The ZEROgrid Impact Advisory Initiative convenes a group of leading researchers to advance consensus and use of consequential impact assessment methods. This paper was introduced to the Impact Advisory Initiative process for consideration and received unanimous support from the assembled experts. The following advisors elect to add their names in support of this paper:

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Carbon Impact of Intra-Regional Transmission Congestion

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Abstract

Carbon accounting frameworks guide policy and decision-making around investments in renewable energy, making them critical to understand in the context of real-world grid operations. In the absence of empirical work assessing the effects of intra-regional congestion on carbon emissions, ongoing policy design assumes that transmission congestion within grid boundaries can be ignored. In this work, we aim to test this assumption by quantifying the frequency and severity of intra-regional congestion and its impacts on carbon emissions and prominent carbon accounting frameworks. This analysis is done in both PJM and ERCOT using nodal locational marginal emissions data. Through several case studies, we find that load that is 100% hourly-matched through load-shifting will often result in significant net operational emissions, and sometimes even increase net emissions relative to annual-matching. This work demonstrates that, in the absence of robust transmission expansion, grid-region boundaries are insufficient to ensure hourly-matching is effective. Impacts of intra-regional transmission congestion are shown to be vital components of effective carbon accounting frameworks, calling into question frequently made assumptions ignoring intra-regional congestion in studies and policy proposals.

Introduction

To meet the urgent need to rapidly decarbonize the grid, wind and solar generation has been deployed at record rates across the United States[1,2]. However, the impact of this deployment on reducing carbon emissions has been dampened. As grids across the US have experienced severe and growing transmission limitations, it is vital to examine the impact on renewable generation's ability to effectively meet load and reduce overall emissions.

The rising penetration of wind and solar power has driven growth in transmission congestion, as wind and solar are often sited close together, far from load centers, and tend to produce power at similar times due to their shared weather conditions. This results in significant amounts of clean power stressing the transmission between regions of renewable energy generation and load centers. These bottlenecks between renewable generation sources and demand limit the generators' ability to effectively displace fossil generators and their associated emissions. As a result, renewable projects in certain locations within a grid region are more valuable than others from a carbon emissions reduction standpoint. Despite that, incentives that inform where projects get built and how credit is attributed for the associated emissions reductions, often don't take these congestion impacts into account.

There is limited literature quantifying the frequency and severity of deliverability limitations within grid-regions. There have been a number of studies[3–5] examining approaches and policies to effectively drive decarbonization; however, they generally ignore intra-regional transmission constraints. These works do identify congestion between regions as an important factor that, when ignored in policy, can lead to significant induced emissions due to the lack of physical deliverability[3,5]. Given the meaningful impact that intra-regional transmission congestion has on system costs and operations in many grid-regions[6,7], it is important to explore its impact on carbon emissions and understand its importance to accurately measure emissions and guide investment, development, and procurement decisions.

The current greenhouse gas (GHG) protocol for carbon accounting does not account for congestion, or the variability of emissions hour-to-hour and across grid-region. Proposed changes to carbon accounting policy largely use 'hourly-matching', which requires that clean generation be generated in the same hour and grid-region as the load it aims to offset. These policies cite grid-regions defined by the Department of Energy (DOE)[8] as 'deliverability regions', with the assumption that energy within these regions is uniformly deliverable.[9] It has been widely asserted that deliverability is essential for effective hourly-matching[10,11]. However, PJM, specified as one of these DOE regions, has 27 defined deliverability areas within the ISO that are used for reliability planning.[12]

There are currently ongoing policy decisions being made today to revise the greenhouse gas protocol[13] and define a hydrogen production tax credit (PTC)[9] that are based on this unrealistic assumption that congestion within grid-regions is minimal and has negligible effects. In a recent letter[14], legislators expressed concern over the possibility of the hydrogen PTC potentially increasing overall emissions. Thus, it is clear that understanding the impact of ignoring intra-region congestion and generally assessing the efficacy of these carbon accounting frameworks is of pressing concern.

In this work, we demonstrate the frequency and impact of intra-regional congestion on deliverability of renewable generation in ERCOT and PJM, which coincide with the 'Texas' and 'Mid-Atlantic' geographic regions as defined by the DOE National Transmission Needs Study[8]. This paper aims to quantify the carbon impact of transmission congestion in these regions using congestion-aware locational marginal emissions (LME) data, and examine how congestion impacts the effectiveness of various emissions policies and accounting frameworks.

