energy consumed in this day is charged by the end of the day. By including the scheduling of SAEV charging into the grid operation model, we allow the charging to be adapted according to the real-time price changes in the electricity wholesale market. And the optimized smart charging profile is an output from the power system simulation. Further elaboration can be found in section 2.3.

Apart from SAEV charging loads, the growing charging load of other EVs are also included in the demand side input, the scale of which is based on the projection of yearly miles travelled from eVMT data. And the pattern of the charging load is assumed to be a combination of 80% nighttime charging, 10% daytime public charging, and 10% daytime workplace charging [52].

Table 1
Notations in the power system optimization model.

Name	Type	Description
g	set	Generator index
$solar, wind$	set	Subset of g, solar and wind generators
t	set	Index for hours
d	set	Index for days
r, o, p	set	Alias sets of regions
ca	set	Subset of r, regions in California
$gtor$	set	Mapping from generator to region
$ttod$	set	Mapping from hour to day
$c^{solar.cost}$, $c^{wind.cost}$	parameter	Solar and wind capacity cost
$c^{storage.cost}$	parameter	Storage capacity cost
$c^{charger.cost}$	parameter	Charging capacity cost
$c^{CO_2.price}$	parameter	Carbon price
$c^{transLoss}$	parameter	Transmission efficiency rate
$c^{storageLoss}$	parameter	Storage efficiency rate
c^{RPS}	parameter	RPS requirement
$c_g^{gen.cost}$	parameter	Generation cost of generator g
$c_g^{CO_2.rate}$	parameter	CO_2 emission rate of generator g
$c_{ro}^{trans.cost}$	parameter	Transmission cost from region r to region o
$c_{rt}^{demandLoad}$	parameter	Baseload and non-SAEV charging load in region r at hour t
$c_{rt}^{evHourlyLoad}$	parameter	SAEV charging load input in region r at hour t
$c_{rd}^{evDailyLoad}$	parameter	SAEV charging load input in region r within day d
c_{solar}^{maxGen}, c_{wind}^{maxGen}	parameter	Initial capacity of solar and wind generation
$c_{rt}^{maxSolar}$, $c_{rt}^{maxWind}$	parameter	Solar and wind generation availability in region r at hour t, under initial capacity
$c_r^{charger.cap.min}$	parameter	The existing charging capacity in the previous model year in region r
x_{gt}^{gen}	variable	Generation from generator g at hour t
x_{rto}^{trans}	variable	Transmission from region r to o at hour t
$x_{rt}^{ev.flexLoad}$	variable	SAEV smart charging load in region r at hour t
$x_r^{new.solar}$, $x_r^{new.wind}$	variable	New solar and wind capacity installed in region r
$x_r^{storage.cap}$	variable	Storage capacity installed in region r
$x_r^{charger.cap}$	variable	Charging capacity installed in region r
$x_{rt}^{storage.soc}$	variable	The storage state of charge in region r at hour t
$x_{rt}^{storage.in}$, $x_{rt}^{storage.out}$	variable	The input and output energy to and from the storage in region r at hour t

2.3. *Emissions from power generation*

To simulate the operation of power plants in response to electricity demand, we employ the Grid Optimized Operation Dispatch (GOOD) model, an economic dispatch and capacity expansion optimization model [46,7]. While this study is focused on the SAEV fleet within the San Francisco Bay Area, the power system is substantially more interconnected. Therefore, we simulate the operation of the entire WECC, to capture the import and export of electricity across different balancing zones. The model co-optimizes the charging scheduling (under smart charging strategy) and charger capacity installation along with economic dispatch of generators and renewable capacity expansion, to find the minimal cost combination to obtain a supply–demand balance in the power system. The simulation is run on an hourly basis, for four representative weeks in each season, from 2022 through 2030. Notations in the model are explained in Table 1.

Objective Function: Total cost of the system

The objective function aggregates the total system cost across all generators, time periods, and regions. The cost includes generation cost, transmission cost, as well as installation cost for new solar, wind, and storage capacity. To avoid charging peaks that requires unreasonable scale of charger capacity, the cost of installing charging infrastructure is also considered in the objective function [54].

$$\min_{\substack{x_{gt}^{gen}, x_{rto}^{trans}, x_{rt}^{ev.flexLoad}, \\ x_r^{new.solar}, x_r^{new.wind}, \\ x_r^{storage.cap}, x_{rt}^{storage.soc}, \\ x_{rt}^{storage.in}, x_{rt}^{storage.out}, \\ x_r^{charger.cap}}} \left(\begin{array}{c} \sum_g \sum_t x_{gt}^{gen} c_g^{gen.cost} + \sum_r \sum_t \sum_o x_{rto}^{trans} c_{ro}^{trans.cost} + \\ \sum_r x_r^{new.solar} c^{solar.cost} + \sum_r x_r^{new.wind} c^{wind.cost} + \\ \sum_r x_r^{storage.cap} c^{storage.cost} + \sum_r x_r^{charger.cap} c^{charger.cost} \\ + \sum_g \sum_t x_{gt}^{gen} c_g^{CO_2.rate} c^{CO_2.price} \end{array} \right) \tag{2}$$

Constraint 1a: Generation should meet total load, with exogenous charging behavior

This constraint ensures real-time balance between generation and demand in each region. It is only active when simulating a scenario with non-smart charging strategy. The demand side consists of two exogenous parameters: SAEV charging load, which is determined as described in Section 2.2; and baseload, which represents all the rest electricity demand, including the charging load of other EVs. The way that the SAEV fleet charge affects the dispatch of generators, the import and export of electricity, and the operation of storage.

$$\left(\begin{array}{c} \sum_{g \in gtor_{gr}} x_{gt}^{gen} + \sum_o x_{otr}^{trans} c^{transLoss} - \sum_p x_{rtp}^{trans} - \\ x_{rt}^{storage.in} + x_{rt}^{storage.out} c^{storageLoss} \\ -\left(c_{rt}^{demandLoad} + c_{rt}^{evHourlyLoad}\right) \end{array} \right) = 0; \forall t, r \tag{3}$$

Constraint 1b: Generation should meet total load, with flexible charging behavior

This constraint is only active when simulating a scenario with smart charging strategy. It is identical to 1a, except that the hourly SAEV charging load is a decision variable. The smart charging schedule is thus determined endogenously by the model and synergizes with the grid operation.

$$\left(\begin{array}{c} \sum_{g \in gtor_{gr}} x_{gt}^{gen} + \sum_o x_{otr}^{trans} c^{transLoss} - \sum_p x_{rtp}^{trans} - \\ x_{rt}^{storage.in} + x_{rt}^{storage.out} c^{storageLoss} \\ -\left(c_{rt}^{demandLoad} + x_{rt}^{evFlexLoad}\right) \end{array} \right) = 0; \forall t, r \tag{4}$$

