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Negative EV Emissions

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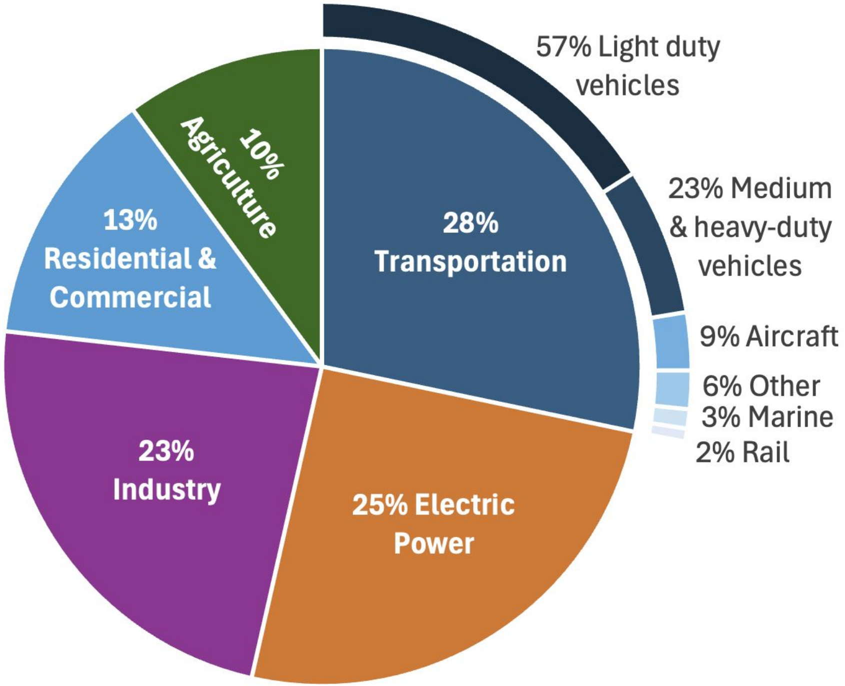
Transportation is the largest source of U.S. GHGs

Most transportation emissions are from cars & light trucks

Transportation and electric power together produce most U.S. GHG emissions



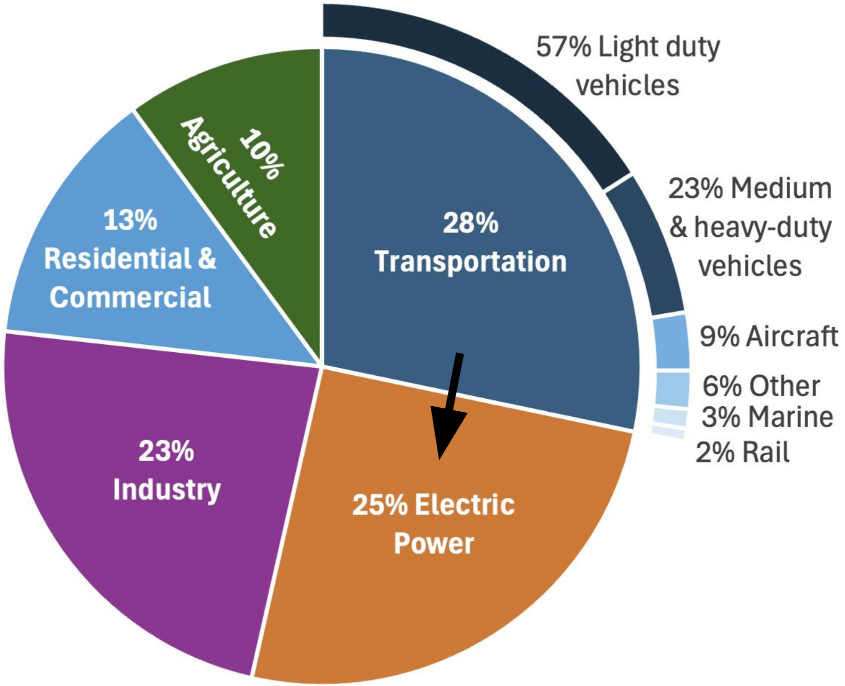
Source: US EPA 2022 US GHG emissions by sector

EVs link the two largest sources

Electrification is the most promising for light-duty vehicles (technologically & economically)

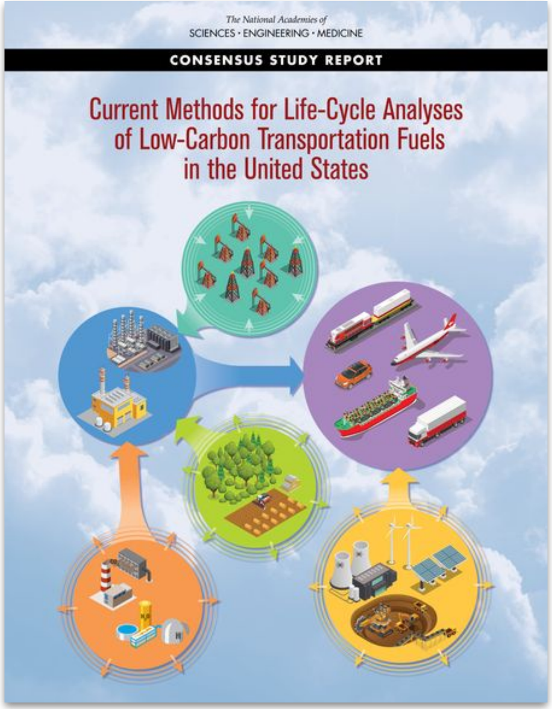
When we electrify vehicles, we reduce tailpipe emissions in the transportation sector but increase demand for electric power

