Variability of the value of Vehicle-to-grid across vehicle and time in future California grid

By

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science (School for Environment and Sustainability)
in the University of Michigan

April 2021

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Abstract: Electric vehicles (EVs) are gaining momentum across the globe as a strategy to combat climate change, however, uncontrolled charging of EVs can create pressure on electricity grid. Along with smart charging (V1G), Vehicle-to-grid (V2G) technology presents an opportunity for a new way of vehicle grid integration that enables EVs to send electricity back to the grid, creating the potential for EVs to provide grid services including electricity generation as well as regulation up and regulation down capacity. This study aims to quantify the economic value of V2G in the 2025 and 2030 California grid using an EV simulation model and a grid Unit Commitment Economic Dispatch model. Scenarios on different renewable penetration and battery cost are included to account for uncertainty in future energy and battery development. Results show a V2G-enabled EVs can generate an average of $32-$48 more total annual net revenue than V1G, most profits come from EVs providing electricity and a small amount from regulation down capacity. From 2020 to 2030, the economic value of V1G and V2G increased, the result also shows a tradeoff exists between renewable deployment and V2G value. V2G can generate a moderate amount of economic benefit given access to electricity and ancillary service wholesale market, which need further policy support and third-party business cases.

Acknowledgment:

Two years of stay in Ann Arbor is coming to an end. I would like to express my deepest gratitude to my supervisor, Dr. Michael Craig, for guiding me through this scholarly adventure. The passion and pursuit for excellence he demonstrated will be a continuing motivation for me. In addition, a thank you to my thesis committee member, Dr. Drew Gronewold. This research is not possible without their gracious support.

I want to thank Cong Zhang, Jason MacDonald from Lawrence Berkeley National Laboratory for their assistance with modeling. My gratitude extends to Alan Jenn from UC Davis, who helped shape the research in an early stage.

I enjoyed spending my study with the SEAS community. My classmates and teachers have diverse cultural and educational backgrounds, but together we create this inclusive environment for everyone to learn and thrive. Their commitments to advance sustainability for the future taught me to be bold and persistent. I want to say thank you to my best friend at SEAS, Luyao, for her accompany throughout the ups and downs of the last two years. Shout outs to my roommates, Crispy, Julia, Tasha, Nisant (also Elwing the cat) for being amazing and always supportive.

Finally, words cannot express my gratitude for my parents and boyfriend. Their unconditional love got me through many long nights.

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Introduction

The transportation and energy sectors are the biggest contributors to GHG emission in the U.S., together responsible for more than 55% of annual GHG emissions (EPA, 2017). In the transportation sector, light-duty vehicles, mostly passenger vehicles, accounts for most (59%) of carbon emissions (EPA, 2020). Systematic decarbonization of passenger vehicles and energy sectors, therefore, is essential for climate mitigation(Edenhofer and et., 2014). One decarbonization strategy is combining vehicle electrification with renewable deployment. With higher renewable energy penetration in the electricity grid, the electrified transportation market will produce significantly less carbon footprint (National Renewable Energy Laboratory (NREL), 2012; Garcia, Freire and Clift, 2018). Additionally, electric vehicles (EVs) can add flexibility to the electricity grid with charging management techniques, helping overcome integration challenges of high wind and solar penetrations.

To harness the various benefits of EVs, many governments in the U.S. and globally have passed policies requiring or incentivizing EVs. In the United States, California is a frontrunner in promoting EVs. In 2018, Executive Order B-48-18 set zero-emission vehicle (ZEV) mandates, requiring 1.5 million ZEVs be on the road by 2025 and 5 million by 2030, with most of the ZEVs estimated to be Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs)(Governor Edmund G. Brown Jr., 2018). In 2020, Executive Order N-79-20 set more aggressive mandates, requiring all new cars and passenger trucks sold in California be ZEVs by 2035(Gavin Newsom, 2020). This fast deployment of EVs creates a great opportunity for climate mitigation and pollution control but also poses challenges for the electricity grid if EVs' charging is unmanaged.

If uncontrolled, increasing energy demand from EVs could exacerbate peaks and ramps in netload, requiring greater generation investment (Coignard, 2018). One way to manage charging is by changing charging time, known as "smart charging" or V1G. Alternatively, "Vehicle to Grid" (V2G) enables EVs to both receive energy and send energy back to the grid, thereby providing more flexibility to the grid (Coignard et al., 2018). While a single EV has limited grid-scale value, in the aggregate EV storage can be large. For instance, 1 million Nissan Leaf model EVs – a fifth of California's 2030 ZEV mandate – can storage 40 GWh in total. A third-party aggregator can coordinate operations across many EVs by bidding into the power market for them as an intermediate agency, as shown in Figure 1.

Since its proposal in 2002 (Letendre and Kempton, 2002), V2G has attracted interest from academic and industry. Intensive studies and pilot projects over the world are testing V2G in real-world conditions (Steward, 2017; Trahand, 2017; Black et al., 2018). V2G has been shown to be technologically and economically feasible to

provide various grid services to the grid (Kempton and Tomić, 2005; Coignard *et al.*, 2018; Liu and Zhong, 2019). These services include demand-response, storage, and ancillary services in the wholesale market(Nunes and Brito, 2017; Coignard et al., 2018; Gnann, Klingler and Kühnbach, 2018; Luo et al., 2020); renewable integration and reliability enhancement in mini-grid or distributed generation system(Zhu, Xia and Chiang, 2018; Carrión et al., 2019; Küfeoğlu and Pollitt, 2019; Chen et al., 2020); distribution level service like transmission congestion reduction. For the customers, BEVs and PHEVs that participate in V2G market would lower their electricity charging bills or even generate net revenue from providing grid services (Agarwal, Peng and Goel, 2014; Schuller et al., 2014; Luo et al., 2020).

While these studies demonstrate potential value in V2G, existing research suffers from several shortcomings, including ignoring changes in future electricity prices, ignoring electricity price impacts of V2G, and simulating limited numbers of EVs with V2G. To begin to fill these gaps, we co-simulate electric grid and EV operations to analyze the economic value of V2G through 2030 in California. Our co-simulation captures future changes in the power system and EV market, as well as interactions between V2G and power system operations. Using this co-simulation platform, we quantify the future value of V2G, providing invaluable information to policymakers, grid operators, and V2G aggregators.

Literature review

Since initial work by Kemptom and Tomic in 2005(Kempton and Tomić, 2005), research on V2G has proceeded down many avenues, e.g. on technical aspects like scheduling algorithms (Bashash et al., 2011; Ortega-Vazquez, Bouffard and Silva, 2013, 2013; Guo and Bashash, 2017; Xiong, Cao and Yu, 2018; Carrión et al., 2019; Yang et al., 2020) and on renewable integration (Garcia, Freire and Clift, 2018; Gnann, Klingler and Kühnbach, 2018; Das et al., 2020). A recent systematic review on 197 papers on V2G between 2015 and 2017 points out that current studies overemphasize technical topics, with only 3% looking at economic and social dimensions (Sovacool et al., 2018).

Despite its potential value, V2G has not scaled up in the U.S. or most of the world due to several challenges, including difficulty to quantify the battery degradation cost of providing V2G, no established driver-centered business model, and inflexible energy market policies preventing EV participation as distributed energy resources (Steward, 2017; Black et al., 2018). If V2G scales up, it's likely to be at least partly driven by market forces, i.e. by providing value to V2G adopters. This paper aims to better understand the economics of V2G for light-duty passenger vehicles because they are the main contributor of GHG in the transportation sector (for commercial fleets, see e.g. (Gnann, Klingler and Kühnbach, 2018)).

Because V2G has not been widely commercialized, research on the potential value of V2G should adopt a prospective lens to quantify its potential future value. This is particularly important given rapid decarbonization of the power system and consequent market consequences like more volatile electricity prices, particularly in California(Seel *et al.*, 2018; U.S. EIA, 2020). Furthermore, given rapidly growing EV numbers and California's mandate for 5 million ZEVs on the road by 2030, V2G analyses should model large numbers of EVs(Argonne National Laboratory, 2021). Finally, large numbers of V2G-enabled EVs will interact with and affect electricity prices, which will in turn affect V2G value and revenues and drive changes in V2G operations. Thus, economic analyses of V2G should capture four critical factors: (1) future grid changes, (2) large EV numbers, (3) V2G interactions with electricity prices, and (4) V2G operational responses to shifts in electricity prices.

Table 1 Literature Review Summary Based on Four Criteria

Paper	Future grid changes	V2G operational responses to electricity price changes	V2G interactions with electricity prices	Number of EVs analyzed
Peterson 2010	No	No	No	1
Pelzer 2013	No	No	No	1
Agawral 2014	No	No	No	10,000
Zeng 2015	No	No	No	
Vivek 2018	No	Yes	No	20
Meisel 2020	Yes	Yes	No	1
Donadee 2019	Yes	No	Yes	5

Research that quantify the value of V2G from non-commercial EV fleets use a wide range of analysis methods, but none capture all four critical features identified above (Table 1). Many previous studies use a price unresponsive model built on static historical electricity or ancillary service market price data(Peterson, Whitacre and Apt, 2010; Agarwal, Peng and Goel, 2014; Pelzer et al., 2014; Zeng, Gibeau and Chow, 2015; Li et al., 2020). These price unresponsive models use historical price data and assume EVs have no impact on market prices. In reality, a communication portal exists between the electricity market operator and EVs for EV scheduling and dispatch(Trahand, 2017). To avoid using historic prices, other studies use prospective simulations and scheduling algorithms that resemble a virtual power plant (VPP) that

optimize EV charging and discharging decision based on electricity market price data(Bhandari, Sun and Homans, 2018; Meisel and Merfeld, 2020). Among the few V2G analyses that consider future grid changes, Coignard looked at how much renewable sources V2G can help integrate in a future grid, but the research didn't quantify the economic value of V2G(Coignard et al., 2018). Additionally, few studies of V2G integrate V2G operations with power system models to explore the value of V2G in future grids. Donadee used a co-optimization dispatch model to analyze the value of V2G in 2030 California grid under different renewable scenarios(Donadee et al., 2019). Yet, this study only modeled 5 EVs, so doesn't capture the impact of large numbers of EV on electricity load or prices.

Overall, no research to date has captured all four of the critical factors we identified for estimating the economic value of V2G. Existing research either (1) uses a retrospective instead of prospective lens , (2) ignore how V2G-enabled EVs would respond to market prices, (3) ignore interactions between V2G and the power system, including whether the grid will accept V2G bids and on how V2G affects electricity prices, and (4) models a significantly lower number of EVs than expected by 2030.