Constraint 2: Flexible SAEV charging load should satisfy daily charging demand

Under smart charging strategy, while the hourly charging load is assumed to be flexible, the aggregate charging demand must be fulfilled within a larger time window.

$$\sum_{t \in ttod_{td}} x_{rt}^{evFlexLoad} - c_{rd}^{evDailyLoad} \geq 0; \forall r, d \tag{5}$$

Constraint 3: Charging capacity limit

The smart charging load of SAEVs per hour is constrained below the installed charging capacity. In this way, the model optimizes the installed charging capacity and smart charging schedule by balancing between the cost generated from installing chargers and the generation & transmission cost saved from smart charging.

$$x_r^{charger.cap} - x_{rt}^{evFlexLoad} \geq 0; \forall r, t \tag{6}$$

Constraint 4: Charging capacity growth

The total charging capacity of the current model year should be greater than that of the last model year.

$$x_r^{charger.cap} - c_r^{charger.cap.min} \geq 0; \forall r \tag{7}$$

Constraint 5 & 6: Resource availability limit on renewable generation

These two constraints make sure that real-time solar and wind generation do not exceed the maximum power available from natural resources (when the sun shines or wind blows). The limit is based on representative solar and wind profiles under initial renewable generation capacity, and the newly installed capacity determined by the model.

$$\left(\begin{array}{c} c_{rt}^{maxSolar} \sum_{solar \in gtor_{solar,r}} c_{solar}^{maxGen} + x_r^{new.solar} c_{rt}^{maxSolar} \\ - \sum_{solar \in gtor_{solar,r}} x_{solar,t}^{gen} c_{solar}^{maxGen} \end{array} \right) \geq 0; \forall t, r \tag{8}$$

$$\left(\begin{array}{c} c_{rt}^{maxWind} \sum_{wind \in gtor_{wind,r}} c_{wind}^{maxGen} + x_r^{new.wind} c_{rt}^{maxWind} \\ - \sum_{wind \in gtor_{wind,r}} x_{wind,t}^{gen} c_{wind}^{maxGen} \end{array} \right) \geq 0; \forall t, r \tag{9}$$

Constraint 7: Renewable generation requirement

This constraint specifies the share of total generation in California that must be fulfilled by renewable energy, which complies with Renewable Portfolio Standards (RPS) in Senate Bill 100. This share is assumed to increase linearly by year from 30% in 2022 to 60% in 2030.

$$\left(\begin{array}{c} \sum_{ca,t} \left(\sum_{solar \in gtor_{solar,ca}} x_{solar,t}^{gen} + \sum_{wind \in gtor_{wind,ca}} x_{wind,t}^{gen} \right) \\ -c^{RPS} \sum_{ca,t} \left(\sum_{g \in gtor_{g,ca}} x_{gt}^{gen} \right) \end{array} \right) \geq 0 \tag{10}$$

Constraint 8: Storage charging dynamic

This constraint ensures the real-time energy balance of the grid storage. In each hour, the aggregate energy level of the storage batteries should be equal to the previous hour's energy level plus the energy input and minus the energy output.

$$x_{rt}^{storage.soc} - x_{r,t-1}^{storage.soc} - x_{r,t-1}^{storage.in} c^{storageLoss} + x_{r,t-1}^{storage.out} = 0; \forall r, t \tag{11}$$

Constraint 9: Storage capacity limit

The amount of electricity stored in the grid storage should never exceed the installed battery capacity.

$$x_r^{storage.cap} - x_{rt}^{storage.soc} \geq 0; \forall r, t \tag{12}$$

Constraint 10 & 11: Storage input/output speed limit

Based on the performance of current lithium-ion batteries, we limit the amount of charging/discharging energy per hour to be below 25% of the total capacity of the grid storage device.

$$.25 x_r^{storage.cap} - x_{rt}^{storage.in} \geq 0; \forall r, t \tag{13}$$

$$.25 x_r^{storage.cap} - x_{rt}^{storage.out} \geq 0; \forall r, t \tag{14}$$

Table 2
Scenarios simulated in the model.

	Adoption Level	Occupancy Rate	Charging Strategy	Carbon Tax
1	Medium	1	Daytime workplace charging	Yes
2	Medium	1	Daytime public charging	Yes
3	Medium	1	Nighttime charging	Yes
4	Medium	1	Uniform charging	Yes
5	Medium	1	Charging inverse to ride requests	Yes
6	Medium	1	Charging inverse to netload	Yes
7	Medium	1	Smart charging	Yes
8	Medium	1	Daytime workplace charging	No
9	Medium	1	Daytime public charging	No
10	Medium	1	Nighttime charging	No
11	Medium	1	Uniform charging	No
12	Medium	1	Charging inverse to ride requests	No
13	Medium	1	Charging inverse to netload	No
14	Medium	1	Smart charging	No
15	Medium	2	Daytime workplace charging	No
16	Medium	2	Smart charging	No
17	Medium	3	Daytime workplace charging	No
18	Medium	3	Smart charging	No
19	Medium	4	Daytime workplace charging	No
20	Medium	4	Smart charging	No
21	Low	1	Daytime workplace charging	No
22	Low	1	Smart charging	No
23	High	1	Daytime workplace charging	No
24	High	1	Smart charging	No

2.4. Scenarios

We examine a total of 24 scenarios distinguished by their assumptions on SAEV adoption level, occupancy rate, charging strategy, and whether carbon tax is applied in the power market, the settings of which can be seen in Table 2. As mentioned in Section 2.1, low, medium, and high SAEV adoption levels correspond to 5%, 10%, and 25% of the current TNC travel demand market size by 2030 respectively. To compare the effects of different charging strategies, SAEV adoption level is controlled at medium, and occupancy rate is controlled at 1 passenger. Among the charging strategies, three of them are based on human drivers' charging behavior: daytime workplace charging, daytime public charging, and nighttime charging. Scenarios under these charging strategies assume that the charging behavior of an SAEV fleet is still largely dependent on people's, or passengers', daily commute and living schedules. The other four charging strategies, on the other hand, assume that without the influence of human drivers' preferences, there are more possibilities of centrally managing the charging of an SAEV fleet by various criteria: uniformly throughout the day (uniform charging), according to travel intensity of the fleet (charging inverse to ride requests), according to netload level (charging inverse to netload), or via real time interaction with the grid operation (smart charging). Comparisons among different SAEV adoption levels and occupancy rates are analyzed under two charging strategies respectively: daytime workplace charging and smart charging. Furthermore, we want to investigate how the application of a carbon tax in the power system can affect the SAEV emissions, and how different charging strategies synergize with this policy. The carbon tax is assumed to be constant over the years, at a price of \$54.7/tCO_2, which is based on the social cost of carbon [55].