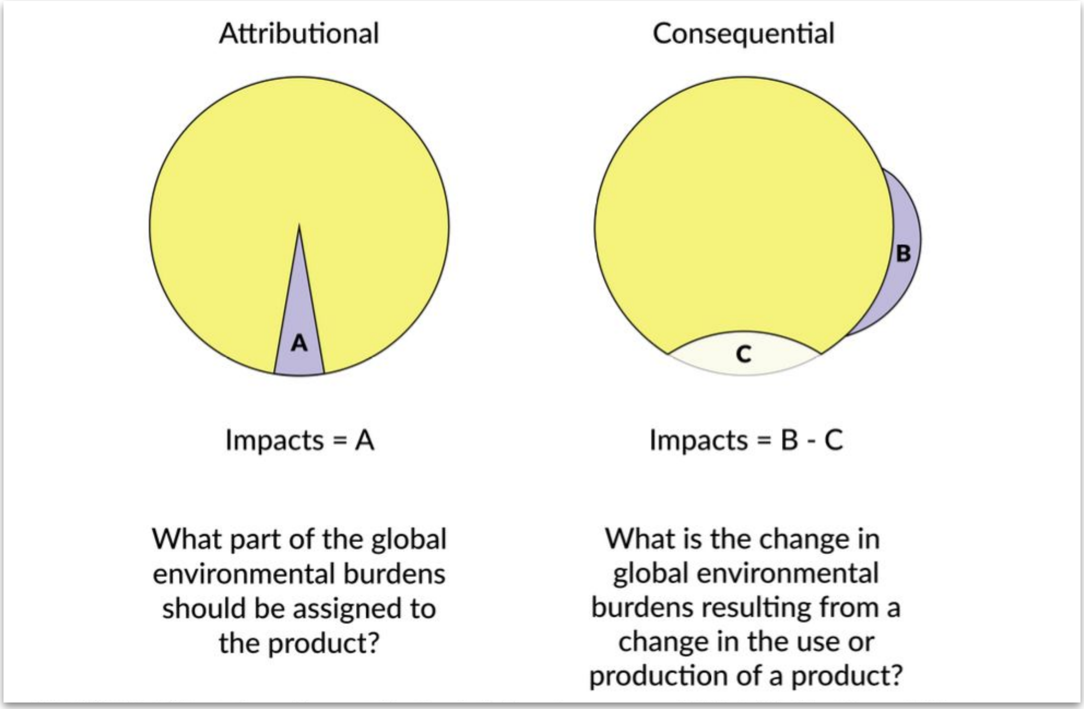
We can assess the net effect with **life cycle assessment** (LCA)



Source: US EPA 2022 US GHG emissions by sector

Two distinct kinds of LCA ask different questions





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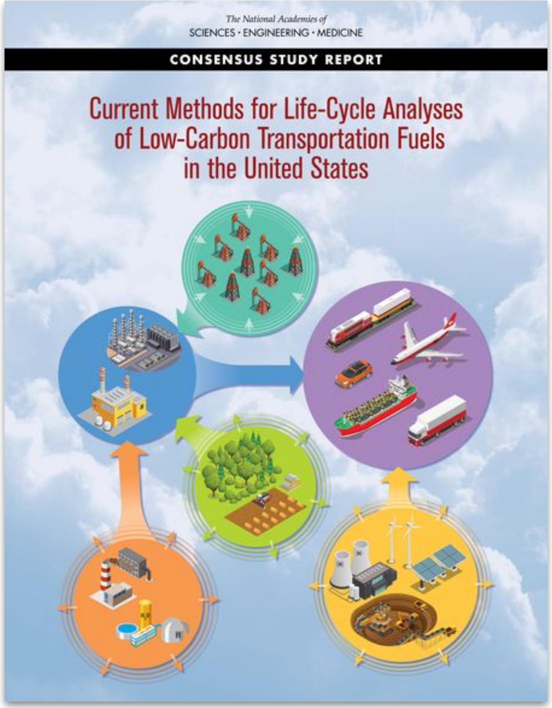
Policy assessment needs consequential LCA



Consequential LCA assesses how a change (e.g.: vehicle or policy adoption) will affect emissions

Recommendation 2-2: When a decision-maker wishes to understand the consequences of a proposed decision or action on net GHG emissions, CLCA is appropriate. Modelers should provide transparency, justification, and sensitivity or robustness analysis for modeling choices for the scenarios modeled with and without the proposed decision or action.

NASEM report recommends using consequential LCA to assess policy impact

Recommendation 3-2: Public policy design based on LCA should ensure through regulatory impact assessment that, at a minimum, the consequential life-cycle impact of the proposed policy is likely to reduce net GHG emissions and increase net benefits to society. Regulatory impact assessments should consider changes in production and use of multiple fuel types (e.g., gasoline, electricity, biofuels, hydrogen).

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Literature & terminology

		Emissions Estimates Based On		
		No change (average)	**Marginal change** (via regression)	**Non-marginal change** (via simulation)
Attributional	**Average** emission rates	Samaras and Meisterling (2008) Michalek et al (2011) Manjuath and Gross (2017) Wong et al (2020)	Incompatible	Incompatible
Consequential	**Short run** endogenous operations exogenous infrastructure	Incompatible	Samaras and Meisterling (2008) Graff Zivin et al (2014) Tamayao et al (2015) Yuksel et al. (2016) Holland et al (2016, 2020, 2022) Tong and Azevedo (2020) Singh et al (2024)	Weis et al (2016) Sheppard et al (2021) Bruchon et al (2024)
	Long run endogenous operations endogenous infrastructure	Incompatible	-	Weis et al (2013) Melaina et al (2016) Gagnon and Cole (2022) Holland et al (2022) Jenn (2023) Hanig et al (2025) Chen et al (2025)

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Most econ studies

Estimating marginal effects

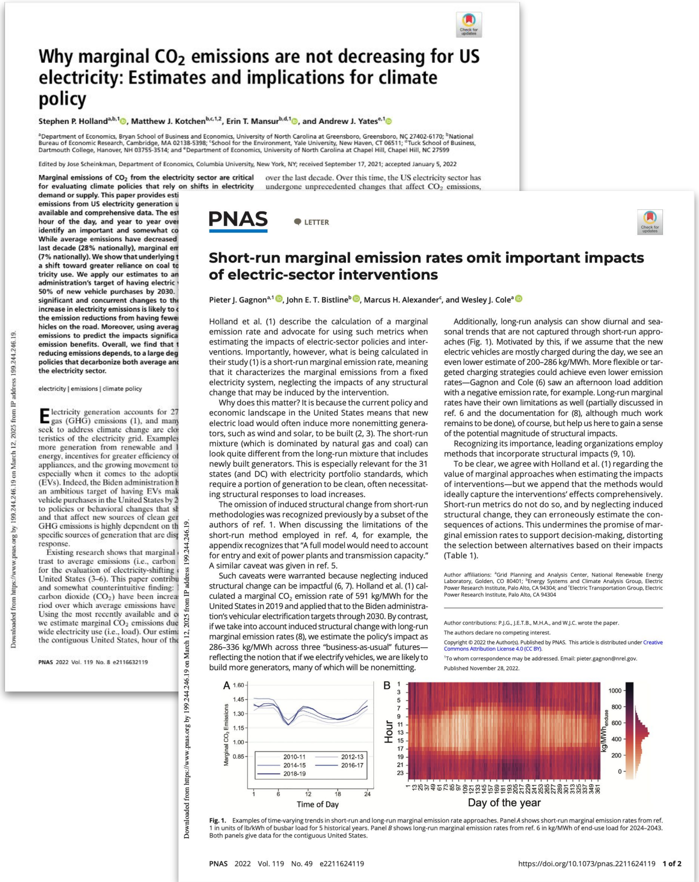
Holland et al. (2022) use short-run marginal emission factors and find that marginal rates are not falling even as the grid cleans up

They apply these marginal rates to estimate the effect of electrifying 50% of the vehicle fleet

