S1. Supplementary Parameters, Data Sources, and Methodologies

Capacity Expansion and Dispatch Modeling

GenX is a linear optimization model configured to make system-wide generator investment and hourly dispatch decisions for least cost system value (fixed and variable) subject to operational, resource availability, and emissions policy, among other, constraints [source] over the course of a future planning year. Inherent to the CEM approach are the conditions of perfect operator foresight and access to load, operability, and cost information for the period being simulated. The CEM framework also assumes perfect competition among competing technology groups and ignorance to future market conditions, such as tax incentives and renewable portfolio standards beyond the study period (i.e. a rolling horizon). Despite these deviations from actual market conditions and outcomes, the strengths of the CEM lie in its ability to approximate the power market operations with a high temporal resolution, which is valuable in studying the dynamic behavior of decentralized V2G resources and their sensitivities to varying market conditions.

On a regional level, we enable system-wide constraints that govern carbon emissions limits, primary and secondary reserve and regulation requirements, and the maximum ancillary service contribution that each generation technology can make. In configuring the energy resources, thermal generators are subject to ramping, up/down time, and stability constraints; while VRE and storage technologies are typically constrained by varying resource availability and intertemporal state-of-charge and charge/discharge capacity limits, respectively. To reduce computational burden, we use linearized clustering to represent thermal unit commitment decisions.

The optimization problem is solved using Gurobi Optimizer (v0.7.6) on a Linux-based server with Intel Xeon Gold 6248 and Intel Xeon Platinum 8260 processors. Additional explanation and mathematical formulations of the native GenX model objective function and constraints are publicly available in its documentation [9].

Vehicle-to-Building Constraint Formulation (Sensitivity)

A destination-based topology is used to study locational V2B dispatch behavior and value. This includes constraining vehicle servicing by where they are parked (i.e. power injected by cars at homes can only service residential loads), limiting V2B service connections to homes and workplaces, and disabling ancillary service contributions to the grid. As for the spatial distribution of EVs, participating EVs are represented as a single aggregate within each node and link the SOCs of EVs parked at homes and workplaces to reflect mobility between locations.

In these cases, we use intermediate auxiliary variables to track and constrain aggregate V2B services at the separate residential and commercial load zones. This means that the aforementioned aggregate power and energy requirements hold, but are further constrained by location-specific parameters. Specifically, the participating EV fleet is still modeled as a single aggregate, using the original energy balance and adhering to aggregate-level SOC constraints. Now, however, we implement specific V2B energy and charge and discharge availabilities for servicing each load center (i.e. the maximum service that can be provide is strictly limited to vehicles at those locations, as opposed to the entire connected fleet, which would be characteristic of an unrestricted distribution grid). Further, to compute associated energy availabilities as well as account for vehicle mobility between destinations, we link the residential and commercial SOCs (state-of-charge) such that total fleet energy is distributed equally among all vehicles and proportionally across locations. This modified formulation is as follows:

Indices and Sets

Notation	Description
$t \in T$	t is a time step and T is the set of time steps over which grid operations are modeled
$T^{start} \in T$	1
$T^{interior} \in T$	$T^{interior}$ is the set of interior series time steps

Decision Variables

Notation	Description
$\Gamma_{EV,t} \in \mathbb{R}_+$	Stored energy level of the EV aggregate at time step t
$\Gamma_{l,t}^{grid} \in \mathbb{R}_+$	Stored energy level of gridded vehicles at time step t, derived from $\Gamma_{EV,t}$ and fraction of grid-connected vehicles available for V2B
$\Pi_{EV,l,t} \in \mathbb{R}_+$	Energy withdrawn from grid by EV aggregate at location *l* at time step t
$\Theta_{EV,l,t} \in \mathbb{R}_+$	Energy withdrawn from grid by EV aggregate at location *l* at time step t

Parameters

Notation	Description
$D_{wheel,t}$	Energy consumed by EV aggregate for driving purposes at time step t
τ^{period}	Number of time steps being modeled
$f_{l,t}$	Fraction of vehicles at location *l* at time step t
Γ_t^{min}	Minimum energy level constraint for EV aggregate at time step t
Γ^{max}	Maximum energy level constraint for EV aggregate
$\Delta_{EV,l,t}^{power}$	Total grid-connected power capacity of EV aggregate at location *l* at time step t
$\Delta_{EV,l,t}^{energy}$	Total grid-connected energy capacity of EV aggregate at location *l* at time step t
η_{EV}^{charge}	Single-trip efficiency of EV charging
$\eta_{EV}^{discharge}$	Single-trip efficiency of EV discharging
η_{EV}^{loss}	Self-discharge rate per time step per unit of installed capacity, 0

To reflect vehicle mobility, total fleet energy level is approximated as proportionally dispersed among vehicle locations as function of fleet fraction at said location. Likewise, for model tractability, charging is proportionally distributed amongst vehicles across locations.

$$\Gamma_{l,t}^{grid} = \Gamma_{EV,t} * f_{l,t}, \quad t \in T \tag{S.1}$$

First, because the EV aggregate represents a large population of decentralized vehicles and vehicle clusters, we permit it to simultaneously charge and discharge. For a given time step, *t*, the total EV state-of-charge (sun of all locational SOC) must remain between a prescribed minimum and the physical maximum. Similarly, the net change in aggregate state of charge must not exceed the uncharged/available *gridded* energy capacity at the start of *t*.

$$\Gamma_t^{min} \leq \sum_l \Gamma_{EV,l,t} \leq \Gamma^{max}, \; t \in T \tag{S.2}$$

$$\sum_l \Pi_{EV,l,t} - \sum_l \Theta_{EV,l,t} \leq \sum_l \Delta_{EV,l,t}^{energy} - \sum_l \Gamma_{l,t}^{grid}, \; t \in T \tag{S.3}$$

The inter-temporal constraints (S.4) and (S.5) relate EV aggregate state-of-charge at the beginning and end of time step *t* to charge/discharge decisions and driving and self-discharge processes. Modeling operations over a single contiguous period, the constraint links the storage inventories of the first time step and the last time step.