To fill this gap, we co-simulate V2G and power system operations for a 2030 California grid and 4 million EVs. Through our co-simulation platform, we capture interactions and price-responsive behavior between V2G and power system operations. Our V2G-enabled EV simulation model is bottom-up and takes into account EV characteristics including driving patterns, charging availability, and EV manufacturing technology advancement. Our power system model optimizes (or dispatches) generator operations to minimize system operational costs given generator and system constraints and V2G operations. Given future uncertainty surrounding EVs and the grid, we test the sensitivity of our results around future renewable deployment and battery technology.

Methods

1. Co-Simulation Platform for V2G and Grid Operations

This study is composed of two optimization problems: 1) V2G-sim optimizes the net revenue for individual EV. V2G-sim first simulates the driving pattern of vehicles and then maximize individual vehicle net revenue by making charging and discharging decision based on EV electricity demand, electricity prices, and regulation capacity price; 2) Unit Commitment and Economic Dispatch (UCED) models optimizes CAISO's daily operation of the energy and ancillary services market. UCED dispatch generators and vehicles based on their bids and energy demand. V2G-sim outputs the bid from EVs fleet as well as extra electricity charge demand from the EVs, the demand and bid from EVs would impact the energy prices, which would in return be

fed back to V2G-sim. These two optimization problems would be solved through iterations.

V2G-sim uses price outputs from UCED to update its input data and produce EV charge and discharge data. Given EV charging and discharging, generator data, and non-EV electricity demand, the UCED dispatches the generator fleet and produces new prices. Our platform iterates between these two models, updating price and vehicle charge and discharge decisions until the results converge, as shown by Figure 2. The study runs on a daily basis for a year and uses daily EV economic profit as the convergence criteria. EV economic profit is calculated as revenues from electricity and regulation services minus electricity charging cost and battery cost, as follows:

$$profit_i = \sum_{h=1}^{24} g_{i,h} * pr_{e,h} + regup_{i,h} * \mathrm{pr}_{\mathrm{up},h} + regdown_{i,h} * pr_{down,h} - d_h *$$

$$pr_{e,h} - \left(g_{i,h} + regup_{i,h} + regdown_{i,h} \right) * pr_{batt} \tag{1}$$

$profit_i$ i denotes EV, h denotes hours. $profit_i$ denotes profit for EV i, $g_{i,h}$ denotes generation, d_h denotes demand, $regup_{i,h}$ denotes regulation up capacity and $regdown_{i,h}$ denotes regulation down capacity. pr denotes price, with e for electricity, up for regulation up, down for regulation down, batt for battery cost.

We set the convergence threshold to the change between iterations in daily profit for each EV dropping to less than $0.05. This convergence criteria balances computational requirements with obtaining stable and accurate results.
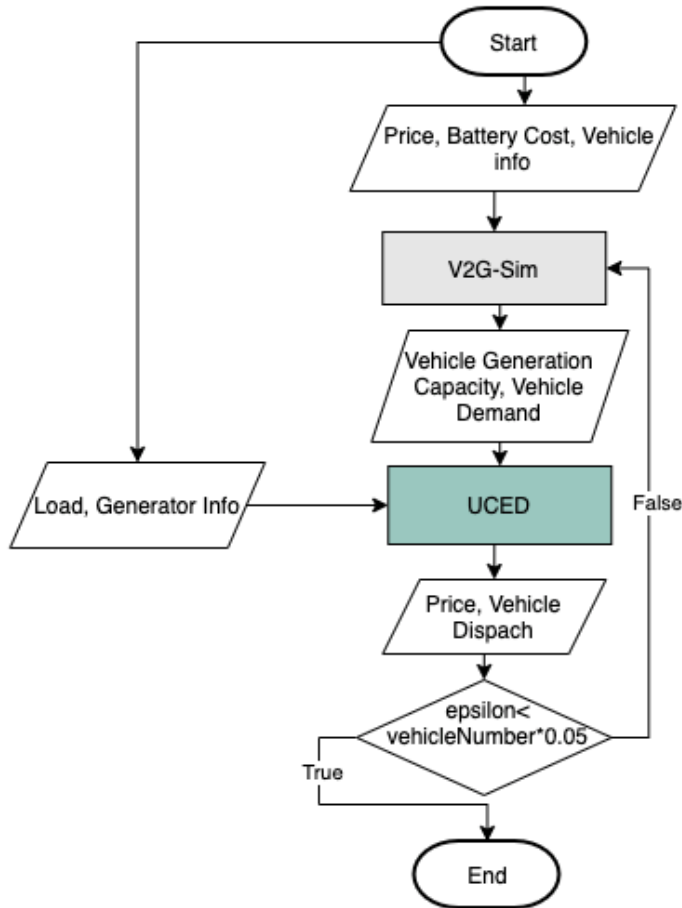
Figure 2 Interactions between V2G-sim and UCED models, price refers to electricity price, regulation up capacity price, and regulation down capacity price.

2. V2G-Sim to optimize V2G operations

V2G-sim simulates EV travel patterns and optimize EV charging and discharging to maximize net revenue. V2G-sim is a Python-based simulation tool developed by the Berkeley National Lab that models the driving and charging behavior of individual EVs (V2G-Sim, no date). With driving itineraries as input, V2G-Sim provides bottom-up modeling from individual EV dynamics. V2G-sim adopts a probabilistic model to simulate EVs interaction with chargers: when arriving at a charger, there is a certain probability that the charger has V2G capability (Level 2 and Level 3 charger is V2G compatible), and a certain probability that the driver would decide to plug in. We assume the EVs charge and discharge at wholesale price. Once plugged into a V2G capability charger, EV is connected to the grid and could choose to sell electricity to the grid if it's profitable for the EV. The model is modified by this study to take electricity and regulation services wholesale price as input and the model optimizes when and how much electricity the EV will charge and discharge to maximize net economic profit.

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The V2G-sim optimization problem is formulated as follows:

$$mmax \ \sum_{i}^{I} \sum_{t=1}^{T} P_{discharge,t,i} h(Pr_{e,t} - Pr_b) - P_{charge,t,i} hPr_{e,t} +$$

$$P_{regup,t,i} h(Pr_{regup,t} - Pr_b) + P_{regdown,t,i} h(Pr_{regdown,t} - Pr_b) \qquad (2)$$

The optimization maximizes net revenue for EVs, it runs every 10 mins for a whole day in every iteration. i denotes individual vehicle, t denotes time index; P denotes power, $P_{discharge,t,i}$ is the charge power at time t for vehicle i, h is the time step duration, $Pr_{e,t}$ is the price of electricity, Pr_b is the price of battery degradation, $P_{discharge,t,i} h(Pr_{e,t} - Pr_b)$ is the electricity net revenue; $P_{charge,t,i}$ is the charge power at time t for vehicle i, $P_{charge,t,i} hPr_{e,t}$ is the cost for charging; $P_{regup,t}$ denotes battery change from providing regulation up capacity, $Pr_{regup,t}$ is the price of regulation up capacity, $P_{regup,t,i} h(Pr_{regup,t} - Pr_b)$ is the net revenue from providing regulation up capacity; $P_{regdown,t}$ denotes battery change from providing regulation down capacity, $Pr_{regdown,t}$ is the price of regulation down capacity, $P_{regdown,t,i} h(Pr_{regdown,t} - Pr_b)$ is the net revenue from providing regulation down capacity.

Energy arbitrage and frequency regulation are considered in the study. The rationale for including grid service other than ancillary services which are shown to be most suitable for V2G is that small market of ancillary services could be quickly saturated in the future with high EVs share(Zhou, Levin and Conzelmann, 2016; Coignard et al., 2018).

In maximum this objective, the model must satisfy numerous vehicles constraints. The key constraint is meeting daily travel energy requirements. To obtain vehicle energy demand, vehicle capacity to provide generation, regulation up, and regulation down capacity which we feed into the UCED model, we aggregate the vehicle charge and discharge from these constraints. While we provide the full set of constraints in the SI, the daily travel energy requirement takes the form:

$$\sum_{t=1}^{k} P_{charge,t,i} h - P_{discharge,t,i} h + P_{regdown,t,i} h - P_{regup,t,i} h \geq e_{min,i,t}, \forall k \in T \quad (3)$$

The aggregated energy of vehicle i, including from charging, discharging, providing regulation up and down capacity cannot go below the minimum energy at any given time.

3. UCED model to optimize power system operations

From V2G-sim, we obtain electricity and regulation reserve sales to the power system from EVs. To optimize power system operations, we use a UCED model. The UCED model is a mixed-integer linear program that minimizes total system electricity, regulation, and startup costs subject to system and generator constraints. Our model includes two types of reserves procured by CAISO and crucial for grid stability: regulation up and regulation down. We focus on these two reserve types over others because of regulation requires smaller amount of charging and discharging than spinning reserves or peak power generation, and are shown to be the most profitable revenue source for V2G(Letendre and Kempton, 2002; Kempton and Tomić, 2005). We ignore transmission constraints, a common simplification in UCED analyses given the lack of public transmission data(Weis *et al.*, 2015; Craig, Jaramillo and Hodge, 2018). We cap the regulation capacity by vehicles given that grid operator will limit the capacity provided by one source to control risks. We formulate the Python-based model in Pyomo and solve it using Gurobi(Hart *et al.*, 2017; Gurobi Optimization, 2020).

We use the UCED to optimize hourly generation and reserve provision decisions over a 48 horizon, which includes a 24-hour optimization period and a 24-hour look-ahead period similar to CAISO's day-ahead market. The model's objective function is:

min (Electricity generation cost + Start up cost + Regulation up cost + Regulation down cost), $\forall t \in T, i \in$ I   (4)

The objective minimize the operational electricity generation cost, start up cost, regulation up cost, and regulation down cost. Where i denotes generators, including renewable, vehicles, and other generators, and t denotes hours.

Electricity generation cost$=\sum_{i,t} mwh_{i,t} (opcost_i + var\_om_i)$ (5)

$mwh_{i,t}$ denotes energy generated by generator i in hour t (MWh), $opcost_i$ is the operational cost of generator i ($/MWh), and var_om_i is the variable operational and maintenance cost of generator i ($/MWh).

Start up cost$=\sum_{i,t} st\_cost_i \ switch_{i,t}$ (6)

st_cost_i is the start up cost($) for generator i to switch on, $switch_{i,t}$ is 1 when the generator i switch on at time t.

Regulation up capacity cost$=\sum_{i,t} regup_{i,t} regcost_i$ (7)

$regup_{i,t}$ is the amount of regulation up capacity(MW) provided by generator i at time t. $regcost_i$ is cost for generator i to provide regulation capacity (\$/MW).

$$\text{Regulation down capacity cost} = \sum_{i,t} regdown_{i,t} regcost_i \tag{8}$$

$regdown_{i,t}$ is the amount of regulation down capacity(MW) provided by generator i at time t. $regcost_i$ is cost for generator i to provide regulation capacity (\$/MW).