Gagnon et al. (2022) critique that large changes will induce long run infrastructure investment decisions, so long run analysis is needed, resulting in much lower marginal rates

Conflation of three issues

1) Marginal vs. non-marginal changes
2) Period over which the change takes place
3) Short run vs. long run effects


Why marginal CO_2 emissions are not decreasing for US electricity: Estimates and implications for climate policy

Stephen P. Holland[a,b,1], Matthew J. Kotchen[b,c,1,2], Erin T. Mansur[b,d,1], and Andrew J. Yates[e,1]

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PNAS LETTER

Short-run marginal emission rates omit important impacts of electric-sector interventions

Pieter J. Gagnon[a,1], John E. T. Bistline[b], Marcus H. Alexander[c], and Wesley J. Cole[a]

Holland et al. (1) describe the calculation of a marginal emission rate and advocate for using such metrics when estimating the impacts of electric-sector policies and interventions. Importantly, however, what is being calculated in their study (1) is a short-run marginal emission rate, meaning that it characterizes the marginal emissions from a fixed electricity system, neglecting the impacts of any structural change that may be induced by the intervention.

Why does this matter? It is because the current policy and economic landscape in the United States means that new electric load would often induce more nonemitting generators, such as wind and solar, to be built (2, 3). The short-run mixture (which is dominated by natural gas and coal) can look quite different from the long-run mixture that includes newly built generators. This is especially relevant for the 31 states (and DC) with electricity portfolio standards, which require a portion of generation to be clean, often necessitating structural responses to load increases.

The omission of induced structural change from short-run methodologies was recognized previously by a subset of the authors of ref. 1. When discussing the limitations of the short-run method employed in ref. 4, for example, the appendix recognizes that "A full model would need to account for entry and exit of power plants and transmission capacity." A similar caveat was given in ref. 5.

Such caveats were warranted because neglecting induced structural change can be impactful (6, 7). Holland et al. (1) calculated a marginal CO_2 emission rate of 591 kg/MWh for the United States in 2019 and applied that to the Biden administration's vehicular electrification targets through 2030. By contrast, if we take into account induced structural change with long-run marginal emission rates (8), we estimate the policy's impact as 286–336 kg/MWh across three "business-as-usual" futures—reflecting the notion that if we electrify vehicles, we are likely to build more generators, many of which will be nonemitting.

Additionally, long-run analysis can show diurnal and seasonal trends that are not captured through short-run approaches (Fig. 1). Motivated by this, if we assume that the new electric vehicles are mostly charged during the day, we see an even lower estimate of 200–286 kg/MWh. More flexible or targeted charging strategies could achieve even lower emission rates—Gagnon and Cole (6) saw an afternoon load addition with a negative emission rate, for example. Long-run marginal rates have their own limitations as well (partially discussed in ref. 6 and the documentation for (8), although much work remains to be done), of course, but help us here to gain a sense of the potential magnitude of structural impacts.

Recognizing its importance, leading organizations employ methods that incorporate structural impacts (9, 10).

To be clear, we agree with Holland et al. (1) regarding the value of marginal approaches when estimating the impacts of interventions—but we append that the methods would ideally capture the interventions' effects comprehensively. Short-run metrics do not do so, and by neglecting induced structural change, they can erroneously estimate the consequences of actions. This undermines the promise of marginal emission rates to support decision-making, distorting the selection between alternatives based on their impacts (Table 1).

Fig. 1. Examples of time-varying trends in short-run and long-run marginal emission rate approaches. Panel A shows short-run marginal emission rates from ref. 1 in units of lb/kWh of busbar load for 5 historical years. Panel B shows long-run marginal emission rates from ref. 6 in kg/MWh of end-use load for 2024–2043. Both panels give data for the contiguous United States.

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	Long run endogenous operations endogenous infrastructure	Incompatible	-	Weis et al (2013) Melaina et al (2016) Gagnon and Cole (2022) Holland et al (2022) Jenn (2023) Hanig et al (2025) Chen et al (2025)

To understand long run effects of large changes, we need work here

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Two studies in R&R on long-run non-marginal effects of EV charging on power systems

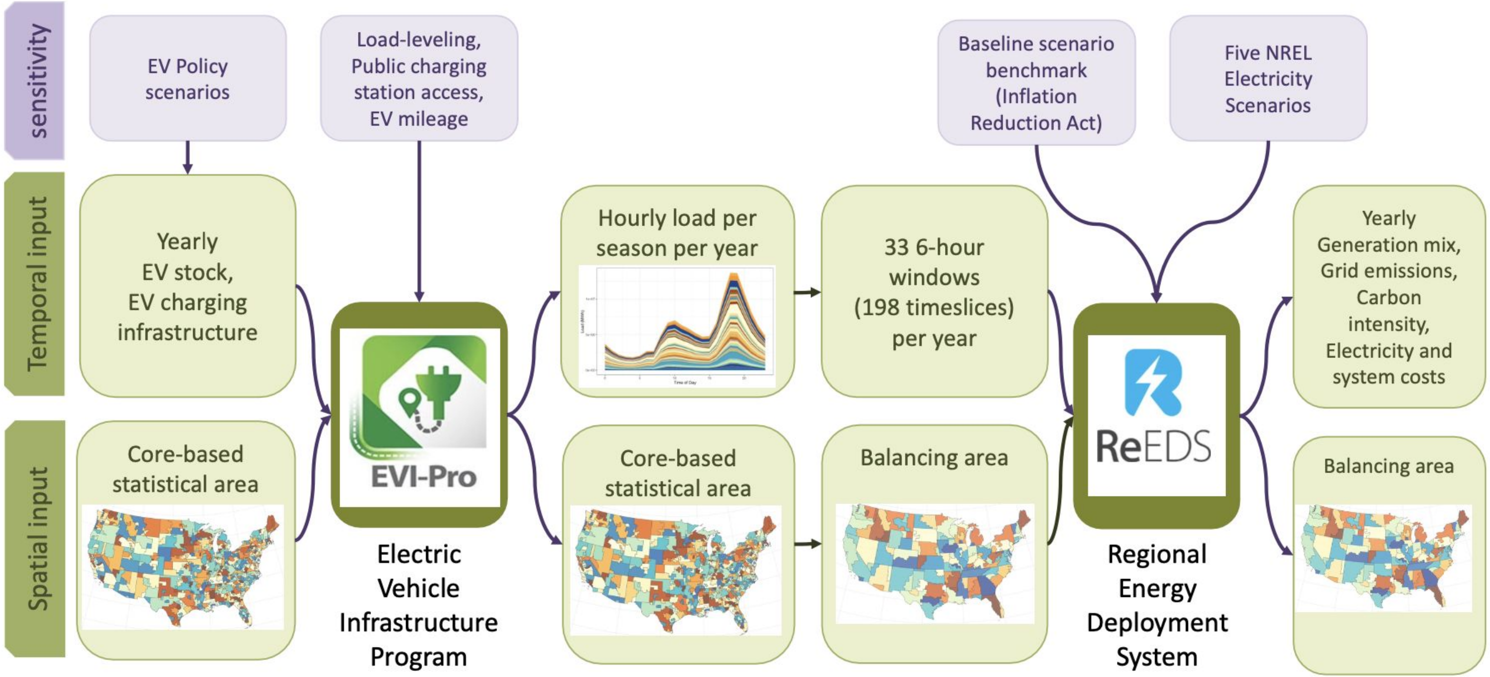
1. **Exogeneous EV load timing** (National)
   Hanig, L., C. Harper, D. Nock and J. Michalek (2025) "Driving the grid forward: How electric vehicle adoption shapes power system infrastructure and emissions," in review.