$$\Gamma_{EV,t} = \Gamma_{EV,l,t-1} - \frac{1}{\eta_{EV}^{discharge}} \sum_l \Theta_{EV,l,t} + \eta_{EV}^{charge} \sum_l \Pi_{EV,l,t} - D_{wheel,t} - \eta_{EV}^{loss} \Gamma_{EV,t-1}, \quad t \in T^{interior} \tag{S.4}$$

$$\Gamma_{EV,t} = \Gamma_{EV,l,t+\tau^{period}-1} - \frac{1}{\eta_{EV}^{discharge}} \sum_l \Theta_{EV,l,t} + \eta_{EV}^{charge} \sum_l \Pi_{EV,l,t} - D_{wheel,t} - \eta_{EV}^{loss} \Gamma_{EV,t\tau^{period}-1}, \quad t \in T^{start} \tag{S.5}$$

For V2B at destination *l*, without ancillary service, maximum total charge and/or discharging rate must be less than power rating OR available stored energy in prior period, whichever is less

$$\Pi_{EV,l,t} \le \Delta_{EV,l,t}^{power}, \; t \in T \tag{S.6}$$

$$\Pi_{EV,l,t} + \Theta_{EV,l,t} \le \Delta_{EV,l,t}^{power}, \; t \in T \tag{S.7}$$

$$\Pi_{EV,l,t} \le \Delta_{EV,l,t}^{energy} - \Gamma_{l,t}^{grid}, \; t \in T \tag{S.8}$$

$$\Theta_{EV,l,t} \le \Gamma_{l,t}^{grid}, \; t \in T \tag{S.9}$$

When modeling cases no ancillary reserved AND only VDR (vehicle demand response), the SOC balances (S.2)-(S.5) are unchanged and constraints (S.6)-(S.9) reduce to:

$$\Pi_{EV,l,t} \le \Delta_{EV,l,t}^{power}, \; t \in T \tag{S.10}$$

$$\Theta_{EV,l,t} \le 0, \; t \in T \tag{S.11}$$

Assigning EV Degradation Cost

For both stationary and V2G storage, we do not model real-time capacity degradation within the CEM, as it introduces increased computational complexity. Furthermore, we assume that ISO CEM decisions are blind to the choices of how the V2G aggregator utilizes individual vehicles and clusters, and so optimizing such decisions are beyond the scope of this work. Rather, to calculate a degradation VOM cost for storage and V2G utilization, we combine 3 elements: (1) real world EV battery degradation data indicating ~10% EV battery capacity fade per 200,000 miles[10], (2) LIB capacity costs of ~$119/kWh (see Table S3), and (3) the assumption that V2G participants must be compensated at least for the pro-rated cost of capacity lost to degradation from V2G cycling. We quantify the magnitude of the fleet-wide degradation cost and its sensitivity to different degradation rates per cycle, and resulting differences in degradation costs per cycle and per distance.

Low-Carbon Emissions Constraints

Massachusetts, with roughly half of New England's population and power, has the highest targets for emission reduction, with a goal of net zero power emissions by 2050. The remaining states' targets are mostly 80% reductions from 1990 levels. Taking the average of net zero and an 80%

region-wide reduction from 1990 electric power emissions (~100 g/kWh), our main case assumes an emissions cap of 50 g/kWh. In addition, our analysis explores a near net zero case (10 g/kWh) and an unconstrained case.

Table S1. 2050 generator cost and performance assumptions, reported in 2019$. Cost data sourced from the 2021 NREL Annual Technology Baseline [11]. *Performance data sourced across several manufacturer* [12,13] *and academic* [14–17] *literature sources . CCFT = Combined Cycle Gas Turbine. CCFT-CCS = Combined Cycle Gas Turbine with Carbon Capture and Storage.*

Generator Parameters	**CCGT**	**CCGT-CCS**	**PV**	**ONSHORE WIND**	**UTILITY BATTERY**	**EV BATTERY**
ATB Classification	Natural Gas_FE	Natural Gas_FE	Solar - Utility PV	Land-Based Wind	Utility-Scale Battery Storage	-
ATB Sub-Type	Gas-CC-AvgCF	Gas-CC-CCS-AvgCF	-	-	6Hr Battery Storage	-
ATB Technology Innovation Scenario	Advanced	Advanced	Advanced	Advanced	Advanced	-
Individual plant nameplate capacity (MW)	573	377	-	-	-	-
Overnight CAPEX ($/MW-ac)	55,700	83,100	29,500	32,200	5,000	-
Fixed O&M costs ($/MW/year)	27,300	55,800	12,451	24,066	12,150	-
Variable O&M costs ($/MWh)	2	5	0	0	0	9.48
Heat Rate (MMBtu/MWh)	6.36	7.16	-	-	-	-
Startup fuel use (MMBtu/MW/start)	0.20	0.20	-	-	-	-
Startup cost ($/MW/start)	62.70	97.44	-	-	-	-
Ramp up rate (% Nameplate Capacity/hour)	1	1	-	-	-	-
Ramp down rate (% Nameplate Capacity/hour)	1	1	-	-	-	-
Minimum stable output (% Nameplate capacity)	0.30	0.50	-	-	-	-
Minimum up time (hour)	4	4	-	-	-	-
Minimum down time (hour)	4	4	-	-	-	-
Maximum capacity contribution to frequency regulation up requirements (%)	67%	67%	0%	0%	100%	100%
Maximum capacity contribution to frequency regulation down requirements (%)	67%	67%	0%	0%	100%	100%
Maximum capacity contribution to spinning reserves up (%)	67%	67%	0%	0%	100%	100%
Maximum capacity contribution to spinning reserves down (%)	67%	67%	0%	0%	100%	100%
Duration (hour)	-	-	-	-	6	-
Roundtrip Efficiency (%)*	-	-	-	-	0.85	0.85
Self-discharge rate (% / hour)	-	-	-	-	0	0