Use of operational emissions impact

In this work, we look solely at *operational* emissions impact which estimates the change in emissions due to a change in operation, and not due to a change to built capacity[15]. This is also often referred to as the short-run emissions impact. We use this as the key metric for several reasons. First, there have been various efforts to validate operational emission factors[15–19]; the ERCOT marginal emissions data used in this paper are one such validated dataset[16]. On the other hand, there are not yet clear methods for validating the long-run 'build impact' of an action.[15] Predictions of build impact vary widely in different studies and are typically based on capacity-expansion model results which depend heavily on model setup and forecast assumptions[20].

Additionally, the total carbon impact of an action is the sum of the operational and build impact emissions.[15] We focus on examining just the magnitude and variation of operating impact as an important component in overall emissions impact and independent from the value of build impact. Understanding when there is meaningful variation in operational impact driven by congestion and error in its accounting methodology is vital to understand in policy design. Furthermore, as the magnitude of variation in the operating impact gets large, it is likely significant relative to both these components of impact, not just operating impact.

What is Congestion?

Transmission congestion refers to restrictions in the transmission network, limiting the flow of power uniformly across a grid. Such restrictions occur when transmission lines reach their maximum allowed power flow, preventing any additional increase in flow. The grid must then compensate by dispatching additional, higher cost generators that can deliver power to the necessary locations on the grid by way of other, unconstrained transmission lines.

Thus, transmission congestion and line losses contribute towards increasing the system wide cost of supplying electricity to the grid by forcing a change in generator dispatch. Both ERCOT and PJM have seen rising system costs associated with congestion, as shown in Figure 2(a). Congestion costs accounted for 8.3% and 2.2% of total system energy costs in 2023 in ERCOT and PJM, respectively.

The system costs of congestion and losses are reflected in how the market sets Locational Marginal Price (LMP). LMP is comprised of three parts to account for these contributing factors:

- LMP_e: energy component of LMP, representing the system-wide marginal energy production cost
- LMP_l: loss component of LMP, representing the cost to produce excess energy required to compensate for system losses
- LMP_c: congestion component of LMP, representing the added energy production cost incurred due to the management of congestion constraints while delivering the required energy to all locations on the grid

The LMP, as constructed by the system operator, is the sum of these three components:

$$LMP = LMP_e + LMP_l + LMP_c \tag{1}$$

noting, however, that ERCOT does not construct a loss component, so LMP_l is set to \$0/MWh for all ERCOT prices[21]. When there is no transmission congestion in a grid, the least-cost set of generators are able to be dispatched to meet load and the congestion component of LMP is zero everywhere. Under these conditions, LMPs are roughly uniform across the grid aside from losses.

Congestion and losses play a similarly important role in determining LMEs. The effects of congestion and losses are not simply an economic construct, but are a reflection of a change to how much power each generator is providing to meet load in a specific location and time. Thus, they directly impact the emissions produced by the grid to provide that power. LME can therefore be defined by an analogous equation to LMP:

$$LME = LME_e + LME_l + LME_c \tag{2}$$

where LME_e, LME_l, and LME_c are the energy, loss, and congestion components of LME.

Each component of LME has a similar formulation to each LMP component for some node i at a specific time interval, as follows:

$$LMP_{e,i} = \lambda, \qquad LME_{e,i} = \lambda^c \tag{3a}$$
$$LMP_{l,i} = \ell\lambda, \qquad LME_{l,i} = \ell\lambda^c \tag{3b}$$
$$LMP_{c,i} = \sum_j \psi_{i,j} \cdot \mu_j, \quad LME_{c,i} = \sum_j \psi_{i,j} \cdot \mu_j^c \tag{3c}$$

where λ and λ^c are the system energy cost and system energy emissions intensity, respectively, ℓ is the loss factor, $\psi_{i,j}$ is the shift factor for constraint j for node i, and μ_j and μ_j^c are the shadow price and shadow carbon intensity for constraint j, respectively. Just as a constraint's shadow price is the system-wide cost saving associated with a one mega-watt increase in the line limit, the shadow carbon intensity is the system-wide carbon emissions reduction associated with a one mega-watt increase in the constraint limit.