2. **Endogenous EV load timing** (PJM)
   Chen, J., M. Craig, J. Michalek, M. Bruchon and P. Vaishnav (2025) "Negative electric vehicle emissions: Vehicle-to-grid can incentivize enough wind and solar investment to reverse EV charging emissions," in review.

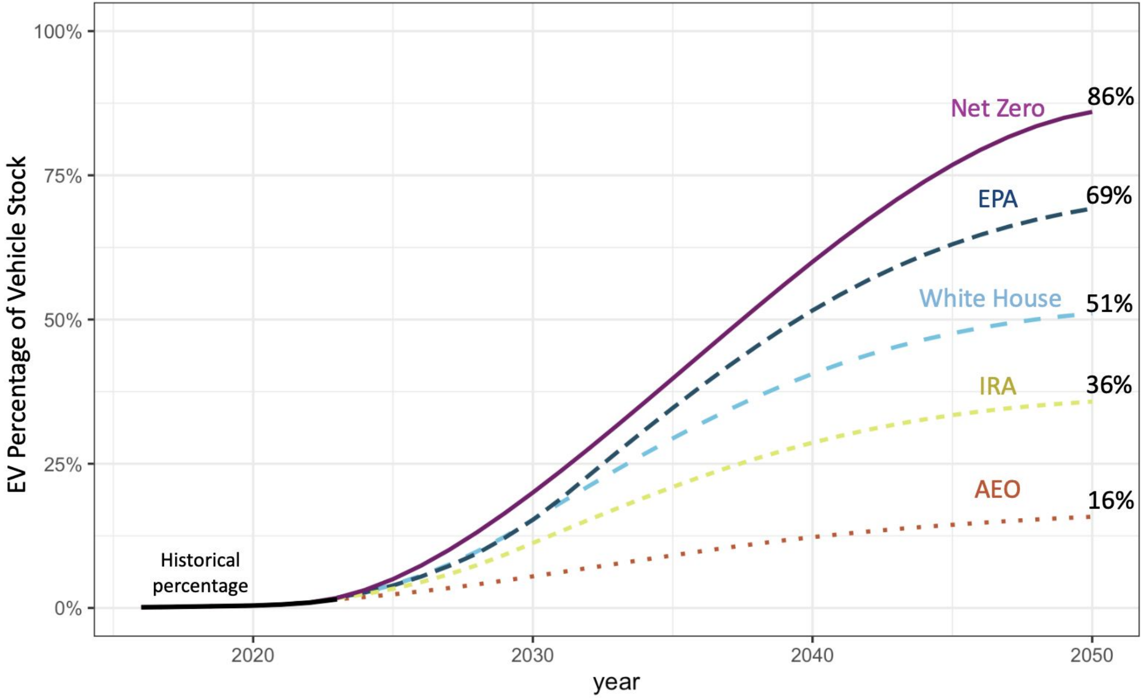
Exogenous EV Load Timing

Hanig, L., C. Harper, D. Nock and J. Michalek (2025) "Driving the grid forward: How electric vehicle adoption shapes power system infrastructure and emissions," in review.

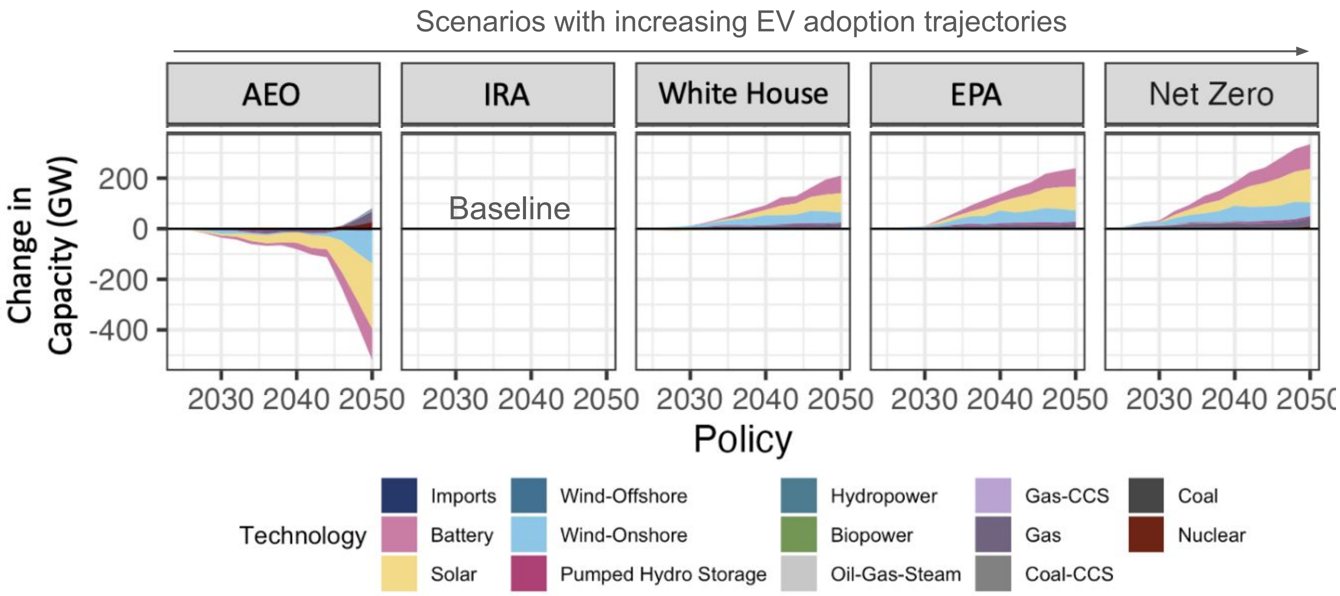
Modeling assumptions



EV adoption scenarios



↑EV adoption : ↑wind, solar, gas & storage capacity



But…

Load timing matters, and flexible loads could have substantial implications

Endogenous (Flexible) EV Load Timing

Chen, J., M. Craig, J. Michalek, M. Bruchon and P. Vaishnaiv (2025) "Negative electric vehicle emissions: Vehicle-to-grid can incentivize enough wind and solar investment to reverse EV charging emissions," in review.