In minimizing this objective, the model must satisfy numerous generator- and system-level constraints. Two key constraints are balancing demand with supply and meeting regulation reserve requirements in each hour. Demand and supply include vehicle energy demand and vehicle generation, different demand and supply from vehicle will change the system constraints and therefore change the prices in the end. To obtain electricity and regulation reserve prices which we feed into the V2G-sim model, we extract the shadow price (or dual variable) from each of these constraints. While we provide the full set of constraints in the SI, the supply and demand balance constraint takes the form:

$$\sum_i mwh_{i,t} \geq demand_t \tag{9}$$

Where $mwh_{i,t}$ is the electricity supply generated by generator i in hour t, and $demand_t$ is the system electricity demand at hour t. This constraint makes sure the sum of electricity generation meets the system demand at any hour.

4. Data and assumptions:

Given its EV mandates, rapid expansion of charging facilities, and quick deployment of renewables, California is an ideal system for V2G valuations(De León, 2018; Governor Edmund G. Brown Jr., 2018; Gavin Newsom, 2020). Thus, we use California as our study system. Given ongoing decarbonization efforts and the current lack of V2G, we run our study through 2030.

Table 2 shows the data sources and assumptions for UCED model and V2G-sim model. For UCED model, we use publicly available generator dataset for the 2019 California generator dataset(U.S. EIA, 2020), maximum and minimum capacity, minimum up time, ramp up rate, operational cost, and start up cost, variable and maintenance cost, fixed cost, and regulation cost(US EPA, 2020), and fuel cost(U.S.EIA, 2019).

For V2G-sim model, data inputs include EV numbers and types; charger numbers, types, and locations; and EV driving patterns. EV itinerary data comes from Californian residents' 2017 National Household Travel Survey result, we assume the EVs have same driving pattern as today, detailed summary data is available in SI. According to California Executive Order B-48-18, California will achieve 5 million ZEV by 2030, including BEV, PHEV, and HFCV(Governor Edmund G. Brown Jr.,

2018). this analysis assumes 30% of the ZEVs would be BEVs, consistent with California Energy Commission's Transportation Energy Demand Forecast 2018-2030(California Climate and Energy Collaborative, 2017). Tesla Model 3 with a battery capacity of 82 kWh is taken as an example EV model for BEV and Toyota Prius with a battery of 12 kWh for PHEV because they are respectively the most popular model in the market. We estimate the availability of charger while referring to previous research with V2G-sim model (Coignard *et al.*, 2018).

One other important aspect is battery degradation cost. It's a common practice to use a flat battery degradation cost in V2G studies(Schuller *et al.*, 2014; Guo *et al.*, 2017). Battery degradation cost is calculated from battery pact cost, with the relevant parameters in a battery research about V2G (Escudero-Garzas, Garcia-Armada and Seco-Granados, 2012; Marongiu, Roscher and Sauer, 2015). For example, for 2030, the forecast of battery pack is at $61/kWh Battery(Bloomberg Finance LP, 2020), using Escudero's research result, the battery degradation cost is $8/MWh.

Table 2 Data sources and major model assumptions

Model	Data	Data Source	2020 baseline	2025 baseline	2030 baseline
UCED	Load	OASIS (CAISO, 2020)	Load stay the same; EV Demand added		
	Generator information	EIA, EPA (U.S.EIA, 2019; O. US EPA, 2020; U.S. EIA, 2020)			More Natural Gas Combined Cycle by 2030
	Regulation Capacity Requirement	NREL report (Lew et al., 2013; Denholm, Sun and Mai, 2019)	0.64% of system demand for regulation up capacity; 0.72% of system demand for regulation down capacity		1% of system demand for regulation up capacity and regulation down capacity
	Cap of regulation capacity provide by EVs		25%		50%
V2G-sim	EV Itinerary	National Household Travel Survey for California 2017(National Renewable Energy	Vehicle travel habit won't change (EVs travel an average amount of 50 miles/day)		

		Laboratory, 2019)			
	Charging Infrastructure	California's Vehicle-Grid Integration roadmap (California ISO, 2014)	Home: L1 17.5%; L2 82.5%;Work: no charger 20% L2 27.5%, DCFC 52.5%; Other place: no charger 20%; L2 27.5%; DCFC 52.5%	Home: L1 18.75%; L2 81.25%;Work: no charger 10% L2 33.75%, DCFC 56.25%; Other place: no charger 10%; L2 33.75%; DCFC 56.25%	Home: L1 20%; L2 80%;Work: L2 40%, DCFC 60%; Other place: L2 40%; DCFC 60%
	EV numbers	California Executive Order B-48-18, California Energy Commission Report (California Climate and Energy Collaborative, 2017; Governor Edmund G. Brown Jr., 2018)	315235 BEV, 652662 PHEV	420000 BEV,870000 PHEV	1023833 BEV, 3172894 PHEV
	EV model		Tesla Model 3 for BEV; Toyota Prius for PHEV		
	Performance Increase	Using 2016 fuel economy performance as baseline	1.26 for BEV; 1.19 for PHEV	1.33 for BEV; 1.25 for PHEV	1.44 for BEV; 1.31 for PHEV
	Battery Capacity	Using 2016 battery capacity as baseline	82kWh; 12kWh	205kWh; 30kWh (2.5 times increase)	246kWh; 36kWh (3 times increase)

Scenarios analyzed:

Table 3 Scenario Design

Scenario	2020 baseline V1G	2020 baseline V2G	2025 baseline V1G	2025 baseline V2G	2025 aggressive V2G	2025 conservative V2G	2030 baseline V1G	2030 baseline V2G	2030 aggressive V2G	2030 conservative V2G
Battery Degradation Cost ($/MWh)	17		12		10	14	8		6	10
Solar & Wind Retail Percentage(%)	32		44		48	40	60		64	56

To capture uncertainty in grid decarbonization and EV development, we construct three sets of scenarios for 2025 and 2030: baseline, aggressive, and conservative (Table 3). These scenarios differ by renewable energy penetrations and battery degradation cost. The baseline scenario assumes California will achieve its Renewable Portfolio Standard (RPS) and battery degradation costs follow Bloomberg forecasts. California's RPS is 44% and 60% of generation comes from renewables by 2025 and 2030, respectively (De León, 2018). The conservative and aggressive scenarios assume lower and higher renewable penetrations, respectively, in each year (Table 3). The conservative and aggressive scenarios also assume higher and lower battery degradation cost, respectively, in each year (Table 3).

To quantify the value of V2G relative to V1G, we run our baseline scenario twice each year, once assuming all EVs and chargers have V2G capabilities and once assuming no V2G capabilities. In the latter, EVs can only receive electricity from the grid but can optimize charging time to minimize charging cost, i.e. engage in V1G.

Results

We first present EV and power system results for our baseline scenario, then test the sensitivity of our results to our aggressive and conservative scenarios.

1. Value of V2G Versus V1G in the baseline Scenario

Fleet-Wide Results

This section compares V1G and V2G in the baseline scenario. Total annual net revenues of V1G are negative in each year, but increase from 2020 to 2030. V1G total annual net revenue in 2020, 2025, and 2030 are $ -63.2, $-57.3, and $-45.5, respectively. Total annual net revenue of V2G first increased and then decreased from 2020 to 2030. V2G total annual net revenue in 2020, 2025, and 2030 are $-23.1, $ -9.8, and $-13.8, respectively.
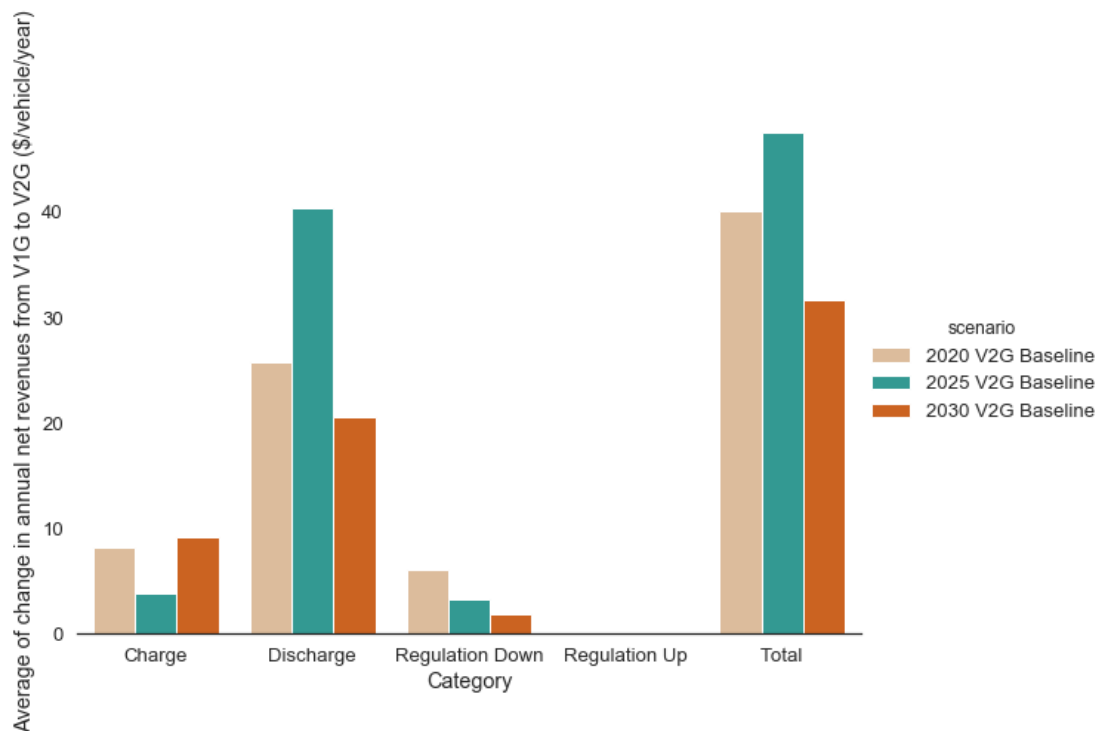

Figure 3: Change in annual net revenues averaged across EVs from V1G to V2G scenarios. Changes in 'total' annual net revenues (right cluster) equal the sum of changes in all other revenues.