3. Results and Discussions

In this section, we present and discuss the results from the scenarios. We begin by showing clips of generation and load profiles from the power system simulation (Section 3.1). Then in Section 3.2, we present carbon emissions from SAEVs over the years, and compare them among different assumptions on adoption level, occupancy rate, charging strategy, and carbon policy. In Section 3.3, we evaluate the relative CO_2 mitigation cost on the system level by switching SAEV charging strategies and how carbon policy influences the results. Finally, in Section 3.4, we verify that there is no conflict between the charging and driving activities of the SAEVs in the fleet.

3.1. Generation/Load patterns

An example of power grid generation and load profile in California in one week is shown in Fig. 4. Since SAEVs are assumed to be only in the San Francisco Bay Area, the charging load from SAEVs is marginal compared with the baseload and other EV loads all over California. In the example of a spring week, the total load in each day has 2 peaks at around 8:00 and 17:00 respectively. As is seen in the generation profile,

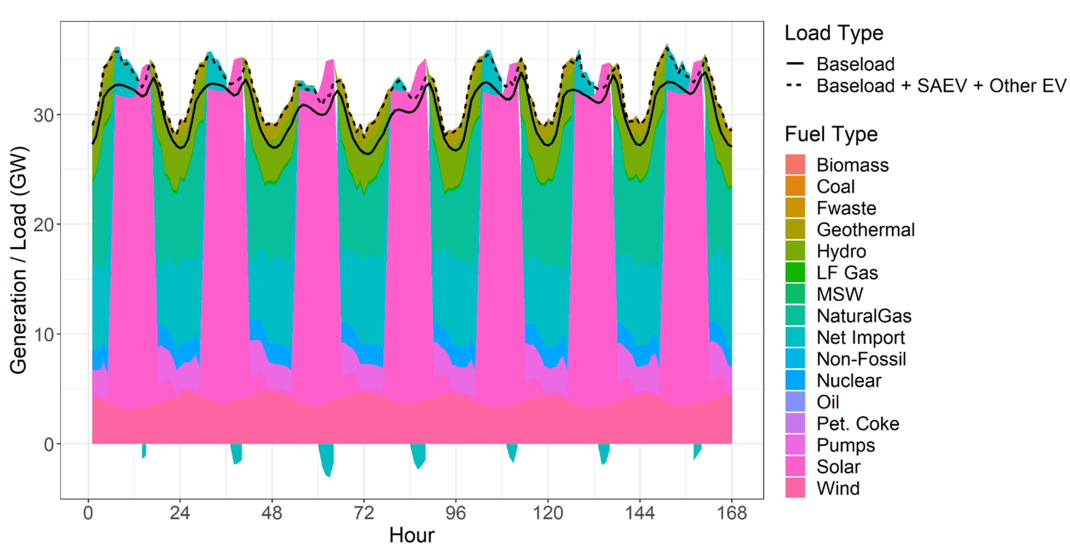

Fig. 4. Generation and load patterns of California in a typical spring week of 2030, with medium SAEV adoption level, occupancy rate of 1 passenger, and daytime workplace charging strategy, without applying carbon tax.

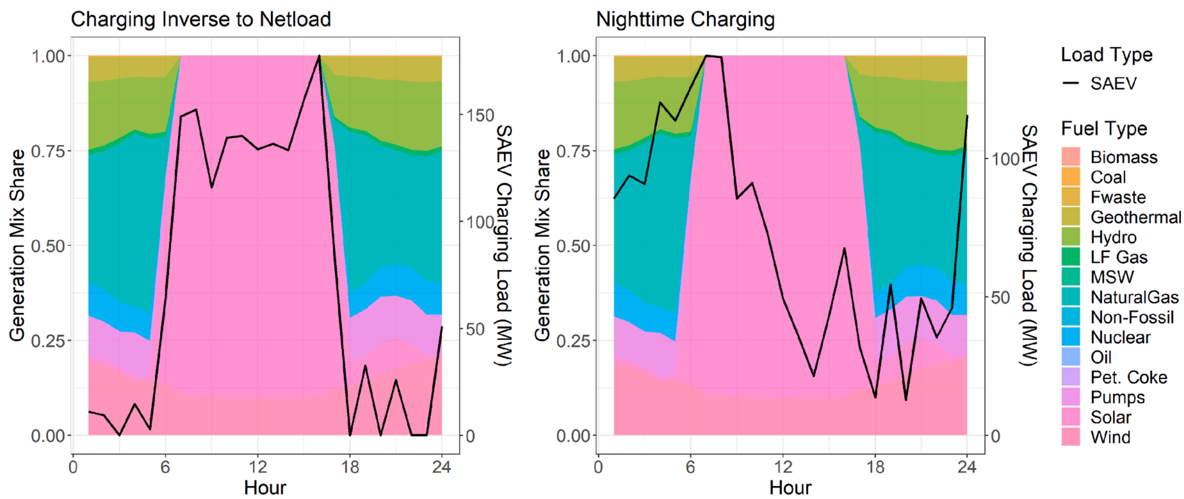

Fig. 5. Hourly generation mix in California and SAEV charging load of different charging strategies, on a typical spring day of 2030, with medium SAEV adoption level, occupancy rate of 1 passenger, and without applying carbon tax.

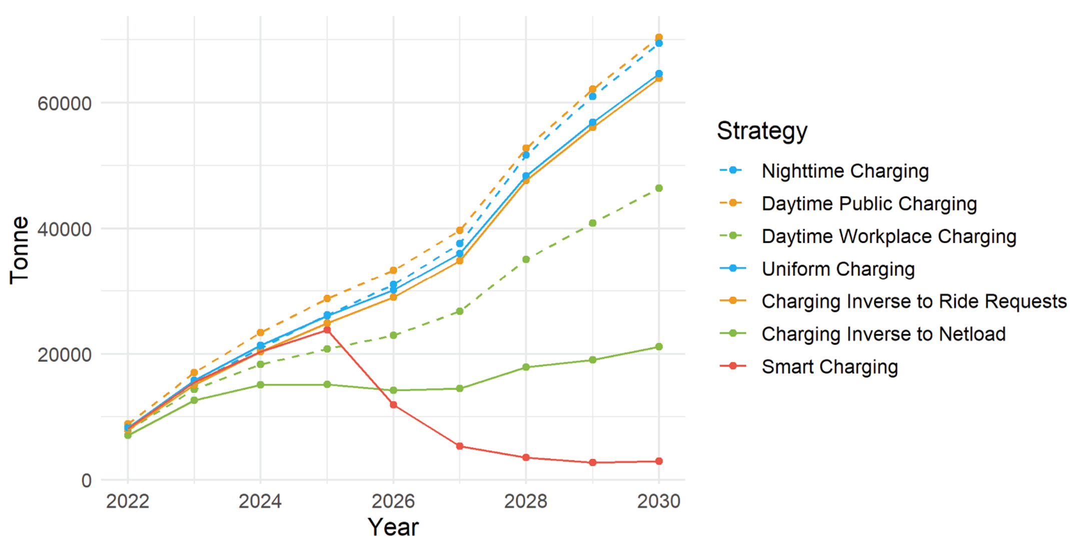

Fig. 6. Total annual CO_2 emission caused by SAEVs in California, under different charging strategies, with medium adoption level and occupancy rate of 1 passenger, without applying carbon tax.

in 2030, with 46% of the total generation being solar, most of the load during the day is met by solar generation. Export of electricity happens in the early afternoon due to excess solar generation. Natural gas generation fills most of the gaps when there is not enough renewable generation available to meet the demand. Fig. 5 shows how SAEV charging schedules correspond to hourly generation mix under different charging strategies. In the two examples, charging inverse to netload aligns better with renewable generation, while most of nighttime charging happens when non-renewables dominate in the generation mix.