Illustrative example

We first illustrate the impact of transmission congestion on both marginal and total emissions in the system using a three-node example, as depicted in Figure 1(a). This example

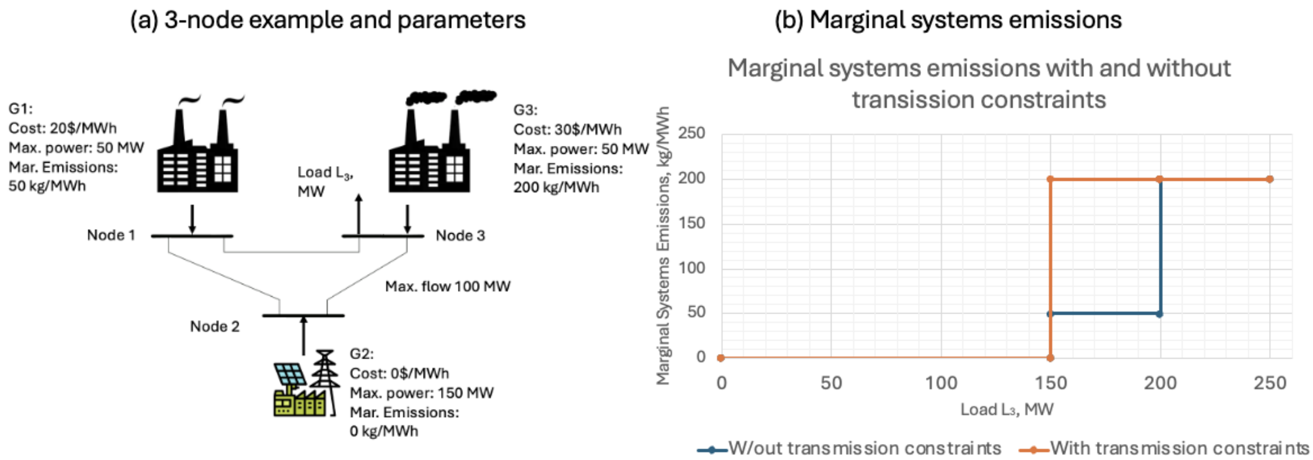


Figure 1: A 3-node example, with the incremental cost, maximum power output and marginal emissions rates for every generator, inspecting the effect of transmission constraints on the marginal systems emissions.

features one fossil generator at node 1, one renewable generator at node 2, and the load at node 3 co-located with another fossil generator. We assume that all lines have the same impedance, line 2-3 has a maximum flow capacity of 100 MW and lines 1-3 and 1-2 have infinite flow capacity. We also assume that, in accordance with the current practice, the system is dispatched in the least-cost manner (i.e., the total production cost is minimized, under the assumption of inelastic demand) and renewable power generation is a must-take resource. For the sake of clarity of our illustration, we make multiple simplifications and avoid modeling some dispatch constraints, including on/off commitment decisions, initial and end-of-day conditions, multi-period constraints, ramp limits, etc. We also simplify multi-piece cost production and emissions characteristics of generators to single-valued functions.

To show the effect of transmission congestion, we examine a scenario for this example of a perfectly known and fixed value of load L_3 = 175 MW, which is an intermediate load value for the system in Figure 1(a). First, if the the given flow capacity limits are ignored, i.e. copper-plate transmission, the resulting dispatch for G1, G2, and G3 is 25, 150, and 0 MW, respectively, which incurs 1250 kg/h of total emissions and the system marginal emission is at 50 kg/MWh (G1 is marginal). However, this dispatch results in flow over line 2-3 of about 108.3 MW, violating the line's flow limit of 100 MW. Thus, to respect the given flow constraints, instead G3 needs to ramp up to meet load at node 1 above 150 MW without flowing additional power over line 2-3, and the least-cost dispatch for G1, G2, and G3 is 0, 150, and 25 MW, respectively, and the flow in line 2-3 is exactly at the limit (100 MW). This dispatch results in the total emissions of 5000 kg/h. Hence, the flow capacity limit leads to different dispatches of the available generation capacity, which in turn changes both the total and marginal emissions.

Next, to illustrate the change in system marginal emissions, under different demand levels, we consider the least-cost dispatch for a range of given, perfectly known and fixed values of load L_3 in Figure 1(b). Our goal is to demonstrate how changes in the load at node 3 affect both marginal and total emissions due to congestion on line 2-3. First, we analyze the case without congestion, i.e., the maximum flow capacity on line 2-3 is ignored. In this case, the marginal emissions are $0\,\mathrm{kg\,CO_2/MWh}$ up to $L_3 = 150$ MW, rising to $50\,\mathrm{kg\,CO_2/MWh}$ when G2 is fully dispatched and G1 is activated to meet loads up to $L_3 = 200$ MW, and then jumps to $200\,\mathrm{kg\,CO_2/MWh}$ when G3 finally turns on. Compared to the congested line case in Figure 1(b), the main difference is that the maximum flow capacity of 100 MW on line 2-3 prevents G2 from turning on after L_3 exceeds 150 MW and requires usage of G3, which is more expensive and has a larger marginal emissions rate. We also note that the least-cost dispatch in the congested case leads to greater total emissions than in the uncongested case.