Using V2G instead of V1G increases total annual net revenue by $32-$48 on average across EVs from 2020-2030 (Figure 3). Total annual net revenue difference mainly comes from V2G generating electricity, i.e. discharging, ranging from $20.5 to $40.4, and the relative revenue possible from frequency regulation are smaller than

discharging. Total annual net revenue first increases and then drops from 2020 to 2030 due to a large increase in discharge revenue from 2020 to 2025, which we further explore below. V2G net revenues from charging also increase, i.e. cost less, than V1G on the order of $5-10 on average across vehicles (Figure 3), the reason is discussed in Figure 4. V2G also enables net revenues from providing regulation down, but these revenues decline from roughly $8-$2 on average across vehicles from 2020-2030.
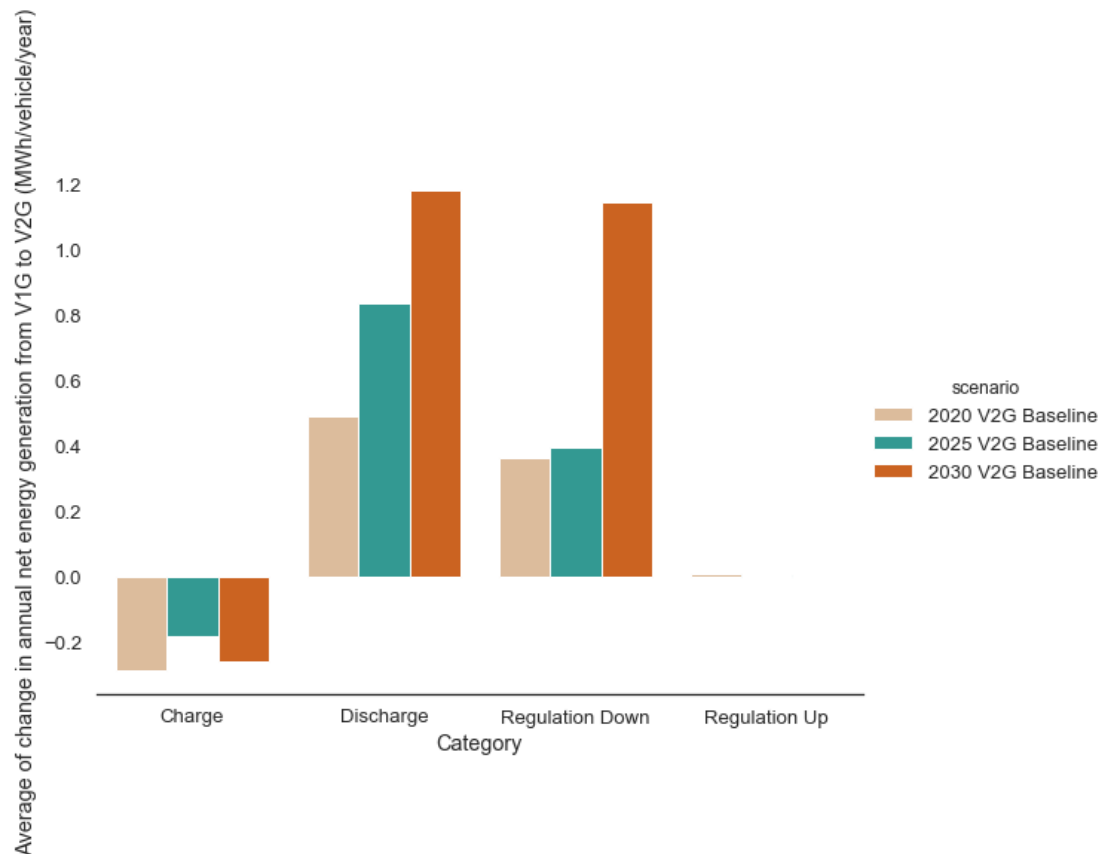

Figure 4: Change in total energy consumed or generated averaged across EVs from V1G to V2G scenarios.

With V2G capability, individual EVs on average generate 0.5-1.2 MWh of electricity and provide 0.4-1.1 MWh of regulation down capacity from 2020-2030, respectively. Fleet-wide, this amounts to 5-49 TWh and 4-48 TWh of electricity and regulation down from 2020-2030, respectively, or 0.21-1.99% of electricity demand and 22-42% of regulation down requirements. Discharging and regulation down provision increase from 2020 through 2030 partly due to declining battery degradation costs. Net energy generation difference between V2G and V1G shows that V2G-enabled EVs charge less energy than V1G (Figure 4), because EV with V2G capacity can charge by providing regulation down capacity. Because charging requirement for V2G is smaller than V1G, charging costs for V2G are lower than V1G (Figure 3, Figure 4).

Despite greater discharging and regulation down provision and less charging through 2030, total annual net revenue and discharge annual revenues increase from 2020 to 2025 then decrease from 2025 to 2030 (Figure 3). Thus, the drop in total annual net revenue and discharge revenues from 2025 to 2030 does not occur due to decreased EV operations (Figure 4), but instead due to reduced prices (Figure 5).
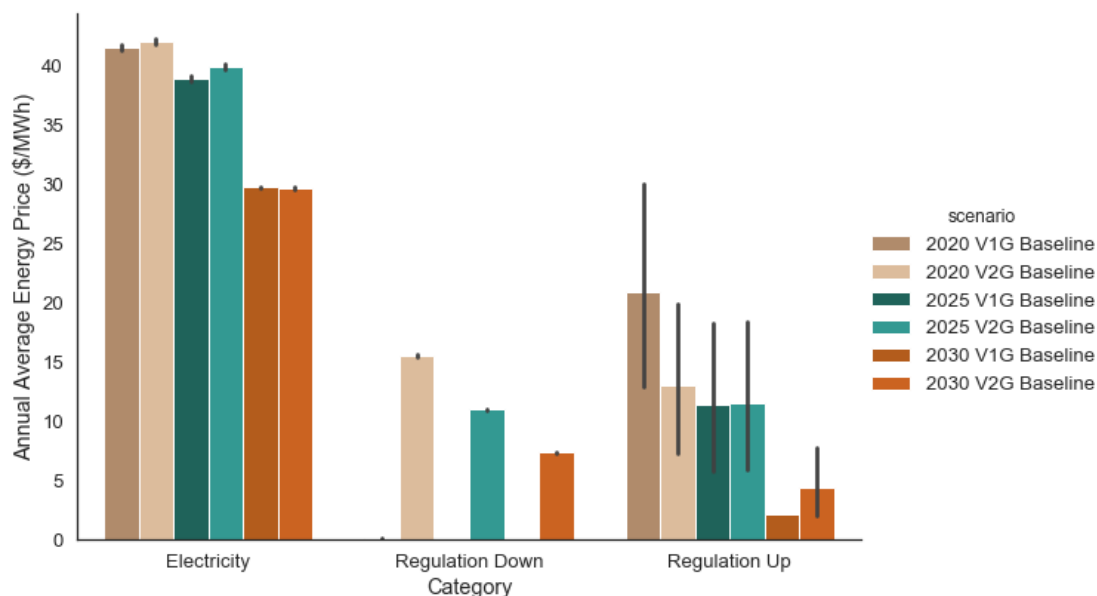

Figure 5: Annual average hourly energy price in V1G and V2G baseline scenarios, error bar shows the 95% confidence interval of energy prices across hours in a given year.

Focusing first on V1G prices across years, electricity prices are significantly higher than regulation capacity prices across years (Figure 5). This explains why most revenue for V2G compared to V1G comes from increased discharge (Figure 3) even though discharged electricity and provided regulation down reserves are similar (Figure 4). All prices experience a decrease from 2020 to 2025 and a greater decrease from 2025 to 2030 (Figure 5). More renewable energy, lower EV operational cost (lower battery degradation cost), and added natural gas generators to integrate EVs and renewable generators through 2030 all contribute to the price decrease. The decrease in prices also explains change of discharge revenue and total annual net revenue from 2020 to 2030. We notice both discharge revenue and total annual net revenue first decreases and then increases from 2020 to 2030(Figure 3) while discharging and regulation capacity both increased (Figure 4). It's because of the decreased in prices from 2025 to 2030 that result in the decrease of discharge revenue and total annual net revenue (Figure 4).

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Regulation down capacity prices with V2G are higher than prices with V1G (Figure 5). The operational cost for EV to provide regulation down capacity is the battery degradation cost. EV's battery degradation cost (\$ 8-17/MW) is higher than most other generators' cost to provide regulation down capacity. For example, geothermal generators have an average marginal cost to provide regulation capacity at \$0.003/MW. In all 3 years, V2G set the marginal cost for regulation down for 91% hours, meaning the grid system would prefer to deploy V2G to provide regulation down capacity and deploy other generator for regulation up capacity.

2. Individual EV Results

Fleet-wide average results could hide significant differences in vehicle-specific outcomes, so we quantify total annual net revenue across EVs for 2020 through 2030 (Figure 6). BEVs and PHEVs have a wide range of net revenues in 2030 when participating in V2G. While the average total annual net revenue of V2G is \$-13.8/vehicle, some EVs makes up to \$258 and others lose nearly \$500 per year. BEV has an average net revenue of \$-0.3, while PHEV has an average net revenue of \$-55.5. To understand the underlying determinants of EV net revenues, we calculated the Pearson correlation coefficient of individual EV characteristics with net revenue (Table 4). Distance travelled is negatively correlated (-0.12) with net revenue, while time spent at home at night is positively correlated (0.18) with net revenue. Time spent at Home at night (mins/day) is the length of time the vehicle spent from its last arrival at home until might. Our result shows that it's the time of day that EV is at home (Time spent at Home at night (mins/day)), rather than total amount of time that EV is at home, that correlates to the different for total annual net revenue. In our model, home and workplaces having higher charger coverage than other places (grocery stores, hospitals, shopping malls, parks). The time that EV can access chargers is important because most of the revenue comes from selling electricity when the cost of electricity is high, and electricity prices between 6-12pm are the highest during the day.
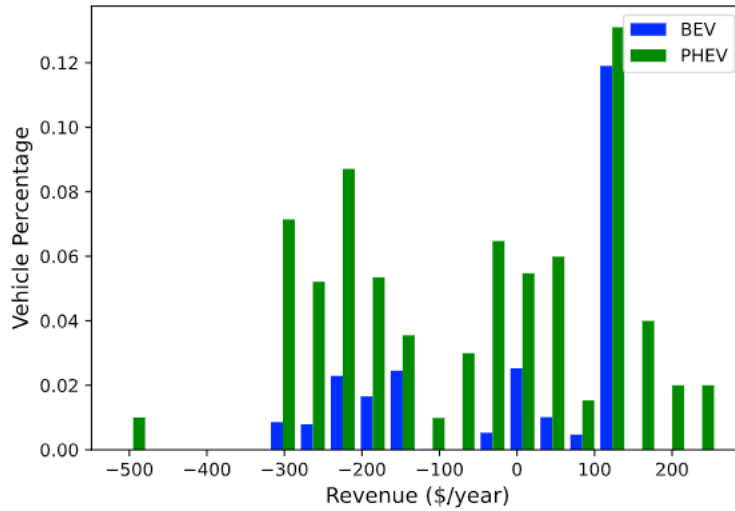
Figure 6: Total annual net revenue of individual EV in 2030 V2G baseline scenario

Table 4 Correlation between daily average EV travel characteristics and annual net revenue in 2030 V2G baseline scenario. A correlation coefficient between 0.1 to 0.3 is considered a small association, correlation coefficient smaller than 0.1 is considered negligible (Schober, Boer and Schwarte, 2018).