Table S2. Economic parameters used to annualize investment costs

Economic Parameters	CCGT	CCGT-CCS	PV	WIND	STATIONARY_BATTERY	EV_BATTERY
Capital recovery period (years)	30	30	30	30	20	-
WACC (%)	4.5%	4.5%	4.5%	4.5%	4.5%	-
Capital Recovery Factor (%)	6.1%	6.1%	6.1%	6.1%	7.7%	-

Table S3. EV and V2G Parameters

Parameter	Value
EV share of LDV stock (%)	60 [18]
Daily vehicle miles traveled per vehicle	30 [19]
Minimum state of charge (%)[1]	20
Minimum start of day travel range (miles)	70
EV fuel economy (miles/kWh)[2]	2.7
EV battery capacity (kWh)[3]	80
EV battery pack cost (2019$/kWh)[4]	118.45
EV cycling degradation rate (%/MWh)	0.1
V2G VOM (2019$/MWh)	9.5
Level 1 charge capacity (kW)	1.9 [20,21]
Level 2 charge capacity (kW)	10 [21–23]
Homes with charger access (%)	90
Workplaces with charger access (%)	20

1. Minimum buffer chosen on basis of good charging heuristics [24].
2. Given uncertainty of future fuel economy, approximated as average of current Tesla Model 3 (~0.25 kWh/mi) and Ford F150 lightning (~0.48 kWh/mi) fuel economies [25].
3. Approximated as average of current average EV battery size (~60 kWh) [26] and Ford F150 lightning standard range (~100 kWh) [27] battery size.
4. To avoid overestimation of future price reduction through 2050, and also considering that the degradation/VOM calculation does not separately include a discharge or labor fees, a contemporary pack price is used.

Table S4. Miscellaneous Optimization Parameters and Constraints

Parameter		Value
Gas price (2019$ /MMBtu)		3.85 [28]
CCGT Emissions Factor (tons CO2/MMBtu)		0.0593 [11]
CCGT-CCS Emissions Factor (tons CO2/MMBtu)		0.0059 [11]
Non-served energy cost ($/MW)		9000 [17]
Non-served operating reserve cost ($/MW)		1000 [17]
Regulation reserve requirement (% of hourly load or available VRE generation)	Load	1 [17]
	VRE	0.32 [17]
Spinning reserve requirement (% of hourly load or available VRE generation)	Load	3.3 (up and down) [17]
	VRE	7.95 (up), 2 (down) [17]

Synthetic Demand Profiles
Synthetic load profiles for the segmented demand centers (residential, commercial, and other) were derived using a combination of ISONE, EIA, and ResStock and ComStock datasets.

The shape of the total ISONE base load is characteristic of the region's 2018 hourly demand profile [29] and is scaled by a factor of 1.27 to track with anticipated population growth [30]. The load share of each demand center is based on aggregated state-level consumption data from the EIA. Residential, commercial, and 'other' loads comprise approximately 44.5%, 40.7%, and 14.7% of annual base load demand, respectively [31]. The annual load shares are mapped to New England electricity hourly load projections derived from NREL's ResStock and ComStock 2018 simulation datasets, which use bottom-up approaches to model fuel-specific energy consumption for state-level residential and commercial building fleets [32,33]. In the absence of additional data, the 'other' load shape (which includes industrials) is assumed to mirror that of commercial consumption. The final synthetic base load profiles are shown in Figure S1. Non-participating EV load data (uncontrolled load) is added to the bases loads as a function of fleet size and participation.

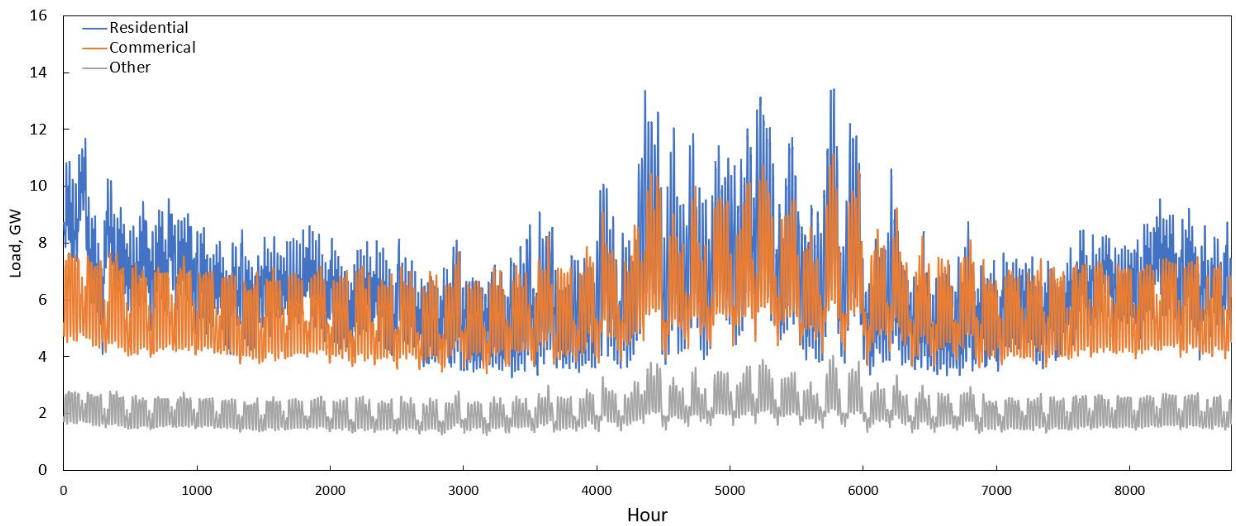

Figure S1: Hourly base load (no EV demand) profiles in residential, commercial, and 'other' demand centers for the 2018 year data.

Solar and Wind Availability Profiles
Hourly wind and solar capacity factors for the 2013 weather year were generated using the ZEPHYR (Zero-emissions Electricity system Planning with HourlY operational Resolution) repository [34]. The tool leverages historical data from the Wind Integration National Dataset (WIND) [35] Toolkit and the National Solar Radiation Database (NSRDB) [36] to generate hourly capacity profiles as a function of geographic position (latitude and longitude). The model assumes that all PV generators employ horizontal single-axis tracking with a north-south axis of rotation and uses a PV DC-to-AC ratio of 1.3. Wind CF data is derived using power curve data from a commercial wind (Gamesa:G126/2500) with a 100 m hub height (Gamesa:G126/2500).