EVs have substantial potential as flexible load

Uncontrolled charging: The EV owner begins charging at full power following the last trip of the day until the vehicle is fully charged

Controlled charging: The EV owner allows the utility to decide charge timing following the last trip of the day, so long as it is fully charged prior to the first trip the following day. Charge timing is optimized to minimize operational cost

Vehicle to grid (V2G): Identical to controlled charging except that charging can be negative (sold back to the grid or displacing home load)

PJM case study

To understand the effects of flexible load on power system outcomes, we zoom in to a detailed case study with the resolution and tractability to model the effects of flexible load

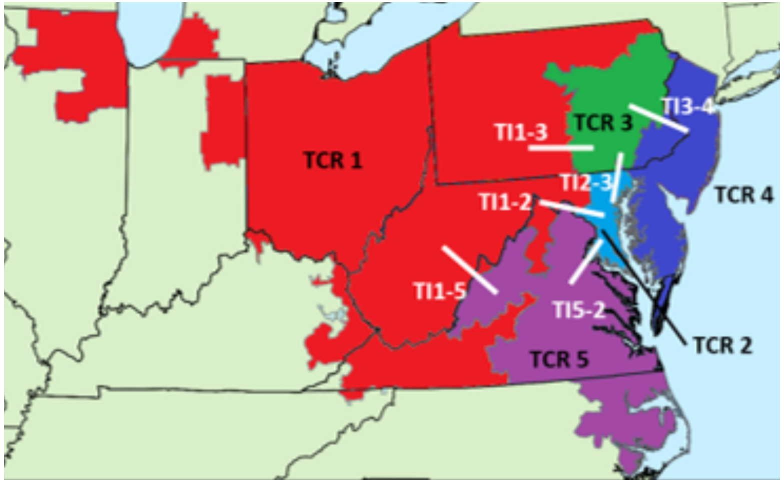
PJM is the largest RTO in the US,
serving 65M people in 13 states + DC

Grid mix similar to North America as a whole

5 transmission-constrained subregions

NHTS data on vehicle travel patterns

Weighted representative sample of vehicles selected to optimally match fleet statistics



Optimization model

Minimize operation costs (generation, startup, and generator, storage and vehicle reserves)

$$\text{Minimize } Z = \sum_{t \in \mathcal{T}} \sum_{i \in I_r} \left(C_i^{\text{VARGEN}} p_{i,t}^{\text{GEN}} + s_{i,t}^{\text{STARTUP}} + C_i^{\text{GENRES}} a_{i,t}^{\text{GEN}} \right) + \sum_{t \in \mathcal{T}} \sum_{k \in \mathcal{K}} C_k^{\text{STR}} a_{k,t}^{\text{STR}} + \sum_{t \in \mathcal{T}} \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} C^{\text{VEH}} a_{v,r,t}^{\text{VEH}}$$

subject to

- Reserve constraints
- Startup and shutdown constraints
- Ramp rate constraints
- Uptime and downtime constraints

Subject to

Generator constraints:

$a_{i,t}^{\text{GEN}} \leq 1/12 * \left(p_{i,t-1} + R_i u_{i,t} + p_i^{\text{GENMIN}}(u_{i,t} - u_{i,t-1}) - p_{i,t}\right) - a_{i,t}^{\text{GENSP}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator regulation reserve offer constraints	(1)
$a_{i,t}^{\text{GEN}} \leq 1/12 * \left(p_i^{\text{GENMAX}} - p_{i,t}\right) - a_{i,t}^{\text{GENSP}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator regulation reserve offer constraints	(2)
$a_{i,t}^{\text{GEN}} \leq 1/12 * \left(p_i^{\text{GENMAX}} u_{i,t}\right) - a_{i,t}^{\text{GENSP}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator regulation reserve offer constraints	(3)
$a_{i,t}^{\text{GENSP}} \leq 1/6 * \left(p_{i,t-1} + R_i u_{i,t} + p_i^{\text{GENMIN}}(u_{i,t} - u_{i,t-1}) - p_{i,t}\right) - a_{i,t}^{\text{GENSP}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator spinning reserve offer constraints	(4)
$a_{i,t}^{\text{GENSP}} \leq 1/6 * \left(p_i^{\text{GENMAX}} - p_{i,t}\right) - a_{i,t}^{\text{GEN}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator spinning reserve offer constraints	(5)
$a_{i,t}^{\text{GENSP}} \leq 1/6 * \left(p_i^{\text{GENMAX}} u_{i,t}\right) - a_{i,t}^{\text{GEN}}$	$\forall i \in \mathcal{I} \neq 1, \forall t \in \mathcal{T}$	Generator spinning reserve offer constraints	(6)
$s_{i,t}^{\text{STARTUP}} \geq \left(u_{i,t} - u_{i,t-1}\right) C_i^{\text{STARTGEN}}$	$\forall i \in \mathcal{I}, \forall t \in \mathcal{T}$	Slack variable reflects startup decision	(7)
$s_{i,t}^{\text{STARTUP}} \geq 0$	$\forall i \in \mathcal{I}, \forall t \in \mathcal{T}$	Slack variable is nonnegative	(8)
$p_i^{\text{GENMIN}} u_{i,t} \leq p_{i,t} \leq p_i^{\text{GENMAX}} u_{i,t}$	$\forall i \in \mathcal{I}, \forall t \in \mathcal{T}$	Min and max output of online generators	(9)
$p_{i,t}^{\text{GEN}} \leq p_{i,t-1}^{\text{GEN}} + R_i u_{i,t-1} + p_i^{\text{GENMIN}} \left(u_{i,t} - u_{i,t-1}\right)$	$\forall i \in \mathcal{I}, \forall t \in \mathcal{T}$	Ramp rate limit	(10)
$p_{i,t-1}^{\text{GEN}} \leq p_{i,t}^{\text{GEN}} + R_i u_{i,t} + p_i^{\text{GENMIN}} \left(u_{i,t-1} - u_{i,t}\right)$	$\forall i \in \mathcal{I}, \forall t \in \mathcal{T}$	Ramp rate limit	(11)
$\sum_{t=2}^{T_i^{\text{UPMIN}} - T_i^{\text{UPSTART}}} \left(1 - u_{i,t}\right) = 0$	$\forall i \in \mathcal{I}$	Minimum uptime (first timesteps)	(12)
$\sum_{t'=t}^{t+T_i^{\text{UPMIN}}-1} u_{i,t'} \geq T_i^{\text{UPMIN}} \left(u_{i,t} - u_{i,t-1}\right)$	$\forall i \in \mathcal{I}, \forall t : T_i^{\text{UPMIN}} - T_i^{\text{UPSTART}} + 1 \leq t \leq \lvert\mathcal{T}\rvert - T_i^{\text{UPMIN}} + 1$	Minimum uptime (middle timesteps)	(13)
$\sum_{t=t}^{T} u_{i,t'} \geq (T - t) \left(u_{i,t} - u_{i,t-1}\right)$	$\forall i \in \mathcal{I}, \forall t \in \lvert\mathcal{T}\rvert - T_i^{\text{UPMIN}} + 2 \ldots$	Minimum uptime (final timesteps)	(14)
$\sum_{t=2}^{T_i^{\text{DTMIN}} - T_i^{\text{DTSTART}}} u_{i,t} = 0$	$\forall i \in \mathcal{I}$	Minimum downtime (first timesteps)	(15)
$\sum_{t'=t}^{t+T_i^{\text{DTMIN}}-1} 1 - u_{i,t'} \geq T_i^{\text{DTMIN}} \left(u_{i,t-1} - u_{i,t}\right)$	$\forall i \in \mathcal{I}, \forall t : T_i^{\text{DTSTART}} + 1 \leq t \leq \lvert\mathcal{T}\rvert - T_i^{\text{DTSTART}} + 1$	Minimum downtime (middle timesteps)	(16)
$\sum_{t'=t}^{T} 1 - u_{i,t'} \geq (\lvert\mathcal{T}\rvert - t) \left(u_{i,t-1} - u_{i,t}\right)$	$\forall i \in \mathcal{I}, \forall t : \lvert\mathcal{T}\rvert - T_i^{\text{DTSTART}} + 2 \leq t \leq \lvert\mathcal{T}\rvert$	Minimum downtime (final timesteps)	(17)