	Time spent at Home at night (mins/day)	Distance Travelled (miles/day)	Time spent at Home(mins/day)	Time Spent on Road(miles/day)	Time Spent at Work(mins/day)
Net Revenue($/year)	0.18	-0.12	0.01	-0.093	0.016

3. Scenario Analysis

To test the robustness of our results to uncertainty in future renewable penetrations and EV development, we conduct a scenario analysis. The aggressive scenario for each year means higher renewable and lower battery cost than baseline, while conservative scenario means lower renewable and higher battery cost than baseline.
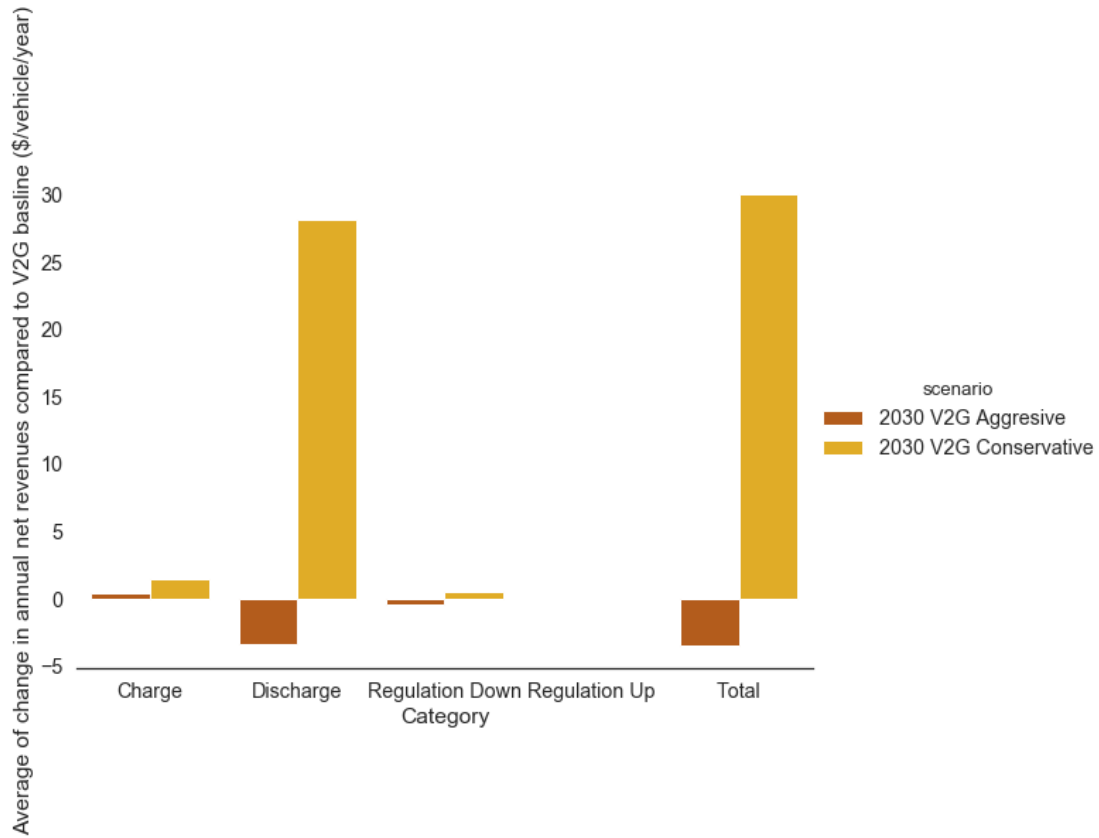
Figure 7: Change in total annual revenues averaged across EVs from V2G aggressive and conservative scenarios to V2G baseline scenario. Changes in total annual net revenue (right cluster) equal the sum of changes in all other revenues.

For 2025, both the conservative and aggressive scenario makes less profit than baseline, for $3 and $4.6, respectively. For 2030, conservative scenario is $30 more profitable than the baseline scenario (Figure 5). 2030 conservative scenario also is the only scenario with a net positive revenue of $16. Positive net revenues in the conservative scenario mostly arise from discharging revenues, which are $24.1 greater than baseline.
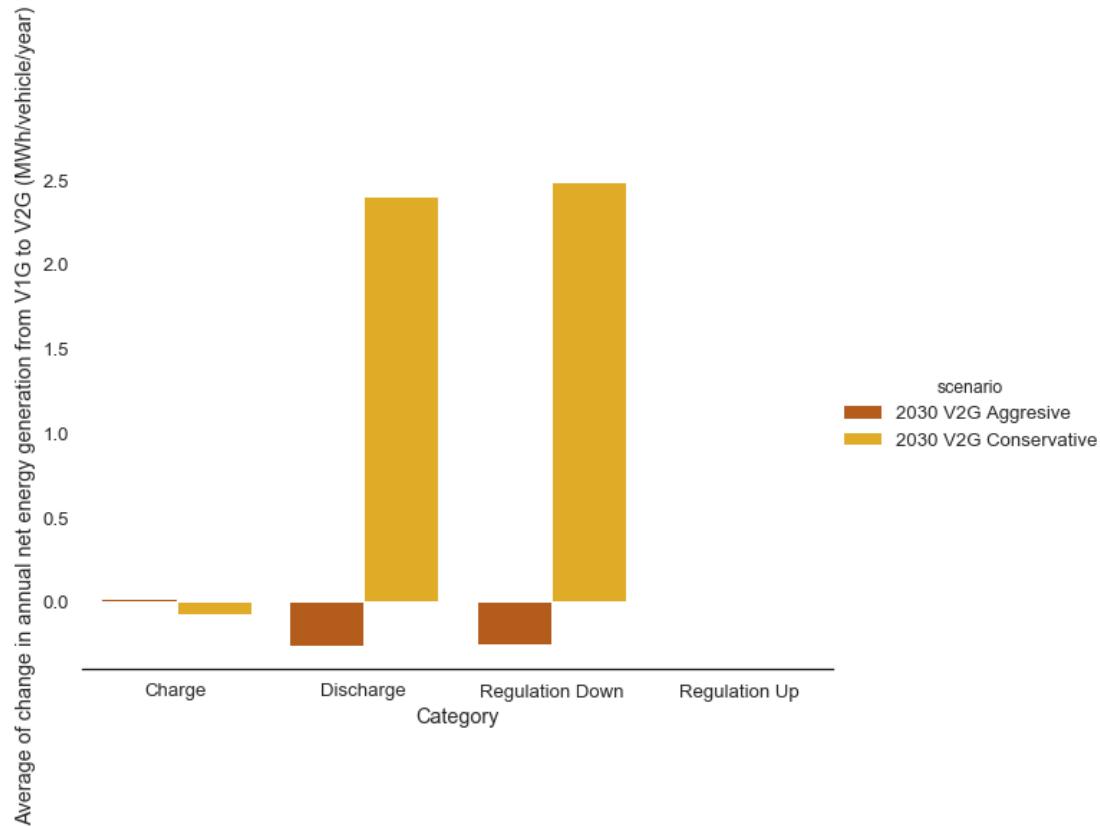
Figure 8: Change in total energy consumed or generated averaged across EVs from V2G aggressive and conservative scenarios to V2G baseline scenario.

2030 conservative scenario provide significantly more discharge and regulation down capacity (Figure 8). We found that in three 2030 scenarios, the sum of wind, EVs, and solar are roughly the same. From aggressive to baseline to conservative scenario, as renewable decrease, EV's percentage increase from 0.01% to 3% because EV's operational cost, which equally to its battery degradation cost from operation, is more expensive than solar and wind but cheaper than others energy source. That explains why in 2030 conservative scenario, V2G creates more energy than 2030 baseline or 2030 aggressive scenarios. In conclusion, lower renewable leaves more room for EV to generate energy and produce revenue.

Conclusions

In order to understand the future value of charge management technology, we use a co-simulation platform of EV and grid operations to analyze the value of V1G and V2G. We found the annual economic value of V2G to be around several dozen dollars. V2G are more profitable than V1G, but the value of V2G and V1G will increase from 2020 to 2030. Most V2G revenue comes from selling electricity instead of providing regulation capacity. V2G are valuable to the grid by providing

significant amount of generation capacity and regulation capacity, but higher renewable in the grid does not necessarily mean higher value of V2G.

Most prior research find that the value of V2G range from hundreds to thousands of dollars. This difference can be explained by two key differences in methods: (1) we optimize future grid operations so we capture price changes (Figure 5) and (2) we include millions of EVs so we capture their effect on prices. Conversely, previous research does not consider whether the electricity or frequency regulation service would actually be dispatched by grid operator, does not consider how EVs will affect prices, and often only model 1-10 EVs(Peterson, Whitacre and Apt, 2010; Agarwal, Peng and Goel, 2014; Pelzer et al., 2014; Zeng, Gibeau and Chow, 2015; Li et al., 2020). To test the effect of ignoring interactions between power market prices and EV operations, we run our baseline scenario for only one EV. We find the annual net revenue of the vehicle to be $2,190, $1,850, and $1,360 in 2020, 2025, and 2030, respectively, in the V2G baseline scenario. These values are in line with previously reported values (Peterson, Whitacre and Apt, 2010; Agarwal, Peng and Goel, 2014; Pelzer et al., 2014; Zeng, Gibeau and Chow, 2015; Li et al., 2020). However, these values are significantly greater than our average annual V2G revenues of $-23 through $ -10 from our baseline scenario with millions of EVs. Thus, capturing interactions between power market prices and EV operations are the main reasons our economic value result is smaller than the other research. It's essential to include power market prices interations with EV operations to avoid overestimating the value of V2G.

While we found V2G is more profitable than V1G in all scenarios, both would cost less in regard to fuel consumption compared to their internal combustion engine (ICE) counterparts. The average annual net revenue for V1G and V2G ranges from -$9.8 to $63.2 from 2020 to 2030. In contrast, we estimate an ICE vehicle with the same driving pattern and energy consumption in California will spend roughly $2,800 for gas annually (AAA, 2018). This difference might be able to nudge vehicle purchase behavior towards EVs. On the other hand, for people who already owns EVs, there is a small economic incentive to participate in V2G revenue. Moreover, because V2G revenues vary widely among EVs, EVs with certain travel patterns can expect to exploit this opportunity more than the others. For example, we found EVs that arrive at home early in the afternoon can generate greater revenues by exploiting high prices in the early evening.