Segmenting the New England region into a mesh of 100 equiangular nodes, individual wind and solar capacity profiles were generated then averaged together for a region-wide profile. Source code and additional methodological details are available in the ZEPHYR repository and accompanying publication supplement [37].

Travel, Storage, and Travel Model Methodology

Weekday and weekend driving statistics for the New England regions were constructed based on the raw trip data and trip weightings from the 2017 National Household Travel Survey (NHTS) [38].

The raw trip data was filtered to include only household LDVs that are driven by the survey respondent (to avoid double counting and apply appropriate weightings) as well as discard mis-entered data. Using the unique household and vehicle identifiers, vehicle trips are chained together and mapped to track the state (driving or parked), location, and mileage of every vehicle over a 24-hour survey period, beginning at 4 AM. When parked, a vehicle can be parked at home, work, or some other location. In this case, we consider the V2G participation is only possible at home and work locations.

Since we are approximate the participating EV fleet as an aggregate rather than individual EVs, we apply statistical household weightings to our results to generate average, aggregate-level statistics of vehicle location and energy consumption as a function of time. This process was repeated for both weekday and weekend survey periods and the results linked to generate profiles for a weeklong period (repeated over the course of the model year). Location data, the fractional share of EVs driving or at different locations, is used to model grid-connected power and energy capacity, and travel the distribution profile informs when and at what rate energy is consumed via driving, as is described in the methods section.

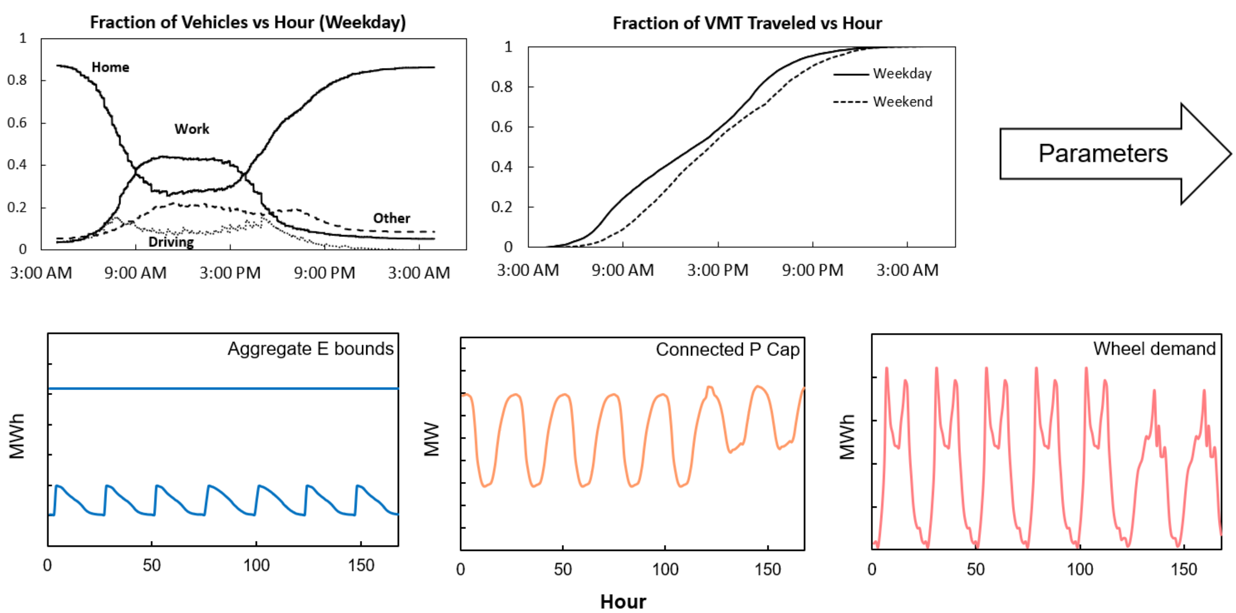

Figure S2: Fleet statistics showing share of vehicles at different locations and travel demand as a function of time **(top row)**. Paired with EV and charger parameters in fleet travel and charger model to generate hourly constraint parameters and travel demand profiles **(bottom row)**.

Basis of Minimum Morning EV Charged Range

For an average gas car:
Gas tank ~13.5 gal. [39]
Gas pumped per gas station visit ~11.7 gal [40].
Fuel level at refueling ~ 13.5 - 11.7 ~ 1.8 gal.
Range ~410 miles [41].
MPG ~ 410 miles/ 13.5 gal ~ 30 mi/gal.
Daily VMT ~30 miles [42].

Derived as follows:

- Assume gas station trip occurs in middle of daily VMT, i.e. at 15 mi.
- Minimum morning fuel level ~ 1.8 gal + 15 mi / 30 mi/gal ~ 2.3 gal
- Minimum morning range ~ 2.3 gal * 30 mi/gal ~ 70 mi.
- Assume that EV drivers in this high-EV 2050 behave similarly to car drivers in 2020, i.e. are comfortable leaving home for their average 30 miles of daily driving with 70 miles of range.
- Assume that in this future, with ~60% of cars = EVs, home chargers are widely available. And thus, that EV range anxiety is much smaller than today.
- Thus, our minimum morning SOC ~ 70 mi of range.

While our calculation follows empirically-based logic, it is far from a definitive prediction of EV driver behavior in 2050. It is plausible that the average EV's required minimum morning range could be significantly lower or higher than 70 miles, because (1) current driver behavior occurs without any payment and V2G payments could make drivers more comfortable with lower ranges, (2) having many more home chargers than home gas stations could make drivers more comfortable with lower ranges, and (3) having many fewer public chargers than public gas stations could make drivers demand higher ranges.