subject to

- Demand-supply constraints
- Transmission constraints
- Wind and solar availability constraints
- Storage energy and power constraints
- PEV battery SOC constraints
- PEV fully charged constraint for first trip of the day

System constraints:

$$\begin{aligned} P_{r,t} = & \sum_{i \in \mathcal{I}_r} p_{i,t}^{\mathrm{GEN}} + \sum_{k \in \mathcal{K}_r} p_{i,t}^{\mathrm{STRD}} - \sum_{k \in \mathcal{K}_r} p_{i,t}^{\mathrm{STRC}} - \sum_{r' \in \mathcal{R} \neq r} (p_{r',r,t}^{\mathrm{RR}}) \\ & + \sum_{r' \in \mathcal{R} \neq r} (p_{r,r',t}^{\mathrm{RR}} \eta^{\mathrm{TR}}) + p_{r,t}^{\mathrm{SGEN}} + p_{r,t}^{\mathrm{WGEN}} - \sum_{v \in \mathcal{V}_r} p_{v,r,t}^{\mathrm{VR}} + \sum_{v \in \mathcal{V}_r} p_{v,r,t}^{\mathrm{DR}} \end{aligned} \quad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad \text{Demand must equal supply} \tag{18}$$

$$- p_{r,r',t}^{\mathrm{RRMAX}} \le p_{r,r',t}^{\mathrm{RR}} \le p_{r,r',t}^{\mathrm{RRMAX}} \quad \forall r \in \mathcal{R}, r' \in \mathcal{R} \neq r, t \in \mathcal{T} \quad \text{Inter-region power flow limits} \tag{19}$$

$$0 \le p_{r,t}^{\mathrm{SGEN}} \le p_{r,t}^{\mathrm{SGENMAX}} \quad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad \text{Regional solar PV output limits} \tag{20}$$

$$0 \le p_{r,t}^{\mathrm{WGEN}} \le p_{r,t}^{\mathrm{WGENMAX}} \quad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad \text{Regional wind generator output limits} \tag{21}$$

$$\phi^{SPIN} * P_{r,t} = \sum_{i \in \mathcal{I}_r} a_{i,t}^{\mathrm{GENSP}} + \sum_{k \in \mathcal{K}_r} a_{k,t}^{\mathrm{STRSP}} + \sum_{v \in \mathcal{V}_r} a_{v,r,t}^{\mathrm{VRSP}} \quad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad \text{Regional spinning reserve requirement must be met} \tag{22}$$

$$\phi^{REG} * P_{r,t} + \phi^{\mathrm{WIND}} * p_{r,t}^{\mathrm{WGEN}} + \phi^{\mathrm{SOL}} * p^{\mathrm{S}} = \sum_{i \in \mathcal{I}_r} a_{i,t}^{\mathrm{GEN}} + \sum_{k \in \mathcal{K}_r} a_{k,t}^{\mathrm{STR}} + \sum_{v \in \mathcal{V}_r} a_{v,r,t}^{\mathrm{VR}} \quad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad \text{Regional regulation reserve requirement must be met} \tag{23}$$

Storage constraints:

$$c_{k,t+1}^{\mathrm{STR}} = c_{k,t}^{\mathrm{STR}} + p_{k,t}^{\mathrm{STRC}} \eta^{STR} - p_{k,t}^{\mathrm{STRD}} / \eta^{STR} \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad \text{Storage state of charge} \tag{24}$$

$$c_k^{\mathrm{STRMIN}} \le c_{k,t}^{\mathrm{STR}} \le c_k^{\mathrm{STRMAX}} \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad \text{Storage unit capacity} \tag{25}$$

$$0 \le p_{k,t}^{\mathrm{STRD}}, p_{k,t}^{\mathrm{STRC}} \le p_k^{\mathrm{STRMAX}} \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad \text{Max charge and discharge of storage units} \tag{26}$$

$$a_{k,t}^{\mathrm{STRSP}} \le p_k^{\mathrm{STRMAX}} - p_{k,t}^{\mathrm{STRD}} + p_{k,t}^{\mathrm{STRC}} - a_{k,t}^{\mathrm{STR}} \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad \text{Max regulation and spinning reserve offer of storage units} \tag{27}$$

$$a_{k,t}^{\mathrm{STRSP}} \le c_{k,t}^{\mathrm{STR}} - a_{k,t}^{\mathrm{STR}} \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad \text{Max regulation and spinning reserve offer of storage units} \tag{28}$$