V2G are valuable to the grid. Previous studies show that V2G can provide more flexibility to grid by providing ramping up and ramping down capacity (Coignard et al., 2018). Our study shows that V2G can also provide a significant amount of generation and regulation down capacity. However, we also found that grids with higher renewable penetration do not necessarily create more economic value for V2G. In particular, relative to the baseline scenario, V2G net revenues are higher in 2030 in

our conservative scenario, which has less renewables and higher battery costs than the baseline scenario. This suggests a trade-off exists between developing renewables and incentivizing EV to participate in grid operation through V2G. This poses a challenge to policymakers to craft policies that benefit renewables and V2G.

This research shows the value of V2G and V1G and how the value would change in the future with change renewable penetration and battery degradation costs. Our research has several limitations. First, our co-simulation platform optimizes operations of the grid and V2G-sim. Future research should expand this co-simulation framework to endogenize generator investment decisions. Second, our research made certain assumptions around charger availability in the future and found it to be impactful in the value of V1G and V2G. Research on how accessibility of charging stations at home, work, and other locations would change EVs charging behavior would be helpful to fill in the gap. Third, our research targeted light duty passenger EVs but does not include commercial EVs fleet. However, the development of V2G is more prevalent and face less challenges for commercial EVs. Most pilot projects in the US for V2G are for commercial medium and heavy duty EVs fleet. They usually have pre-defined schedule and more certainty around when and where they will be able to connect to the grid and provide energy services, they also tend to have bigger battery pack capacity and can provide more energy with a relative small fleet (Gnann, Klingler and Kühnbach, 2018). More studies into the value for commercial EVs can be of particular interest for future research. These studies could leverage our co-simulation platform to model EV and grid operations, thereby capturing key interactions between the two and properly valuing V2G in commercial EVs.

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Supportive Information

SI.1: Unit Commitment and Economic Dispatch Model Formulation

This section provides the formulation of the Unit Commitment and Economic Dispatch Model that we used to determine vehicle dispatch and energy prices. The optimization used "pyomo" to formulate optimization models and used "gurobi" as the solver.

SI.1.1: Definition of Variables, Parameters, and Sets

Variables	Definition
$mwh_{g,t}$	Energy generated by generator g in hour t (MWh)
$regup_{g,t}$	Amount of regulation up capacity provided by generator g in hour t (MW)
$regdown_{g,t}$	Amount of regulation down capacity provided by generator g in hour t (MW)
$on_{g,t}$	Condition of generator g in hour t, 1 means the unit is on, 0 means the unit is off
$switch_{g,t}$	If generator g is switching on in hour t, 1 means the unit is switching on, 0 means otherwise
$mwh\_h_{h,t}$	Energy generated by hydro generator h in hour t (MWh)
$regup\_h_{h,t}$	Amount of regulation up capacity provided by hydro generator h in hour t (MW)
$regdown\_h_{h,t}$	Amount of regulation down capacity provided by hydro generator h in hour t (MW)
$on\_h_{h,t}$	Condition of hydro generator h in hour t, 1 means the unit is on, 0 means the unit is off
$switch\_h_{h,t}$	If hydro generator h is switching on in hour t, 1 means the unit is switching on, 0 means otherwise
$mwh\_s_{s,t}$	Energy generated by solar generators s in hour t (MWh)
$regup\_s_{s,t}$	Amount of regulation up capacity provided by solar generators s in hour t (MW)
$regdown\_s_{s,t}$	Amount of regulation down capacity provided by solar generators s in hour t (MW)
$on\_s_{s,t}$	Condition of solar generators s in hour t, 1 means the unit is on, 0 means the unit is off
$switch\_s_{s,t}$	If solar generators s is switching on in hour t, 1 means the unit is switching on, 0 means otherwise
$mwh\_w_{w,t}$	Energy generated by wind generators w in hour t (MWh)
$regup\_w_{w,t}$	Amount of regulation up capacity provided by wind generators w in hour t (MW)

$regdown\_w_{w,t}$	Amount of regulation down capacity provided by wind generators w in hour t (MW)
$on\_w_{w,t}$	Condition of wind generators w in hour t, 1 means the unit is on, 0 means the unit is off
$switch\_w_{w,t}$	If wind generators w is switching on in hour t, 1 means the unit is switching on, 0 means otherwise
mwh_veh_t	Energy generated by vehicles in hour t (MWh)
$regup\_veh_t$	Amount of regulation up capacity provided by vehicles in hour t (MW)
$regdown\_veh_t$	Amount of regulation down capacity provided by vehicles in hour t (MW)

Parameters	Definition
t	Horizon Hours Range
$demand_t$	Hourly demand during planning horizon hour range
regup_margin	Percentage of regulation up capacity requirement to demand
regdown_margin	Percentage of regulation down capacity requirement to demand
cap	The cap of regulation capacity provided by vehicle
ini_on$_g$	Initial condition for generator g, 0 if generator is offline, 1 if generator is online. Initial value is 0
ini_mwh$_g$	Initial energy provided by generator g. Initial value is 0
$maxcap_g$	Maximum capacity of generator g (MWh)
$mincap_g$	Minimum capacity of generator g (MWh)
$opcost_g$	Operational cost of generator g ($/MWh)
var_om_g	Variable operational and maintenance cost of generator g ($/MWh)
st_cost_g	Start up cost of generator g ($)
$ramp_g$	Ramp rate of generator g
$minup_g$	Minimum up time of generator g (hr)
$regcost_g$	Cost to provide regulation capacity of generator g ($/MW)
ini_on_h$_h$	Initial condition for hydro generator h, 0 if generator is offline, 1 if generator is online. Initial value is 0
ini_mwh_h$_h$	Initial energy provided by hydro generator h. Initial value is 0 (MWh)
$maxcap\_h_h$	Maximum capacity of hydro generator h (MWh)
$mincap\_h_h$	Minimum capacity of hydro generator h (MWh)
$opcost\_h_h$	Operational cost of hydro generator h ($/MWh)
$var\_om\_h_h$	Variable operational and maintenance cost of hydro generator h ($/MWh)
$st\_cost\_h_h$	Start up cost of hydro generator h ($)
$ramp\_h_h$	Ramp rate of hydro generator h
$minup\_h_h$	Minimum up time of hydro generator h (hr)

$regcost\_h_h$	Cost to provide regulation capacity of hydro generator h ($/MW)
$maxcap\_s_t$	Maximum capacity of solar generators in hour t (MWh)
$opcost\_s_s$	Operational cost of solar generators s ($/MWh)
$var\_om\_s_s$	Variable operational and maintenance cost of solar generators s ($/MWh)
$st\_cost\_s_s$	Start up cost of solar generators s ($)
$ramp\_s_s$	Ramp rate of solar generators s
$minup\_s_s$	Minimum up time of solar generators s (hr)
$maxcap\_w_t$	Maximum capacity of wind generators in hour t (MWh)
$opcost\_w_w$	Operational cost of wind generators w ($/MWh)
$var\_om\_w_w$	Variable operational and maintenance cost of wind generators w ($/MWh)
$st\_cost\_w_w$	Start up cost of wind generators w ($)
$ramp\_w_w$	Ramp rate of wind generators w
$minup\_w_w$	Minimum up time of wind generators w (hr)
veh_batteryCost	Battery operational cost of vehicles ($/MWh)
$gen\_capacity\_veh_t$	Maximum energy capacity of vehicles in hour t (MWh)
$regup\_capacity\_veh_t$	Maximum regulation up capacity of vehicles in hour t (MW)
$regdown\_capacity\_veh_t$	Maximum regulation down capacity of vehicles in hour t (MW)

Sets	Definition
W	Wind generators
S	Solar generators
H	Hydro generators
V	Vehicles
G	Other Generators
T	Hours

SI.1.2: Objective Function

UCED simulates the grid operators daily economic dispatch decision, which aims to minimizes total operational economic cost to dispatch all generators to meet electricity demand. Total operational costs include costs of electricity generation, start-up costs, regulation up capacity, and regulation down capacity. The UCED runs over a 24-hour optimization horizon in hourly increments and includes an additional 24-hour period. The second 24-hour period is a "look-ahead period" to bring additional information into the current 24-hour optimization horizon.

$$\text{Electricity Generation cost} = \sum_{g,t}[\, mwh_{g,t}\, (opcost_g + var\_om_g\,)] +$$

$$\sum_{w,t}[\, mwh\_w_t(opcost\_w_w + var\_om\_w_w\,)] + \sum_{s,t}[\, mwh\_s_t\, (opcost\_s_s + var\_om\_s_s\,)] + \sum_{h,t}[\, mwh\_h_t\, (opcost\_h_h + var\_om\_h_h\,)] +$$

$$\sum_{v,t}[\, mwh\_v_t\, (opcost\_v_s + var\_om\_v_s\,)]$$

$$, \forall t \in T, g \in G, w \in W, s \in S, h \in H, v \in V$$

$$\text{Start up cost} = \sum_{g,t} st\_cost_g\, switch_{g,t} \quad , \forall t \in T, g \in G$$

$$\text{Regulation up cost} = \sum_{g,t}[\, regup_{g,t} regcost_g\,] +$$
$$\sum_{v,t}[\, regup\_veh_v veh\_batteryCost\,] , \forall t \in T, g \in G, v \in V$$

$$\text{Regulation down cost} = \sum_{g,t}[\, regdown_{g,t} regcost_g\,] +$$
$$\sum_{v,t}[\, regdown\_veh_v veh\_batteryCost\,] , \forall t \in T, g \in G, v \in V$$

$$\min (\text{Electricity Generation cost + Start up cost + Regulation up cost + Regulation down cost}) , \forall t \in T, g \in G, w \in W, s \in S, h \in H, v \in V$$

SI.1.3: Logical Constraint
Logical constraints determine that variable $switch_{g,t}$, $switch\_w_t$, $switch\_s_t$, each generator can not be turned in

$$switch_{g,t} \geq 1 - on_{g,t-1} - (1 - on_{g,t})$$

SI.1.4: Demand Supply Constraint

$$\sum_{g,w,s,h,v}[\, mwh_{g,t} + mwh\_w_t + mwh\_s_t + mwh\_h_t + mwh\_v_t] \geq \text{ demand}_t$$

Where $mwh_{g,t}, mwh\_w_t, mwh\_s_t, mwh\_h_t, mwh\_v_t$ is the electricity supply generated by generator in hour t, and demand$_t$ is the system electricity demand at hour t. This constraint makes sure the sum of electricity generation meets the system demand at any hour.