3.2. Emissions from SAEVs

To calculate the emissions from the power generation that correspond to SAEV charging loads, the average emission rate per hour in the power system is calculated and multiplied with the SAEV charging load in each hour.

In Fig. 6, the total annual CO_2 emissions from SAEVs under different charging strategies are shown over the years from 2022 to 2030. For non-smart charging strategies, total emissions generally increase by year, mainly due to the gradual increase in SAEV fleet size. Nighttime charging and daytime public charging are the most carbon intensive, because most of the charging under these two strategies happen at hours without a lot of solar generation. Charging inverse to ride requests generates similar amounts of CO_2 as uniform charging. Daytime workplace charging is the third cleanest overall. It is also the least carbon intensive among the strategies extracted from existing charging patterns, which are mainly influenced by people's commuting behaviors. Among all the non-smart charging strategies, charging inverse to netload is the closest to smart charging in terms of CO_2 emissions. Like smart charging, this strategy also adjusts charging schedule according to information from the grid, but this information is based on estimated projections of renewable generation and demand profiles, instead of real-time interaction with the power market. Generally, by adjusting SAEV charging strategy without interacting directly with grid operation, we observe a CO_2 emission reduction of up to 50,000 tonnes in 2030, under medium adoption level and occupancy rate of 1 passenger.

The benefits of smart charging begin to expand as the grid becomes cleaner and the SAEV fleet expands. The emission reduction is found to be as high as 60,000 tonnes of CO_2 in 2030, saving up to 95% of the emissions under other charging strategies. However, smart charging is not always the best strategy for emission reduction. In earlier years of our analysis, when the installed renewable capacity is not high enough,

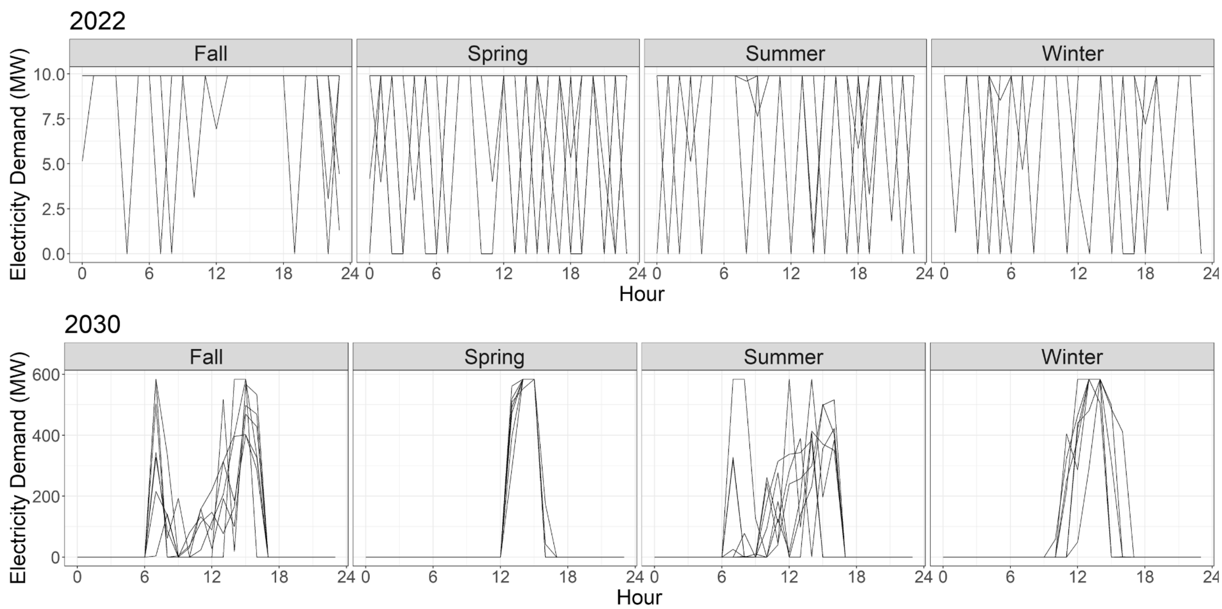

Fig. 7. Smart charging profiles in different seasons in 2022 and 2030, under medium adoption level and occupancy rate of 1 passenger, without applying carbon tax.

the hourly electricity price does not vary substantially with the fluctuation of renewable availability. Thus, smart charging is scheduled randomly throughout the day, as is seen in the upper graph of Fig. 7. This makes it perform worse than some of the non-smart charging strategies in terms of emissions before 2026. With the increase in renewable capacity in later years, the price of electricity tends to drop more substantially when there is a large amount of renewable generation during the day. Since the charging is scheduled towards hours with lower electricity prices, smart charging patterns tend to become more clustered (following renewable generation) as shown in the lower graph of Fig. 7. Thus, the smart charging load corresponds to lower emissions in later years, which offsets the effect from the fleet size expansion, and reveals more significant benefits compared with the other strategies. This implies that the effect of adapting the SAEV charging load according to real-time electricity price signals depends on the renewable penetration level of the power system.

Note that the smart charging pattern in later years is not consistent among different seasons. This is due to the different base load patterns in different seasons in California. In spring and winter, the base load has two peaks during the day; while in summer and fall, the valley is filled into a larger peak in the middle of the day by the cooling demand. When SAEV charging synergizes with grid dispatch, it tends to fill in the valleys to minimize peak load overall, to avoid installation of additional generation capacity. Thus, in spring and winter, the charging is scheduled around noon time; while in summer and fall, charging tends to be in early morning and late afternoon.

We also compare emissions from SAEVs across different SAEV adoption levels. Generally, the total annual CO_2 emissions from SAEVs increase linearly with the expansion of fleet size. According to simulation results, in 2030, high adoption level of SAEVs generate more than 4 times more CO_2 than low adoption level under daytime workplace charging strategy. Switching to smart charging can more than offset this impact of fleet expansion. Switching from other charging strategies to smart charging can cause an emission reduction of up to 70% more than the effect of merely downsizing the SAEV fleet.