PEV constraints:

$$c_{v,r,t+1}^{\mathrm{VEH}} = c_{v,r,t}^{\mathrm{CHG}} - p_{v,r,t}^{\mathrm{VR}} \eta_v^{\mathrm{VEH}} - N_{v,r} M_{v,t} \eta_v^{\mathrm{VEH}} \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad \text{PEV state of charge} \tag{29}$$

$$10\% N_{v,r} B_v \le c_{v,r,t}^{\mathrm{VEH}} \le 90\% N_{v,r} B_v \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad \text{PEV battery capacity} \tag{30}$$

$$c_{v,r,t}^{\mathrm{VEH}} = 90\% N_{v,r} B_v \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t = T_v^{\mathrm{DEPART}} \quad \text{PEVs fully charged when departing home} \tag{31}$$

$$c_{v,r,t+1}^{\mathrm{VEH}} = c_{v,r,t}^{\mathrm{CHG}} - p_{v,r,t}^{\mathrm{VR}} / \eta_v^{\mathrm{CHG}} + p_{v,r,t}^{\mathrm{DR}} * \eta_v^{\mathrm{CHG}} N_{v,r} M_{v,t} \eta_v^{\mathrm{VEH}} \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad \text{PEV state of charge} \tag{32}$$

$$0 \le p_{v,r,t}^{\mathrm{VR}}, p_{v,r,t}^{\mathrm{DR}} \le N_{v,r} A_{v,t} R_v^{\mathrm{MAXCHG}} \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad \text{PEV charge rate limit} \tag{33}$$

$$0 \le c_{v,r,t}^{\mathrm{VEH}} \le N_{v,r} B_v \quad \forall v \in \mathcal{V}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad \text{PEV battery capacity} \tag{34}$$

$$a_{v,r,t}^{\mathrm{VRSP}} \le N_{v,r} A_{v,t} R_v^{\mathrm{MAXCHG}} - p_{v,r,t}^{\mathrm{DR}} + p_{v,r,t}^{\mathrm{VR}} - a_{v,r,t}^{\mathrm{VR}} \quad \forall r \in \mathcal{R}, \forall v \in \mathcal{V} \quad \text{Max regulation and spinning reserve offer of vehicle fleets}$$

$$a_{v,r,t}^{\mathrm{VRSP}} \le c_{v,r,t}^{\mathrm{VEH}} - a_{v,r,t}^{\mathrm{VR}} \quad \forall r \in \mathcal{R}, \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{35}$$

(36)

Power system scenarios design

Exogenously determined with
EIA860, NEEDS, PJM Dataminer
excl. wind & solar PV output and installation

A range of power system configurations with different wind and solar penetration

Power system operation simulation

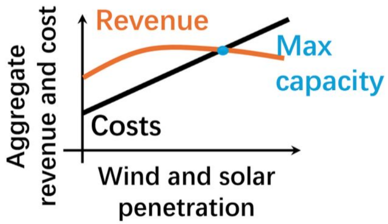
Unit commitment economic dispatch (UCED) model

Assessment of annual wind and solar revenues and costs

Annual revenues:
Calculated energy revenues with UCED prices, plus capacity market revenues

Annual costs:
Estimated with ATB annualized capital costs and O&M costs

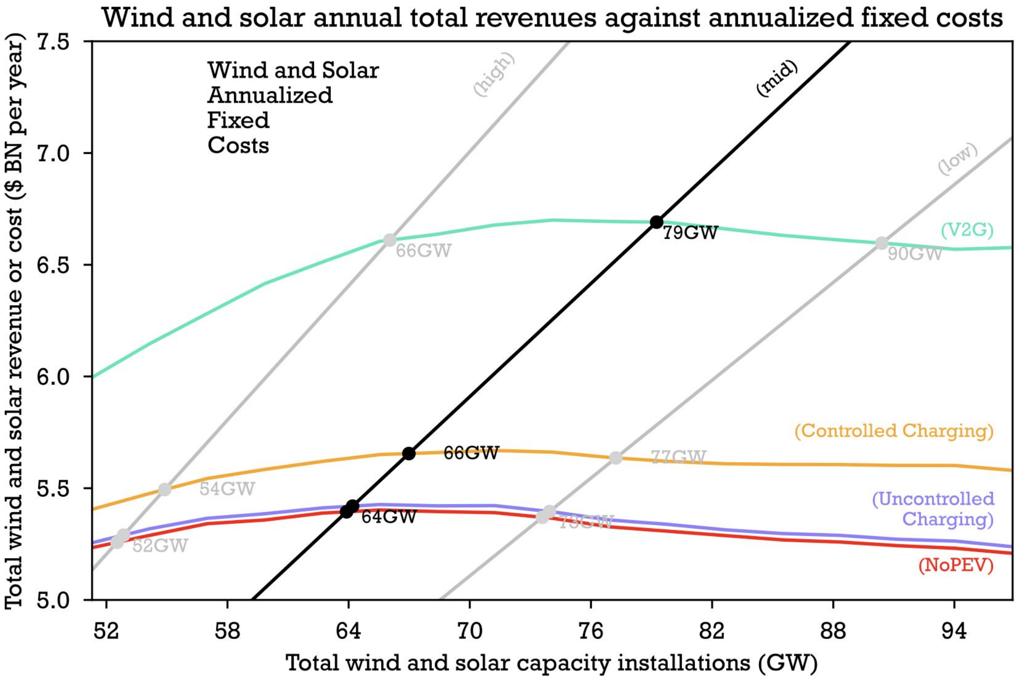
Identify maximum economically viable wind and solar penetration



Assume the generator revenues of this year represent annual revenues over the lifetime of the project

Identify the point with the maximum economically viable wind and solar penetration

We find the maximum profitable wind+solar capacity under each scenario

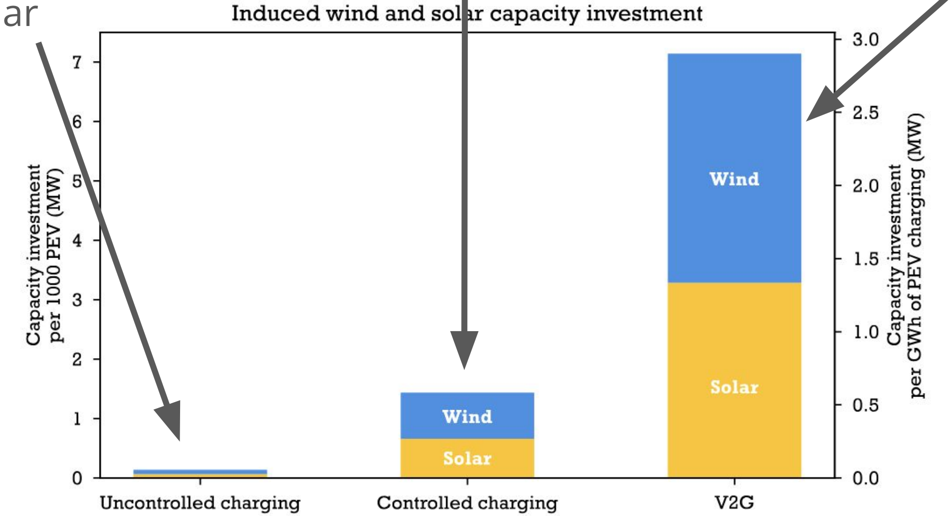


Flexible load increases incentives to invest in wind and solar capacity

If 10% of the PJM fleet were electrified: Not much incentive to build new wind & solar