SI. 1.5: Regulation Up Capacity Constraint

$$\sum_{g,h,v}[\, regup_{g,t} + regup\_h_t + regup\_v_t] \geq \text{ demand}_t * \text{regup\_margin}$$

$regup_{g,t}, regup\_h_t, regup\_v_t$ are the amount of regulation up provided by other generators, hydro generator, and vehicles (solar and wind can not provide regulation up capacity). The system regulation up capacity demand at hour t is proportional to the electricity demand$_t$, and the proportion is denoted by regup_margin. This constraint makes sure the sum of regulation up capacity meets the system regulation capacity demand at any hour.

$$regup\_v_t \leq \text{demand}_t * \text{regup\_margin} * cap$$
This constraint caps the amount of regulation up capacity that vehicles can provide.

$$regup_{g,t} \leq on_{g,t} * mapcap_g - mwh_{g,t}$$
$on_{g,t}$ is 1 when generator is online at hour t, $mapcap_g$ is the maximum capacity generator g can provide. this constraint makes sure that regulation up capacity can only be provided by generator that's online, and that the amount of regulation up capacity that vehicles can provide does not exceed the maximum capacity minuse the electricity generation it's providing

SI. 1.6: Regulation Down Capacity Constraint

$$\sum_{g,h.v}[regdown_{g,t} + regdown\_h_t + regdown\_v_t] \geq \text{demand}_t * \text{regdown\_margin}$$

$regdown_{g,t}, regdown\_h_t, regdown\_v_t$ are the amount of regulation down capacity provided by other generators, hydro generator, and vehicles (solar and wind can not provide regulation capacity). The system regulation down capacity demand at hour t is proportional to the electricity demand$_t$, and the proportion is denoted by regdowb_margin. This constraint makes sure the sum of regulation down capacity meets the system regulation capacity demand at any hour.

$$regdown\_v_t \leq \text{demand}_t * \text{regdown\_margin} * cap$$
This constraint caps the amount of regulation down capacity that vehicles can provide.

$$regdown_{g,t} \leq mwh_{g,t} - on_{g,t} * mincap_g$$
$on_{g,t}$ is 1 when generator is online at hour t, $mincap_g$ is the minimum stable capacity generator g can provide. this constraint makes sure that regulation down capacity can only be provided by generator that's online, and that the amount of regulation down capacity that vehicles can provide does not go below the minimum stable capacity.

SI 1.7: Maximum Capacity Constraint
$$mwh_{g,t} \leq on_{g,t} * mapcap_g$$
For each generator g, generation provided can not exceed the maximum capacity at any hour.
$$mwh\_w_t \leq on\_w_t * mapcap\_w_t$$
$$mwh\_s_t \leq on\_s_t * mapcap\_s_t$$
$$mwh\_h_t \leq on\_h_t * mapcap\_h_t$$
$$mwh\_v_t \leq mapcap\_v_t$$

The same maximum capacity constraint applies to wind, solar, hydro, and vehicle generators. The constraints are slightly different because the maximum capacity of

wind, solar, hydro, and vehicle change across time, denoted by $mapcap\_w_t, mapcap\_s_t, mapcap\_s_t$, and $mapcap\_v_t$.

$$mwh_{g,t} + regup_{g,t} - regdown_{g,t} \leq mapcap_g$$

For each generator g, generation provided and capacity provided can not exceed the maximum capacity at any hour.

SI.1.8: Minimum Capacity Constraint

$$mwh_{g,t} \geq on_{g,t} * mincap_g$$

For each generator g, generation provided cannot be below the minimum capacity at any hour.

SI.1.9: Vehicle Regulation Capacity Constraints:

$$regdown\_v_t \leq regdown\_capacity\_v_t$$
$$regup\_v_t \leq regup\_capacity\_v_t$$

The amount of regulation capacity provided by vehicles cannot exceed the regulation capacity of vehicles. Regulation up and regulation down capacity of vehicles are output from V2G-sim model.

SI.1.10: Minimum Up Time Constraints:

$$on_{g,t} - on_{g,t-1} \leq on_{g,k}$$

$$\forall t > 1, k > t, k < \min(t + minup_g - 1, 48)$$

This constraint limits that each generator must meet the minimum up time constraints. 48 is the horizon hours. $on_{g,t}$ is 1 when the generator is on, it's 0 when the generator is off.

SI.1.11: Ramp Rate Constraints:

$$mwh_{g,t} - mwh_{g,t-1} \leq ramp_g * on_{g,t} + mincap_g * switch_{g,t}$$

$ramp_g$ is the ramp rate of generator g. $mwh_{g,t} - mwh_{g,t-1}$ is the difference of generation in two neighboring hours, which is also the rate of ramping up, this ramping up rate can not exceed ramp rate plus the minimum capacity when it turns on.

$$mwh_{g,t-1} - mwh_{g,1} \leq ramp_g * on_{g,t-1} + mincap_g * (on_{g,t-1} - on_{g,t} + switch_{g,t})$$

This constraint is to limit the ramping down of generator g. Ramping down rate can not be smaller than ramp rate plus the minimum capacity when it turns off.

$$mwh\_w_t - mwh\_w_{t-1} \leq ramp\_w_g * on\_w_t$$
$$mwh\_s_t - mwh\_s_{t-1} \leq ramp\_s_g * on\_s_t$$

$$mwh\_h_t \text{-} mwh\_h_{t-1} \leq ramp\_h_g * on\_h_t$$

$$mwh\_w_{t-1} \text{-} mwh\_w_t \leq ramp\_w_g * on\_w_{t-1}$$
$$mwh\_s_{t-1} \text{-} mwh\_s_t \leq ramp\_s_g * on\_s_{t-1}$$
$$mwh\_h_{t-1} \text{-} mwh\_h_t \leq ramp\_h_g * on\_h_{t-1}$$

Similar ramping up and ramping down rate constraints also applied to wind, solar, and hydro generators.

SI.2: V2G-sim Formulation

This section provides the formulation of V2G-sim Model that we used to determine vehicle charge and discharge profiles. The optimization used "pyomo" to formulate optimization models and used "gurobi" as the solver.

SI.2.1 Definition of Variables, Parameters, and Sets

Variables	Definition
$P_{charge,t,i}$	Charging power at time t from vehicle i (W)
$P_{discharge,t,i}$	Discharging power at time t from vehicle i (W)
$P_{regup,t,i}$	Power to provide regulation up capacity at time t from vehicle i (W)
$P_{regdown,t,i}$	Power to provide regulation up capacity at time t from vehicle i (W)
$on_{regdown,t,i}$	Binary variable, on is 1 when $P_{regdown,t,i}$ is nonzero, and on is 0 when $P_{regdown,t,i}$ is 0.
$SOC_{t,i}$	SOC of vehicle i at time t

Parameters	Definition
$Pr_{e,t}$	price of electricity at time t ($/MWh)
$Pr_{regup,t}$	price of regulation up capacity at time t ($/MW)
$Pr_{regdown,t}$	price of regulation down capacity at time t ($/MW)
Pr_b	price of battery degradation($/MW)
h	time step duration (10mins)
$e_{min,i,t}$	Minimum energy for vehicle i at time t
$e_{max,i,t}$	Maximum energy for vehicle i at time t
$e_{final,i}$	Final SOC for vehicle i during the time horizon
$genCap_t$	Generation cap for all vehicles at time t

$regupCap_t$	Regulation up cap for all vehicles at time t
$regdownCap_t$	Regulation down cap for all vehicles at time t
$Pmax_{t,i}$	Maximum power for vehicle i at time t
$Pmin_{t,i}$	Minimum power for vehicle i at time t

Set	Definition
T	time
I	vehicles

SI.2.2 Objective Function

The V2G-sim optimization problem is formulated as follows:

$$max \sum_{i}^{I} \sum_{t=1}^{T} P_{discharge,t,i} h(Pr_{e,t} - Pr_b) - P_{charge,t,i} hPr_{e,t}$$

$$+ P_{regup,t,i} h(Pr_{regup,t} - Pr_b) + P_{regdown,t,i} h(Pr_{regdown,t} - Pr_b)$$

The optimization maximizes net revenue for EVs, it runs every 10 mins for a whole day in every iteration. i denotes individual vehicle, t denotes time index; P denotes power, $P_{discharge,t,i}$ is the charge power at time t for vehicle i, h is the time step duration, $Pr_{e,t}$ is the price of electricity, Pr_b is the price of battery degradation,

$P_{discharge,t,i} h(Pr_{e,t} - Pr_b)$ is the electricity net revenue; $P_{charge,t,i}$ is the charge power at time t for vehicle i, $P_{charge,t,i} hPr_{e,t}$ is the cost for charging; $P_{regup,t}$ denotes battery change from providing regulation up capacity, $Pr_{regup,t}$ is the price of regulation up capacity, $P_{regup,t,i} h(Pr_{regup,t} - Pr_b)$ is the net revenue from providing regulation up capacity; $P_{regdown,t}$ denotes battery change from providing regulation down capacity, $Pr_{regdown,t}$ is the price of regulation down capacity,

$P_{regdown,t,i} h(Pr_{regdown,t} - Pr_b)$ is the net revenue from providing regulation down capacity.

SI.2.3 Maximum Power Constraints

$$P_{charge,t,i} \leq Pmax_{t,i}$$

The power to charge cannot exceed the maximum power.

$$P_{discharge,t,i} \geq Pmin_{t.i}$$

The power to discharge cannot go below the minimum power.

$$P_{regdown,t,i} \leq Pmax_{t.i} * on_{regdown,t,i}$$

The power for regulation down capacity cannot exceed the maximum power.

$$P_{regup,t,i} \leq -Pmin_{t.i} * (1 - on_{regdown,t,i})$$

The power for regulation up capacity cannot go below the minimum power. Regulation up capacity also can not be provided when regulation down capacity is being provided.

SI.2.4 Energy Constraints

$$\sum_{t=1}^{k} P_{charge,t,i}h - P_{discharge,t,i}h + P_{regdown,t,i}h - P_{regup,t,i}h \geq e_{min,i,t}, \forall k \in T$$

The aggregated energy of vehicle i, including from charging, discharging, providing regulation up and down capacity cannot go below the minimum energy at any given time.

$$\sum_{t=1}^{k} P_{charge,t,i}h - P_{discharge,t,i}h + P_{regdown,t,i}h - P_{regup,t,i}h \leq e_{max,i,t}, \forall k \in T$$

The aggregated energy of vehicle i, including from charging, discharging, providing regulation up and down capacity cannot exceed the maximum energy at any given time.

$$\sum_{t=1}^{T} P_{charge,t,i}h - P_{discharge,t,i}h + P_{regdown,t,i}h - P_{regup,t,i}h \geq e_{final,i}$$

The final aggregated energy of vehicle i, including from charging, discharging, providing regulation up and down capacity should be equal to or bigger than the final energy requirement.

SI.2.5 Cap Constraints

$$\sum_{i=1}^{I} P_{discharge,t,i} \leq genCap_t$$

The generation from all vehicles cannot exceed the cap of generation.

$$\sum_{i=1}^{I} P_{regdown,t,i} \leq regdownCap_t$$

The total of regulation down capacity from all vehicles cannot exceed the cap of regulation down.