S2. General Supplementary Results

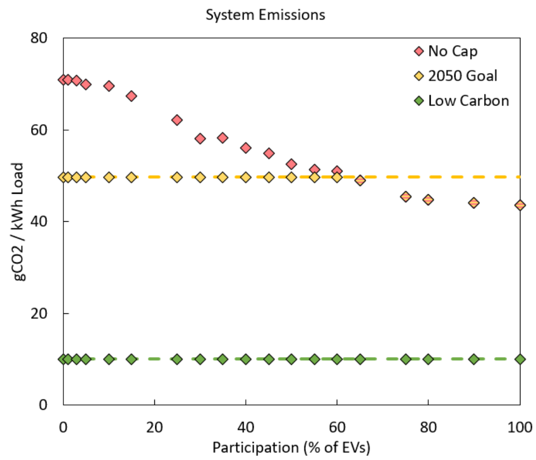

Figure S3: System emissions as a function of V2G participation rate under different emissions constraints. The 2050 Goal and Low Carbon emissions constraints correspond to caps of 50 gCO2/kWh load and 10 gCO2/kWh load, respectively. At high participation rates, the base case's (2050 goal) cost-optimal solution is no longer constrained by the emissions cap.

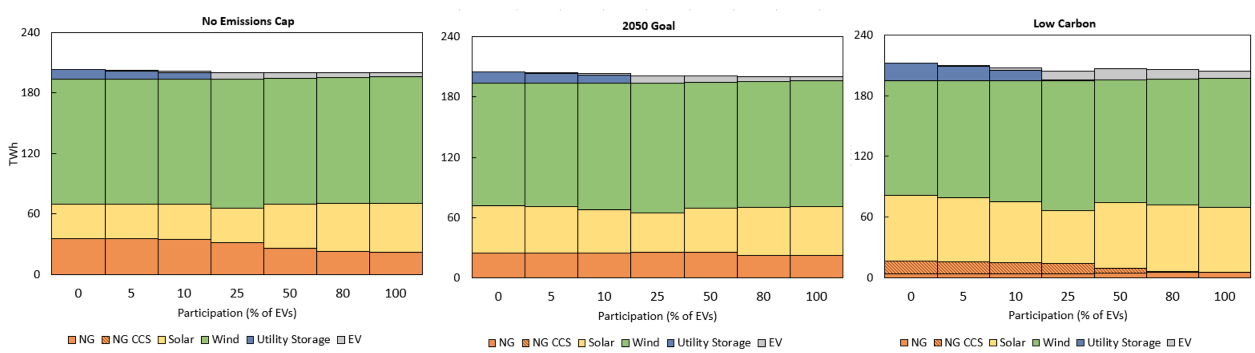

Figure S4: Power generation shares of technologies as a function of V2G participation rate and emissions constraints. The 2050 Goal and Low Carbon emissions constraints correspond to caps of 50 gCO2/kWh load and 10 gCO2/kWh load, respectively.

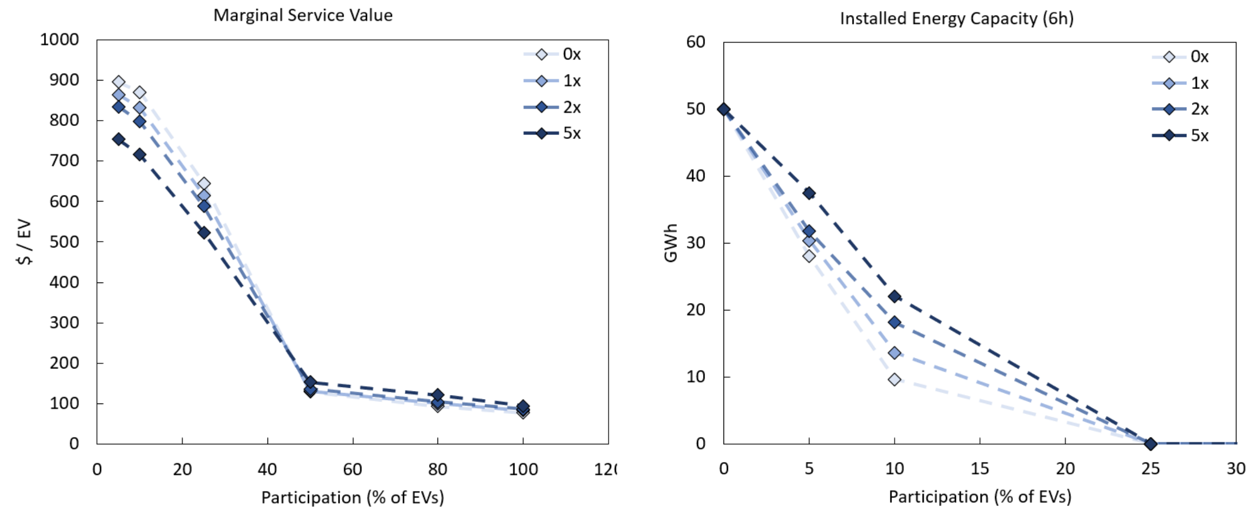

Figure S5: Sensitivity analysis EV battery degradation VOM relative to base case (1x), 9.5 2019$/MWh. As anticipated, the higher cost (or penalty) associated with increased V2G power injection/cycling decreases marginal value and slows the displacement of storage, but not by a prohibitive amount.

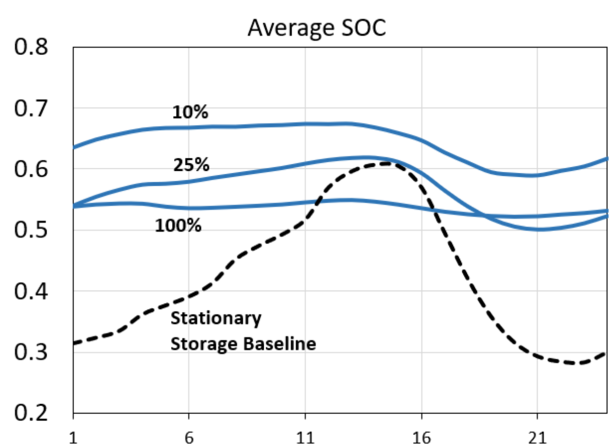

Figure S6: Day-averaged state of charge profiles for V2G aggregate at different participation levels, compared against that of stationary storage in the 2050 emissions base case.