We note that the simplifications made in this illustrative example tend to underestimate distortions between the uncongested and congested cases, as further discussed in the studies below which are based on real-world settings. Reversing these simplifications and scaling the experiments to a realistically large network obstructs flow-based analysis and requires indirect inference.

Methods

Locational Marginal Emissions estimation

We calculate nodal LME values and the subcomponents at 5 minute resolution for all nodes in ERCOT and PJM for 2018 to 2024. We aggregate to hourly LME data by averaging the sub-hourly LMEs to align the temporal resolution with the generation data, enabling all analysis to be performed using hourly-resolution data. The LME data is available from REsurety, Inc. at api.resurety.com.[22] [a]

We calculate LME and the components using equations 2 and 3, which are represented in matrix notation as:

$$\begin{aligned} \mathbf{LME} =& \mathbf{A} \begin{bmatrix} \lambda^c \\ \boldsymbol{\mu^c} \end{bmatrix} \\ \text{where } \mathbf{A} =& \begin{bmatrix} (\mathbf{1} + \boldsymbol{l})_n & \boldsymbol{\Psi}^T \end{bmatrix} \end{aligned} \tag{4}$$

where μ^c is a vector of shadow carbon intensities of transmission constraints and Ψ' is an n x m shift-factor matrix.[23]

The method we use for calculating LMEs is different in PJM and ERCOT due to the availability of data provided by the two different ISOs. The following sections detail the specifics involved in calculating LMEs in each ISO.

PJM LMEs

PJM publishes LME data directly, however they only provide nodal LME values for load nodes, which is insufficient for the analysis in the paper looking at the impact on renewable generation. We extrapolate this data by taking advantage of the formulation of LME in equation (4), and solve for system energy carbon intensity and constraint shadow carbon intensities, as

$$\begin{bmatrix} \lambda^c \\ \boldsymbol{\mu^c} \end{bmatrix} = \mathbf{LME}'/\mathbf{A}' \tag{5}$$

where the prime denotes that the object is limited to the subset of nodes for which PJM publishes LMEs. With the shadow carbon intensities computed for all binding constraints in each interval, we can then directly calculate LMEs and the components for all nodes using equations (4) and (2). We additionally apply some quality filtering of the data to remove time intervals when LMEs have unrealistically large magnitude or the above solution is ill-conditioned. The fraction of data being removed due to these filters is very small.

ERCOT LMEs

We calculate LME values in ERCOT using a nodal dispatch model that uses the generator data, offers, system shift factors, nodal LMP, and constraint shadow prices published by ERCOT. We use that data to first marginal generators based on offers and LMP for each time-interval. We then estimate the marginal change in dispatch of those marginal generators that would be required to meet incremental change in load at each node. This is done by solving for least cost energy while both (1) maintaining the balance of energy and load, and (2) holding the flow over non-violated binding transmission constraints fixed, such that those constraints are not violated. Once we have estimated the marginal change to dispatch, the LME is calculated by scaling the change in generator dispatch by the generator emissions

[a] Academic researchers and institutions can request free access to LME data through this API by contacting carbon@resurety.com

rate. The generator emissions rates are estimated from Energy Information Agency (EIA) reported fuel type, fuel consumption, and net generation data published in the EIA-923 report[24], along with the EPA fuel-specific emissions data[25]. These LME estimates have been validated in a study comparing marginal emissions datasets, in which it was found to be the most accurate dataset.[16]

Wind and Solar Generation

We use hourly wind and solar data for operational projects to calculate avoided emissions of all existing projects within ERCOT and PJM. ERCOT publishes the 60-day SCED Generation Resource[26], which includes hourly operational 'base point' generation data, as well as the generation High-Sustained Limit (HSL) which indicates the hourly potential wind and solar generation, ignoring curtailment.