Occupancy rate is another essential determinant of SAEVs' environmental impacts. Generally, the total CO_2 emission value is inversely correlated to the average occupancy rate of an SAEV fleet. Results show that there is a 50% decrease in the amount of emissions when occupancy rate increase from 1 to 2, a 33% decrease from 2 to 3, and a 25% decrease from 3 to 4. The decreasing marginal returns imply that environmental benefits can be achieved most efficiently if future SAEV fleets can keep an average occupancy rate of at least 2 passengers per vehicle.

On a per-passenger-mile basis, the SAEV emissions are at the scale of less than 70 g CO_2/mi, which is more than 5 times cleaner than modern day ICVs [56]. When calculated on a per-vehicle basis, the SAEV emissions under different charging strategies are shown in Fig. 8 (a). The scale of the emissions per SAEV is several tons per year. Since the effect of fleet expansion is depleted, this value mainly reflects the general change of emission rates in the grid during the time that SAEVs charge. Generally, SAEVs are less carbon intensive over the years as the grid gets cleaner. The emissions from non-smart charging strategies have a trend of decreasing at first and slightly increase in the later years. This is mainly due to the change in natural gas generation, which takes up more than 90% of the fossil fuel generation in California. Due to the higher capacity cost of wind generation, the model increases only solar capacity to meet the RPS requirements. As solar capacity increases over the years, the natural gas generation during the day is gradually replaced by solar generation; while during the night, natural gas generation increases due to the increasing charging load. The former effect dominates in the early years, but after solar has covered most of the daytime demand, the latter effect starts to reveal. The emissions from smart charging can be higher than some of the other strategies in early years, but it decreases more drastically than others in later years due to the flexibility in charging pattern.

Emission outcomes before and after applying carbon tax in the power market can also be seen in Fig. 8. From Fig. 8 (a), we can see that generally the introduction of carbon tax decreases the overall scale of emissions, by forcing a more aggressive adoption of low-carbon generation resources in the grid. In Fig. 8 (b), we show an example of comparing the environmental benefits that an SAEV achieves between applying carbon tax under a high-emission charging strategy (from red dashed line to red solid line) and switching to a low-emission charging strategy (from red dashed line to blue dashed line). The former outweighs the latter in early years. But in later years, as the grid gets cleaner, the emission savings from switching to smart charging becomes greater than that from applying carbon tax. This result confirms the importance of managing SAEV charging schedule in a way that aligns with low-carbon generation outputs in the grid.

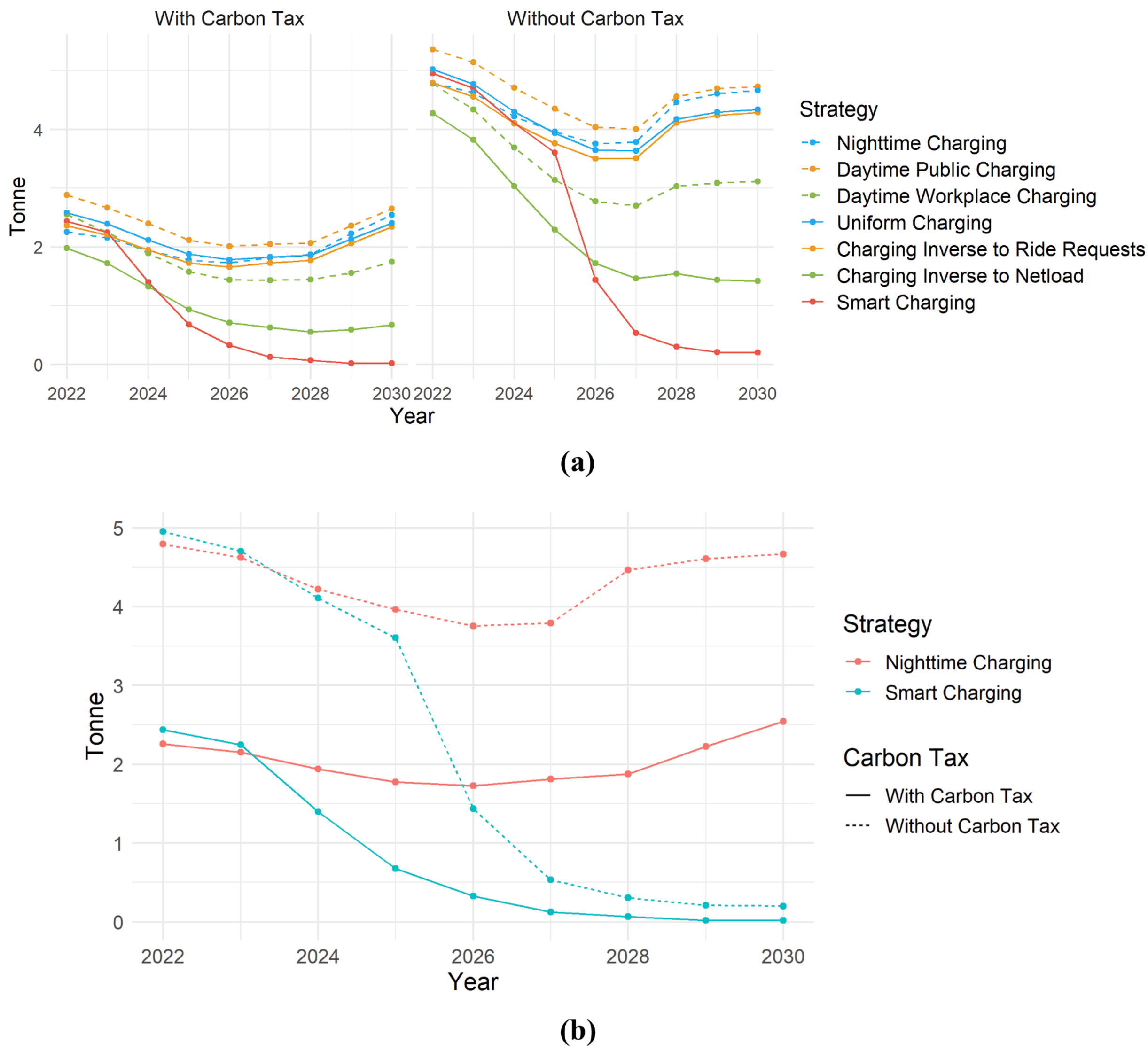

Fig. 8. Annual CO_2 emission per SAEV in California, under different charging strategies, with medium adoption level and occupancy rate of 1 passenger.