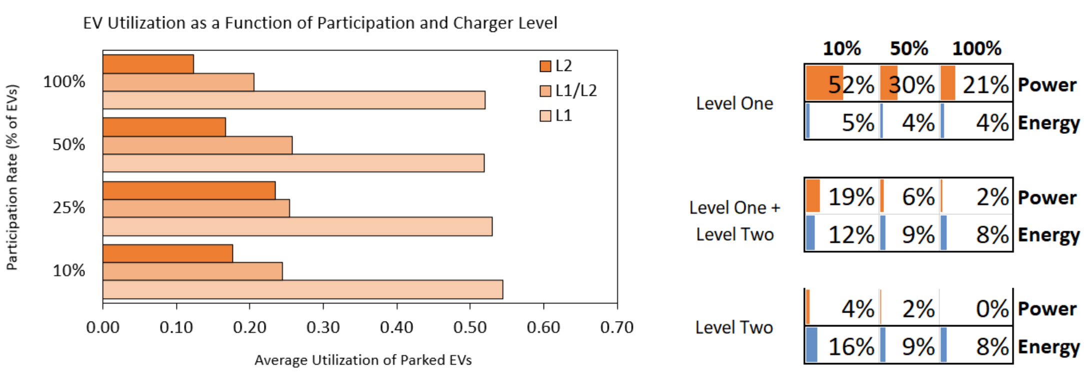

Figure S7: Binding Constraints of V2G services at different charger levels and participation rates. EV power capacity utilization as a function of participation and charger level **(left)** and breakdown of fraction of hours V2G is constrained (within 5% of binding constraint) by power or energy limitations at different participation rates **(right)**.

Table S5. Key V2G Utilization Statistics Under Different Participation Rates and Scenarios

Baseline Participation	**5%**	**10%**	**15%**	**25%**	**50%**	**75%**	**90%**	**100%**
% of hours injecting to grid	6.7%	9.0%	12.6%	21.1%	18.8%	16.4%	13.4%	12.4%
Charge (TWh)	2.80	6.05	9.45	17.81	26.51	35.02	39.99	43.25
Power (TWh)	0.73	1.84	3.09	6.89	6.05	5.05	4.33	3.79
% of Charge Returned to Grid	26.2%	30.5%	32.7%	38.7%	22.8%	14.4%	10.8%	8.8%
Home Only Participation	**5%**	**10%**	**15%**	**25%**	**50%**	**75%**	**90%**	**100%**
% of hours injecting to grid	7.2%	8.8%	13.5%	20.9%	18.8%	15.4%	13.4%	12.4%
Charge (TWh)	2.88	5.99	9.31	17.71	26.50	35.02	39.99	43.25
Power (TWh)	0.80	1.80	2.97	6.81	6.05	5.05	4.33	3.79
% of Charge Returned to Grid	27.8%	30.0%	31.9%	38.5%	22.8%	14.4%	10.8%	8.8%
Work Only Participation	**5%**	**10%**	**15%**	**25%**	**50%**	**75%**	**90%**	**100%**
% of hours injecting to grid	15.2%	17.8%	15.3%	10.8%	7.8%	6.7%	5.5%	5.8%
Charge (TWh)	2.44	4.32	6.36	10.35	20.32	30.25	36.01	40.15
Power (TWh)	0.42	0.38	0.46	0.56	0.79	0.98	0.94	1.16
% of Charge Returned to Grid	17.4%	8.8%	7.3%	5.4%	3.9%	3.3%	2.6%	2.9%

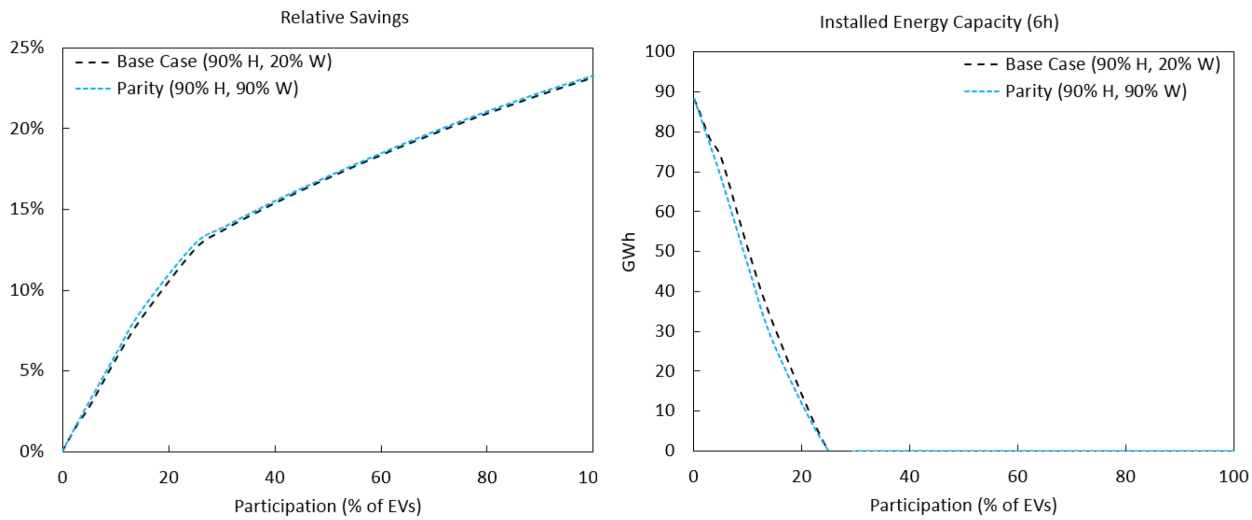

Figure S8: Sensitivity of net savings (left) and installed stationary storage energy capacity (right) as a function of EV fleet participation rate and V2G access level. All cases assume a 100% Level 2 charger share. The base case assumes 90% and 20% home (H) and workplace (W) charger availability, respectively. "Parity" indicates a 90% charger accessibility for both home and workplace charging, with all other elements identical to the base case.