SI.3: Data Summary

SI.3.1: 2017 National Household Travel Survey driving pattern summary

Table 1 Daily driving pattern summary

	Distance travelled (miles)	Time spent at Home at night (mins)	Time spent at Home(mins)	Time Spent at Work(mins)	Time Spent on Road(miles)
mean	50.37	420.21	3089.10	738.51	194.28
std	50.97	181.21	764.77	813.75	134.23
min	1.79	70.00	1680.00	0.00	24.00
25%	17.39	296.75	2472.00	0.00	90.00
50%	35.41	390.00	2986.50	0.00	165.00
75%	64.55	534.50	3829.50	1572.75	261.00
max	310.60	975.00	4245.00	2295.00	855.00

SI.4: Result

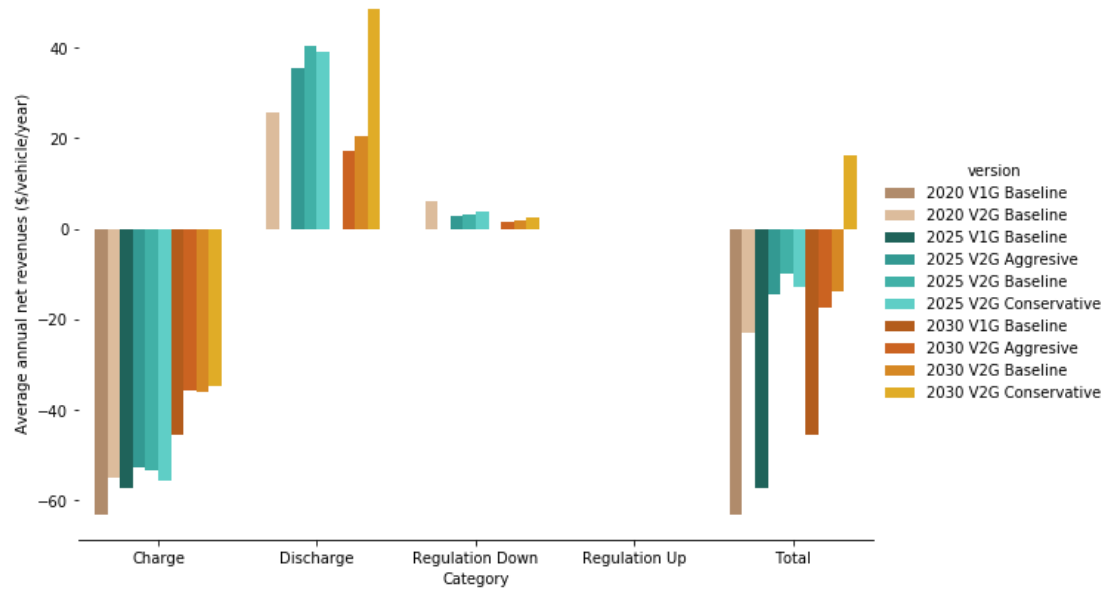SI.4.1: Fleet annual average net revenue for all scenarios

Figure 1: Annual net revenues averaged across EVs. 'total' annual net revenues (right cluster) equal the sum of all other revenues.

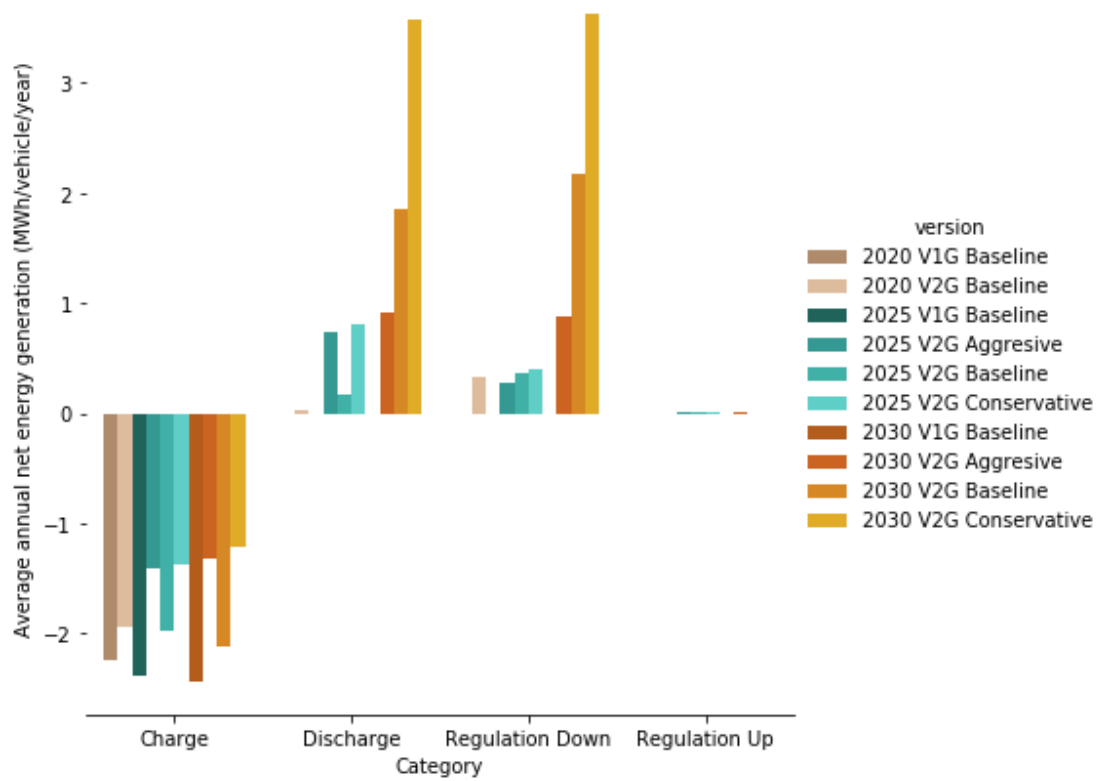SI.4.2: Fleet annual average energy generation for all scenarios

Figure 2: Annual net energy generation averaged across EVs.
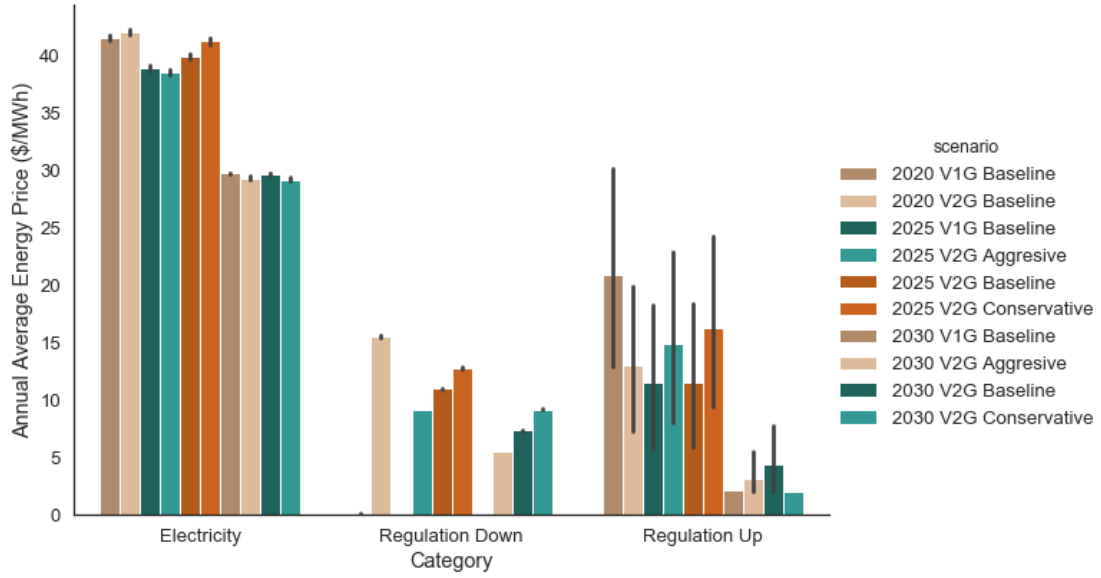
SI.4.3: Energy prices for all scenarios

Figure 3:Energy prices for all scenarios.

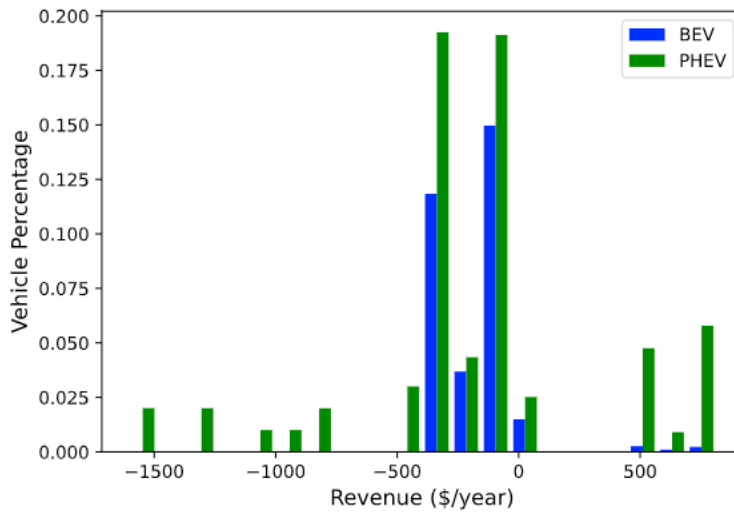SI.4.4: Individual Vehicle Result for 2020 and 2025 V2G baseline scenario

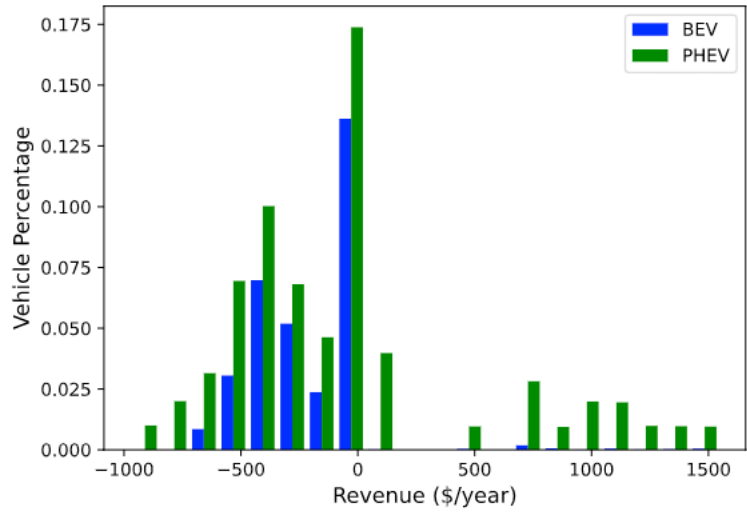Figure 4: annual net revenue of individual vehicle in 2020 V2G baseline

Figure 5: annual net revenue of individual vehicle in 2025 V2G baseline