3.3. Relative CO_2 mitigation cost by switching SAEV charging strategy

Next, we evaluate the system-level impact of switching SAEV charging strategy on the total emissions and costs in the Californian power grid. The charging strategy that causes the most CO_2 emissions from all generators in California is seen as baseline, which is nighttime charging among the scenarios without carbon tax, and daytime public charging among those with carbon tax. Then we calculate the relative CO_2 mitigation and the change in total generation cost if we switch from the most carbon-intensive strategy to other strategies. Results for 2030 are shown in Fig. 9 and Fig. 10, respectively for scenarios with and without carbon tax. Generally, switching to less carbon-intensive charging strategies (positive CO_2 mitigation) could save generation cost (negative cost) at the same time. The relative CO_2 mitigation and cost savings are generally lower after applying carbon tax. This is because the total emissions are largely reduced with carbon tax, and therefore the effect of switching between charging strategies becomes less significant. Despite this decrease in overall values, the relative advantage of smart charging compared to other strategies becomes more obvious after applying carbon tax. Before applying carbon tax, smart charging saves 25% more CO_2 and 28% more cost than the second cleanest strategy; while with a carbon tax, these advantages are increased to 40% more CO_2 savings and 42% more cost savings. This is because that smart charging can better take advantage of the fluctuation in electricity price signals that is amplified by adding a carbon tax.

The relative CO_2 mitigation cost of switching charging strategy is calculated via dividing the relative cost by the CO_2 mitigation value. Results can be seen in Fig. 11, where the scale can reach around \$-50/ tCO_2, with the negative value indicating monetary savings. This implies that generally, managing SAEV charging has the potential to be a highly cost effective GHG abatement approach. Note that when there is no carbon tax, although “charging inverse to ride requests” has relatively low absolute values in CO_2 mitigation and cost savings, it appears more cost effective than other strategies on a per-tCO_2 basis. The application of a carbon tax, on the other hand, synergizes better with the charging strategies that could better utilize renewable generation.

3.4. SAEV fleet vehicle activities

Since the model simulates SAEV travel profiles and charging profiles separately, we need to verify that the managed charging schedules do not conflict with the travel behaviors. In other words, the vehicles driving and charging should not add up to exceed the total fleet size at any hour. The share of SAEVs that are driving is estimated by dividing the total travel distance of the fleet at each hour by an average velocity of 30 miles/hour. Assuming that the EV chargers are DC fast chargers at

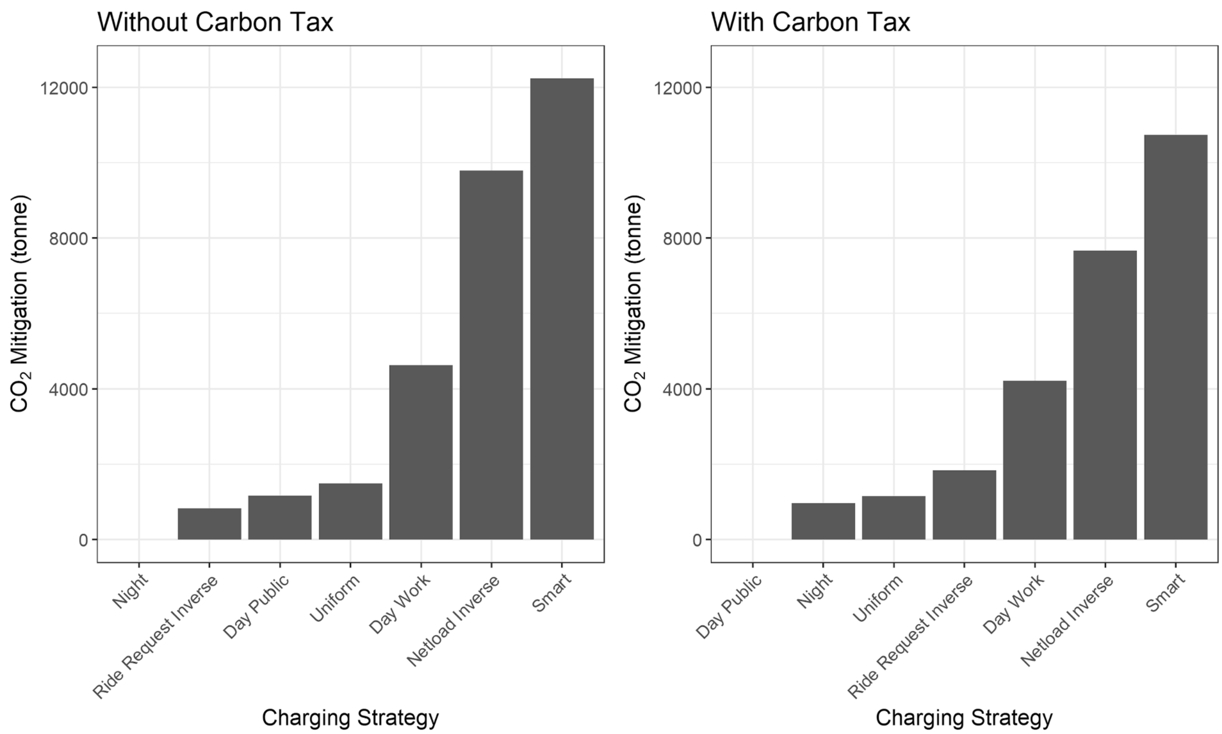

Fig. 9. Relative CO_2 mitigation by switching from the most carbon-intensive charging strategy to other charging strategies for SAEVs, under medium adoption level and occupancy rate of 1 passenger, 2030, California.