S3. Vehicle-to-Building Supplementary Results

We also formulate a case to evaluate Vehicle-to-Building technology, in which vehicles only serve local loads and not the grid. This is because significant shares of stationary charging infrastructure are anticipated to be located at residential and commercial real-estate, and we are curious to probe bidirectional charging impact in cases where only demand response and injection are available (ancillary service capabilities will require specialized equipment for each vehicle as well as overcoming regulatory challenges). Serving the spatial load profiles (Figure 1), we again assume that adequate distribution infrastructure is installed within the region and do not model line losses. As for the spatial distribution of EVs, participating EVs are represented as a single aggregate within each node and link the SOCs of EVs parked at homes and workplaces to reflect mobility between locations.

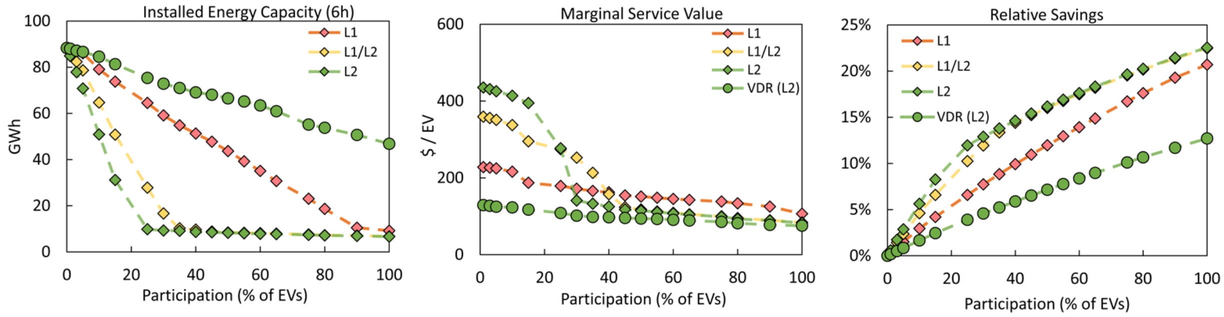

Figure S9: installed stationary storage energy capacity (left), marginal vehicle service value (center), V2B net savings (right) as a function of EV fleet participation rate and charging infrastructure. L1, L1/L2, and L2 indicate 100:0, 50:50,and 0:100 Level 1/Level 2 charger shares, respectively. VDR (L2) indicates demand response only with all Level 2 charging.

Figure S9 shows V2B net savings (left), marginal vehicle service value (center), and installed stationary storage energy capacity (right) as a function of EV fleet participation rate and charging infrastructure. In the base V2B scenario (100% Level 2 chargers), despite the reductions in available power capacities and load accessibility and no ancillary servicing, V2B still realizes net savings and storage displacements exceeding 20% and 90%, respectively (Figure 10). As V2B participation increases, the remaining stationary storage increasingly derives value via the ancillary service markets, satisfying as much as half of regulation and reserve requirements.

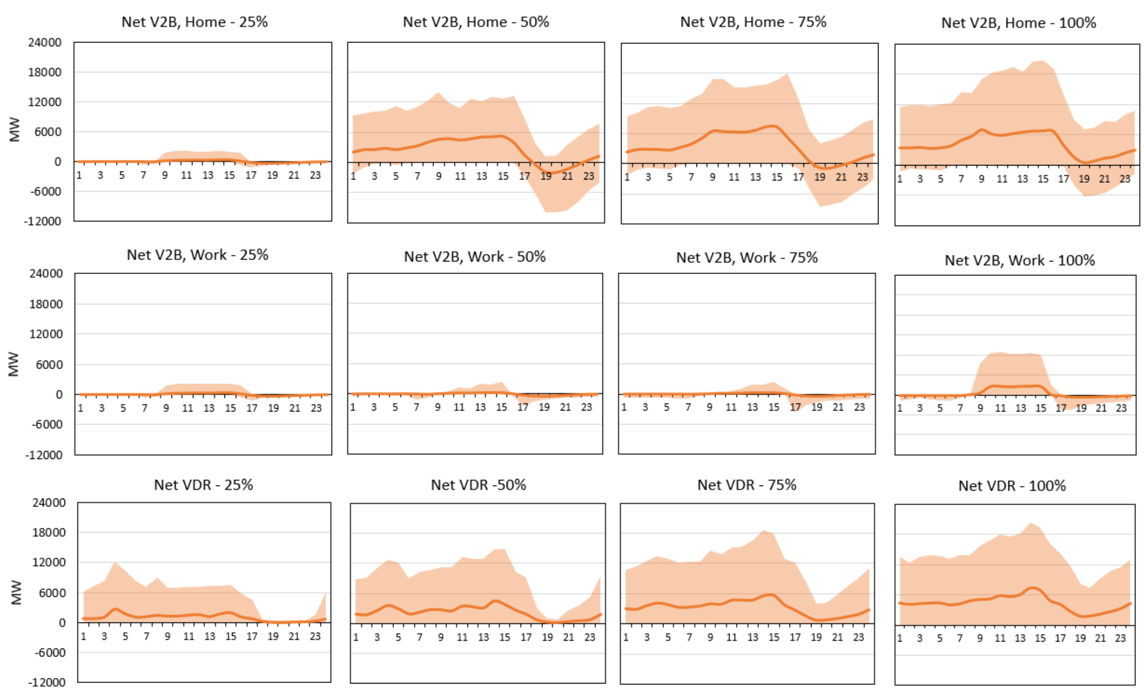

Figure S10: Daily averaged net service profiles of the participating V2B EV aggregate at residential (top row) and commercial (middle row) areas, as well as all areas in the VDR-only case. Positive values indicate net charging and negative values indicate net injection to the grid. The shaded region is the middle 90th percentile of service values. When restricted to VDR only, similar daytime charging patterns are observed, but with less overall energy throughput since the charged energy only serves EV travel demand.