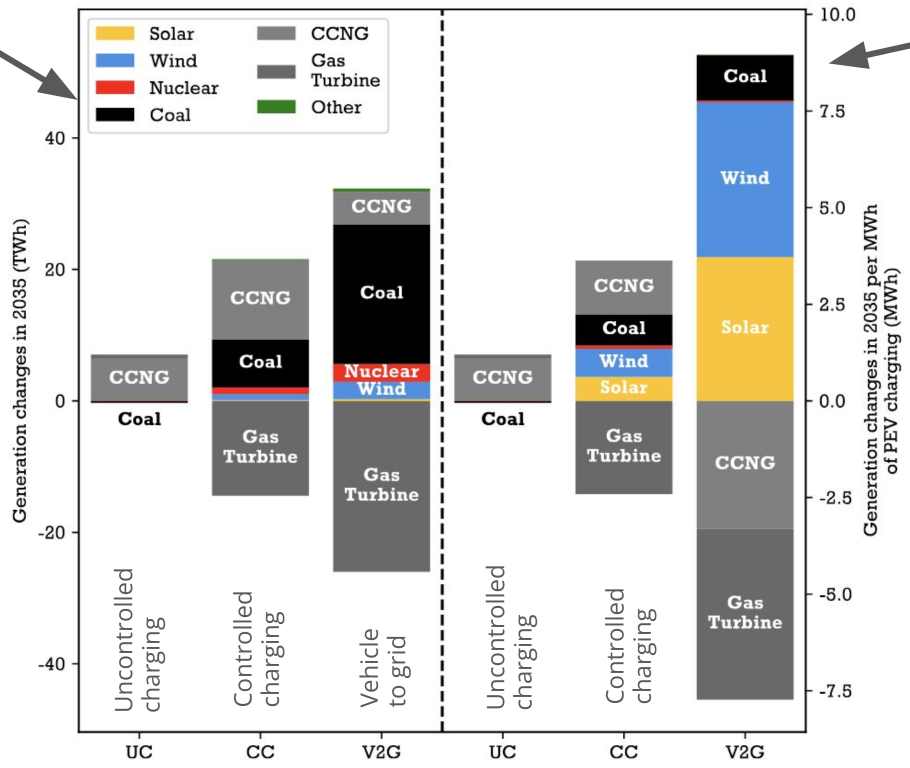
+ utility-controlled charging: Profitable to add 3GW of wind and solar

+ V2G: Profitable to add 15GW of wind and solar



Allowing capacity expansion changes the effects of flexible EV load on generation

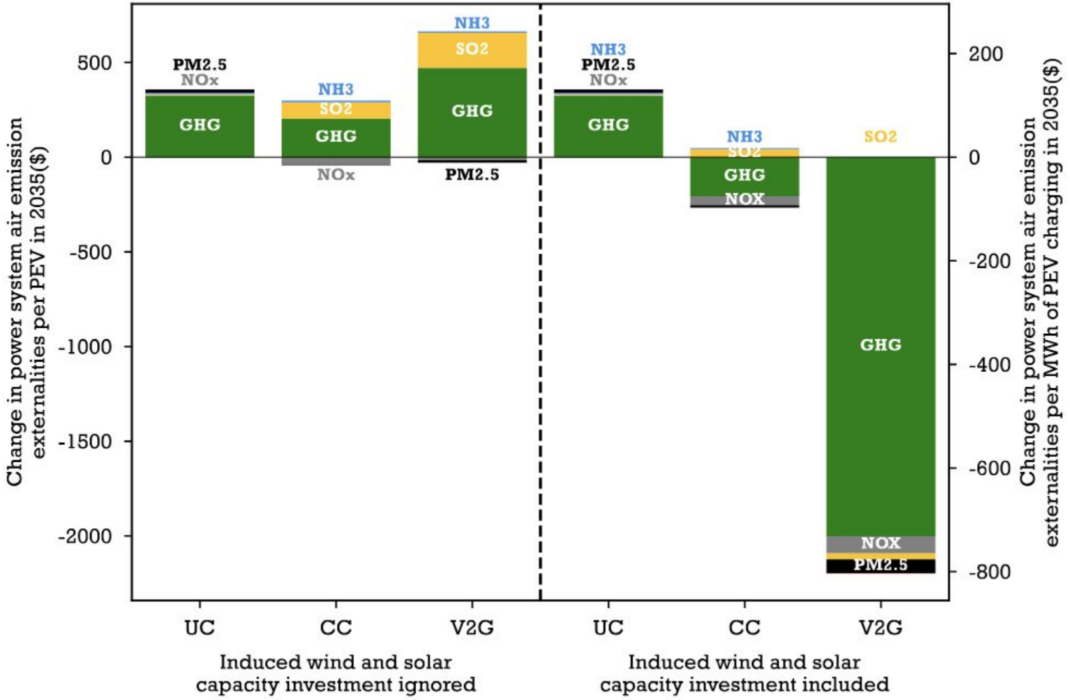
Without induced capacity expansion, flexible EV load allows **coal** to displace gas



With induced capacity expansion, flexible EV load allows **wind & solar** to displace gas

Induced capacity expansion lowers emissions, flips sign

Flexible load and especially V2G can make it profitable to build so much more wind & solar that the net effect of **adding** EV load is to **reduce** total grid emissions



Robustness checks

Table 2: Sensitivity Analysis: Robustness of V2G Results to Parameter Variations.
Estimates are relative to the base case V2G effect estimates.

Input parameters	Baseline value	Tested value	Induced wind and solar capacity investment per PEV	Annual system cost reduction per PEV per year	Annual emissions externality reduction per PEV	Interpretation
Stationary storage capacity	5.4 GW 42 GWh	14 GW 56 GWh	-74%	-80%	-71%	PEV V2G has smaller (but positive) benefits for power systems with more stationary storage.
Transmission capacity	Varies	2× baseline	+21%	+25%	+32%	PEV V2G has larger benefits in power systems with more transmission capacity.
PEV fleet penetration	10%	20%	-15%	-19%	-32%	Larger PEV fleets yield diminishing returns.
Wind to solar capacity ratio	1.17	1.43 0.96	+4% +20%	+14% +14%	+4% +4.5%	PEV V2G benefits vary with assumed wind-to-solar ratio.

Caveats

Simulation/Optimization: Cannot capture all possible effects that determine power system operations in practice, but our unit commitment models are similar in many ways to those used by system operators

Capacity Expansion: Solving for optimal capacity expansion with the time scope, resolution, and vehicle resolution needed to assess load flexibility is intractable, but it is also not critical. We instead model scenarios of wind and solar expansion at ratios suggested by the interconnection queue, and we test alternative assumptions. Key findings are robust.

Perfect Information: Charging control scenarios represent best-case outcomes with perfect lookahead, optimal dispatch, and full participation – an aspirational bound we might approach with improved data and forecasting.

Non-Market Factors: Capacity investment scenarios examine what is profitable to build. Actual investment is affected by many other factors (regulation, permitting, politics, etc.)

More information

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