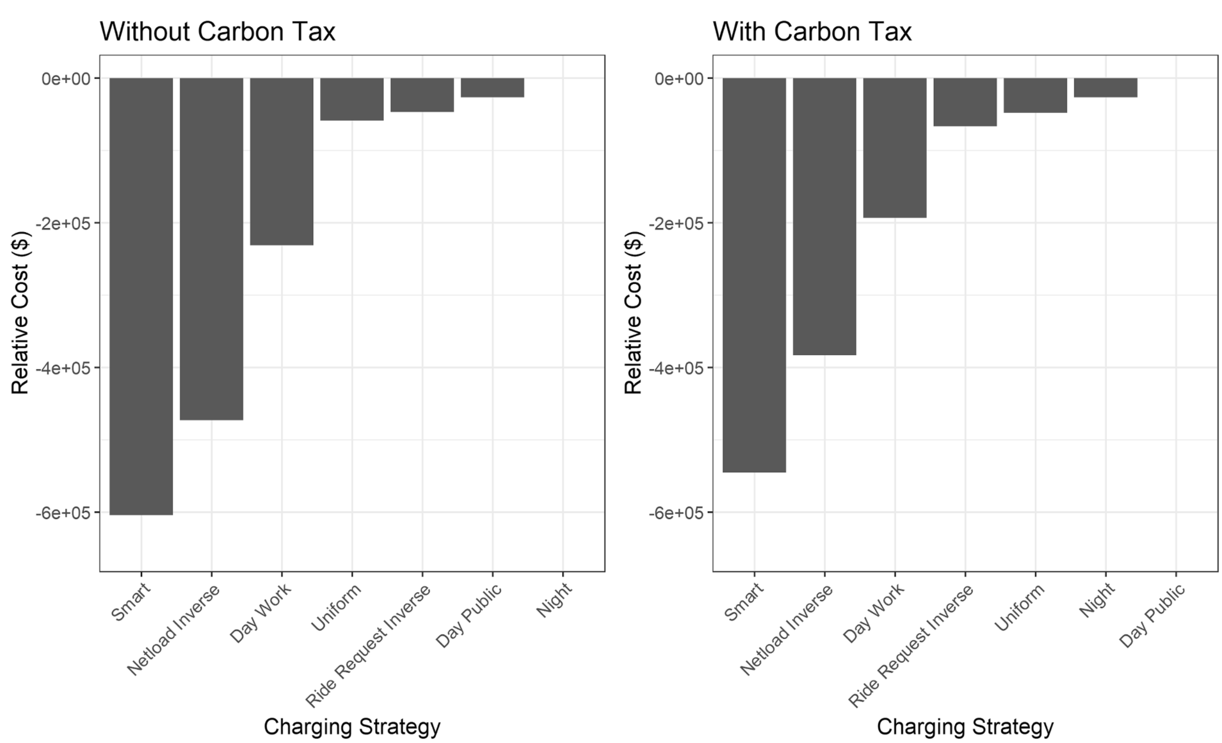

Fig. 10. Relative generation cost by switching from the most carbon-intensive charging strategy to other charging strategies for SAEVs, under medium adoption level and occupancy rate of 1 passenger, 2030, California.

150 kW each, the share of SAEVs that are charging is estimated via dividing the total charging demand at each hour by the charging rate of 150 kW. The sum of the two shares tends to be higher: 1) under smart charging in later years– where the charging load has higher peaks; and 2) under higher occupancy rate and lower adoption level – where the fleet size is smaller, and thus the share of vehicles charging tends to be higher. An additional "worst-case scenario" of low adoption level and occupancy rate of 4 passengers is run for verification, which has 1860 SAEVs in the fleet in 2030. Fig. 12 shows a clip of the hourly shares in the typical spring week of 2030 under smart charging. The sum of the shares

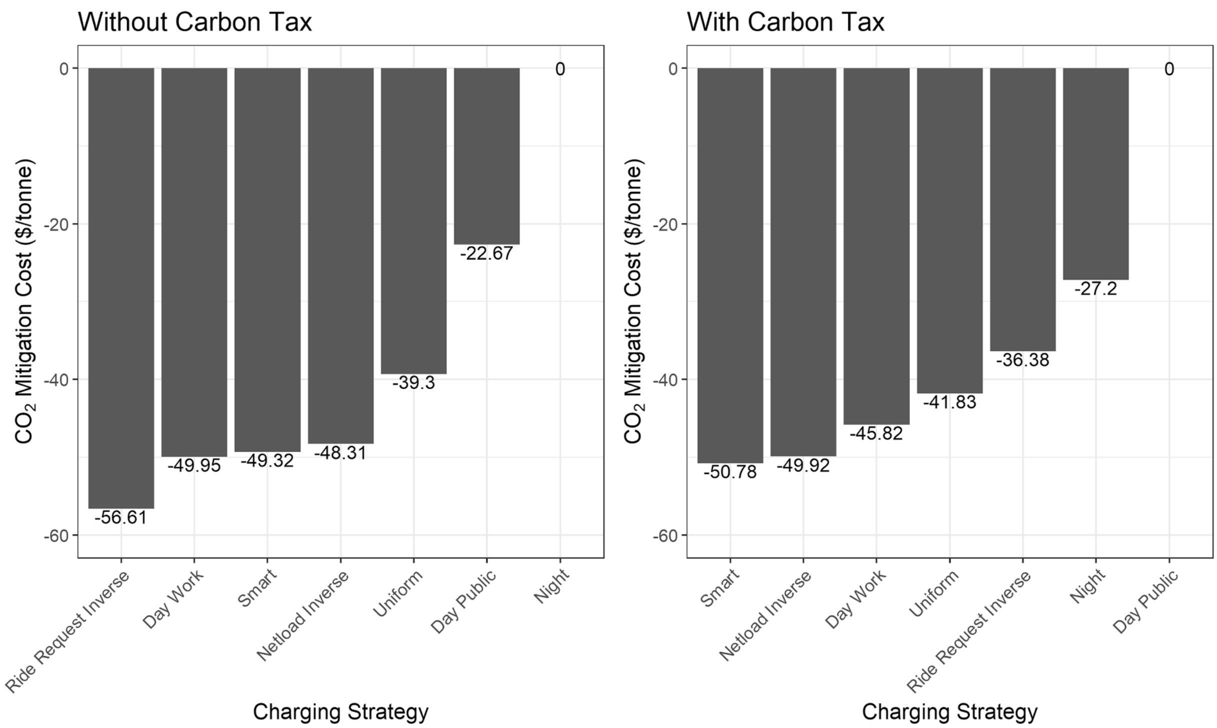

Fig. 11. Relative CO_2 mitigation cost by switching from the most carbon-intensive charging strategy to other charging strategies for SAEVs, under medium adoption level and occupancy rate of 1 passenger, 2030, California.

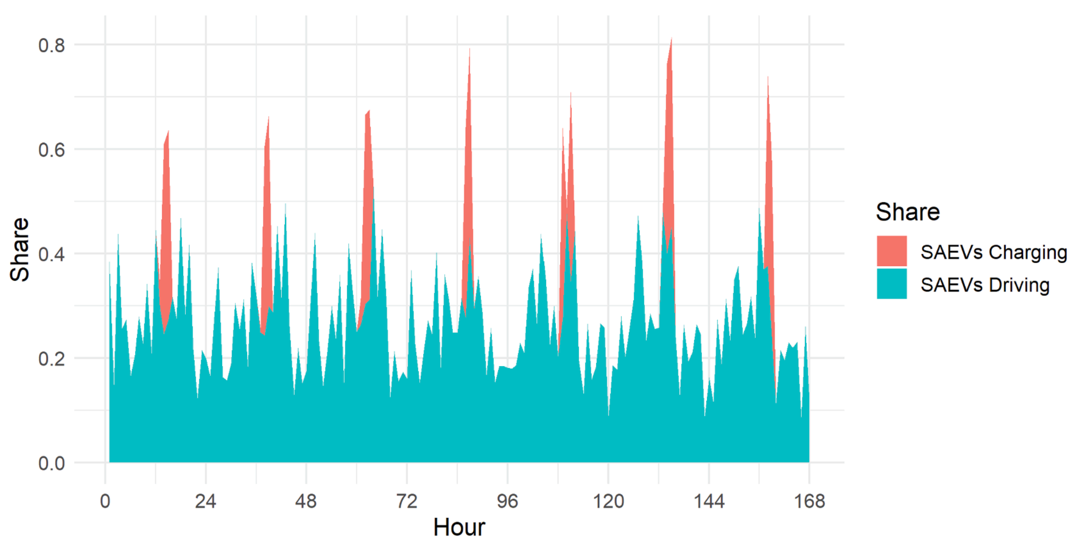

Fig. 12. Share of SAEVs charging and driving by hour, in 2030, with low adoption level of SAEVs, occupancy rate of 4 passengers, and smart charging strategy, without applying carbon tax.

remains below 1 even at charging peaks, which indicates that there is no conflict between the driving and charging activities in the model on an aggregated perspective of the whole SAEV fleet.