In Figure S10, we examine utilization patterns to understand optimal V2B dispatch as a function of location and service type. In residential areas, the vehicle aggregate strictly charges during midday hours, coinciding with solar generation profiles and net charging on the order of 10 GW at high participation levels. Evening charging is not entirely eliminated, however, due to daytime charging constraints (gridded capacity peaks in the evenings) and variation among daily load profiles. Power is injected back to the grid when base and uncontrolled EV loads peak in the evening. EVs in commercial areas offer less injection to the local load. Peak commercial demand, on average, coincides with midday VRE solar generation and there is less connected EV capacity in the evenings. Yet, midday commercial charging is still valuable because it indirectly shapes evening residential loads. Vehicle mobility effectively shuttles stored energy between locations and results indicate that it is most valuable to shave evening peaks, if at all. Restricted to VDR alone, similar daytime charging patterns are observed, but with less overall energy throughput since the charged energy only serves EV travel demand.

Given the relatively small amount of V2B power serviced to commercial loads (Table S6), we assess the impact of confining V2B infrastructure to only residential areas while still allowing charging/demand response at commercial load centers. We observe that given sufficient residential charging infrastructure, there is minimal impact on stationary storage displacement and overall system value, which suggests that the system is not necessarily constrained against maximum natural gas capacity (i.e. can utilize available wind and stationary storage) when servicing commercial loads with V2B. Only when residential charge capacity is significantly lower are the effects significant. Of course, much of this is a function of relatively flat demand profiles and little charge capacity to begin with, so we anticipate the infrastructure implications to change in cases of high work charging access and/or if commercial sectors exhibit more regular load peaks with increased electrification.

Table S6. Key V2B Utilization Statistics at Different Participation Rates.

Participation	**10%**	**15%**	**25%**	**50%**	**75%**	**100%**
% of Charge Returned to Grid	**32.8%**	**35.2%**	**37.6%**	**21.3%**	**13.4%**	**8.3%**
Charge (TWh)	6.18	9.72	17.01	25.34	33.80	42.08
Power (TWh)	2.02	3.42	6.39	5.40	4.52	3.49
Share Injected to Residential	**92.2%**	**91.0%**	**88.2%**	**79.1%**	**69.6%**	**61.8%**
% of hours injecting to res	7.1%	10.2%	16.7%	13.3%	11.0%	8.1%
% of residential base served	2.0%	3.4%	6.3%	5.1%	4.1%	3.1%
% of total base load served	1.2%	1.9%	3.6%	2.9%	2.2%	1.6%
Share Injected to Commercial	**7.8%**	**9.0%**	**11.8%**	**20.9%**	**30.4%**	**38.2%**
% of hours injecting to com	10.5%	12.2%	17.8%	14.7%	12.2%	10.1%
% of commercial base served	0.2%	0.5%	1.1%	1.7%	2.1%	2.1%
% of total base load served	0.1%	0.2%	0.5%	0.8%	1.0%	1.0%

Table S6 also shows that power injection value for V2B is primarily derived from shaving residential loads, where evening load peaks are most prevalent and are complementary to high daytime VRE generation. At low participation rates unsupervised charging dominates evening residential loads while commercial loads typically fluctuate less hour-to-hour and have virtually zero evening EV charging. The power service share becomes more equitable at higher participation when charging demand is distributed. For these cases, during hours when not operating against a marginal increase in natural gas dispatch, the values of V2B servicing a base load in different zones are equal from the system operator's perspective. Likewise, we also demonstrate that commercial area V2B capabilities (as opposed to VDR) have minimal impact on stationary storage displacement and overall system value (breakdown provided in Figure S11). Thus, one should closely evaluate the ROI of bidirectional infrastructure in these areas. Note that like the main cases, this result is a function of case study assumptions and parameters, with relatively flat commercial load profiles and low charger access to begin with (20% access). We anticipate the infrastructure implications to change in cases of high work charging access and/or if commercial sectors exhibit more dramatic load peaks with increased electrification

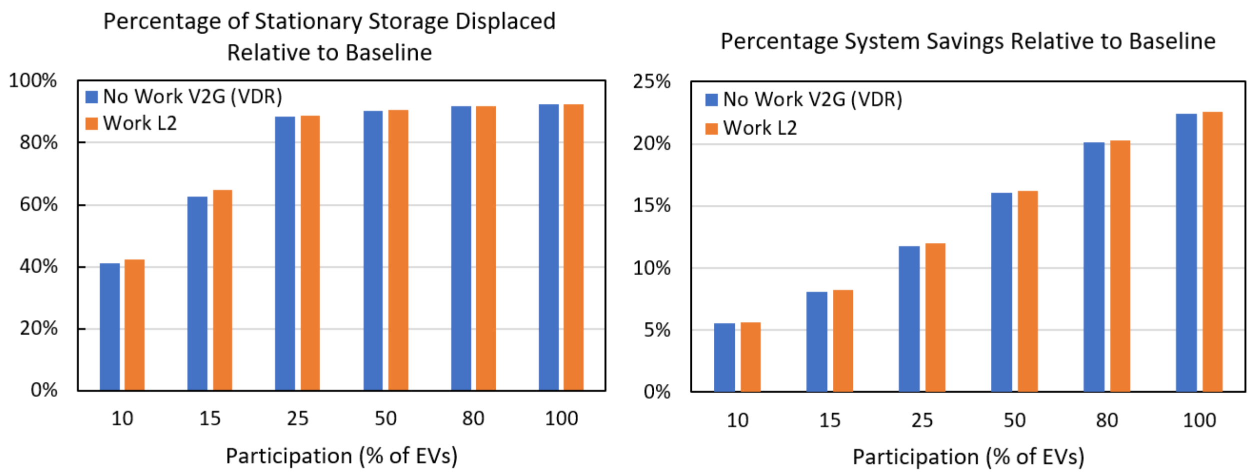

Figure S11: Total storage displacement (left) and overall system value savings (right) as a function of residential and workplace charging infrastructure across different participation rates.

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