4. Conclusion

In this study, we expand the GOOD power system dispatch model to investigate the potential emission benefits of SAEV fleets, with respect to grid development, charging infrastructure expansion, carbon policy, SAEV market penetration, travel behaviors, as well as charging strategies, under the aggressive climate policy in California. We adopt unique real-world TNC vehicle travel data and the empirical charging activity data to conduct more precise simulations of SAEV driving and charging patterns. Based on these data, the SAEV fleet emissions are projected through 2030.

Results show that under the Californian power grid, SAEVs can be more than 5 times less carbon intensive than modern day ICVs on a per-passenger-mile basis. The emission benefits would increase as the grid becomes cleaner and as SAEV adoption expands. And keeping an average occupancy rate of at least 2 passengers per trip could lead to significant emission savings. The extent of aligning charging strategy with renewable power output is an essential determinant of the environmental benefits of an SAEV fleet. We consistently find that synergizing SAEV charging with grid operation can yield substantial economic and environmental advantages. At higher levels of renewable penetration, smart charging can generate up to 95% less emissions than

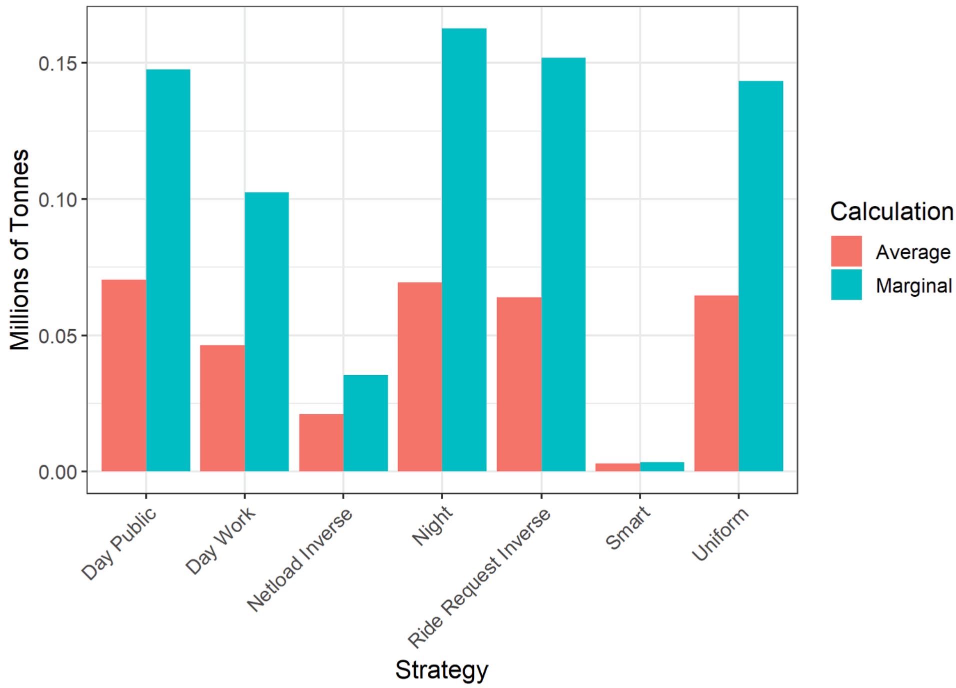

Fig. A1. Difference between average and marginal calculation of CO_2 emission, on the total annual CO_2 emission caused by SAEVs in California in 2030, with medium adoption level and occupancy rate of 1 passenger, without applying carbon tax.

other charging strategies. The complement of a carbon tax can further amplify the advantage of smart charging by approximately 1.5 times in the cost-effectiveness of emission mitigation. However, the emission benefits of smart charging are sensitive to the renewable penetration level in the power system. It will take some time for the generation mix to become clean enough, and for the real-time vehicle-grid communication to realize technically. Before that, managing SAEV charging based on netload projections could also achieve considerable emission benefits, which could reduce up to 70% CO_2 emissions compared with other charging strategies apart from smart charging.

Relevant policies have already been passed in California. Senate Bill 1014, enacted in 2018, requires CARB and California Public Utilities Commission (CPUC) to develop GHG mitigation targets for TNCs on a per-passenger-mile basis, which is known as Clean Miles Standard [3]. Senate Bill 500, signed in 2021, requires all new autonomous vehicles to be ZEVs after 2030. Our results suggest that the adoption of SAEVs can be an effective means to meet these targets. Expansion of these aggressive policies into other parts of the country or even the world could further increase the role of SAEVs. To maximize the emission benefits of SAEVs, policymakers should also incentivize renewable integration in the grid, enable and encourage real-time interaction between SAEV charging operation and the power market, as well as consider the implementation of a carbon tax.

Of course, our findings should be interpreted in light of the limitations of the modeling framework. In our assumptions, we do not account for the influence of occupancy rate on the deadheading factor, as well as the possible decrease in SAEV power draw in the future as technology develops. The aggregate modeling perspective abstracts away from many details in individual vehicle operations, such as the constraint of battery size on the driving and charging schedules of each vehicle. The model focuses on the temporal scheduling of SAEV charging, and lacks consideration on the spatial feasibility of the charging strategies mentioned. Furthermore, if the SAEVs are able to perform real time interaction with the grid operation, there is possibility that the fleet could inject electricity back into the grid at times with excess demand – often referred to as “vehicle to grid (V2G)”. In our model, we consider only unidirectional charging and do not include the option of V2G. While these limitations may add some uncertainty to our results, we have provided insights on how SAEVs can bring substantial emission benefits cost-effectively.

CRediT authorship contribution statement

Yanning Li: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Xinwei Li:** Methodology, Formal analysis, Investigation, Data curation. **Alan Jenn:** Conceptualization, Methodology, Software, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

The emissions from SAEVs are calculated via average emission rate in each hour. To confirm the consistency of results under different calculation methods, we also applied marginal calculation. The power system simulation is run with and without the SAEV charging loads to obtain the marginal CO_2 emissions caused by SAEVs. Comparison of results under both average and marginal calculations can be seen in Fig. A.1. Emissions under marginal calculation are generally higher than those under average calculation. This is because under economic dispatch, the marginal power plant that is turned on should be more expensive than, if not the same as, the average generation cost in that hour. And the more expensive, the more likely that the power plant is more carbon intensive too. This difference is particularly small under smart charging and charging inverse to netload, because most of their charging hours align with high solar generation hours, and thus the marginal generation is still likely to be solar, or generation that has very low cost and emission rate. Despite this general difference in absolute volume of emissions, it can be observed that the comparison among different strategies remains consistent between the two calculation methods.

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