PJM does not publish hourly generation data at the individual project level. We instead model the wind and solar generation using generation models developed by REsurety, Inc. The wind model uses MERRA-2 wind speed, wind direction, and temperature data[27] as the meteorological input data and uses site-specific hub heights and power curves to model wind generation. Observed monthly generation from EIA[24] as well as hourly wind speeds from REsurety's proprietary internal database are used to bias correct the modeled generation output. The solar generation model uses high-resolution solar irradiance data from an external vendor as an input to pvlib[28], an open-source package for modeling solar PV output. The operational project characteristics are based on the EIA 860 report[29].

Quantifying Emissions Impact

After the LME and generation data have been obtained, we can then use the LME data to calculate the immediate emissions impact of a specific renewable project's generation. An incremental change to generation or load at a node on the grid results in an equivalent change in the dispatch of the marginal generators. This produces a change in emissions equal to the nodal marginal emissions rate scaled by the magnitude of the change. We thus estimate the impact of the generation of a wind or solar project at node i as the LME_i scaled by the project generation, G_i, for each time interval t, such that the total avoided emissions is calculated as:[15,30]

$$\text{Avoided Emissions} = \sum_t LME_i(t) \cdot G_i(t) \quad (6)$$

Similarly, the induced emissions from a load at node j of magnitude L_j is calculated as:

$$\text{Induced Emissions} = \sum_t LME_j(t) \cdot L_j(t) \quad (7)$$

The difference between the induced emissions from load and the avoided emissions from procured renewable generation yields the net emissions.

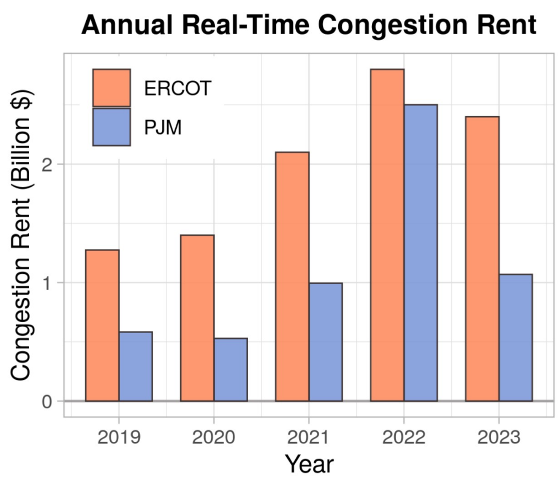
Results

Emissions Impact of Congestion

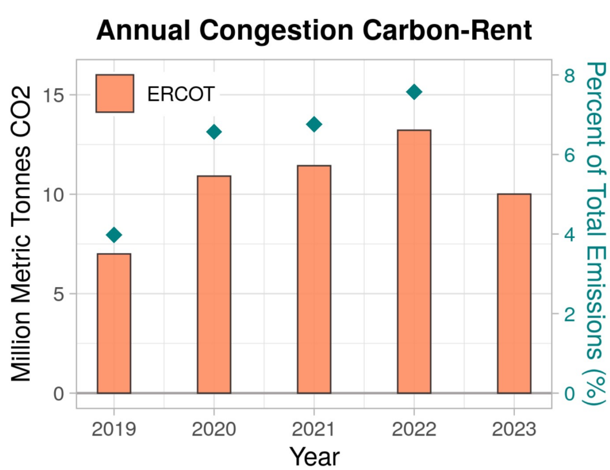
First, we quantify the overall impact that transmission congestion has had on system-wide carbon emissions. We calculate the annual 'congestion carbon-rent' for ERCOT for 2019 to 2023 in Figure 2(b), in both tonnes of CO_2 and as a percentage of total ERCOT emissions. Analogous to the economic metric 'congestion rent', the congestion *carbon*-rent represents the total increase in emissions due to transmission congestion across the ISO, calculated as the sum of the shadow carbon intensity of each constraint times the flow over the constraint. This is only calculated for ERCOT as the constraint flows are not publicly available for PJM.

We see that transmission congestion creates a significant system-wide increase in emissions, and the impact has grown over time, nearly doubling from 2019 to 2022. This suggests that if congestion were alleviated, ERCOT emissions could drop by on the order of a ten-million tonnes CO_2. This metric is not a perfect representation of the exact drop in carbon emissions, however it is indicative of the scale and trend of the problem introduced by congestion and the potential opportunity for carbon reduction through reducing the frequency and severity of congestion.

These results demonstrate the significant degree of transmission congestion in ERCOT and the emissions impact of that congestion. In the following section, we discuss the implications of ignoring that transmission congestion when designing policy around decarbonization.



(a) Reported ISO-wide congestion rent



(b) Calculated ISO-wide congestion carbon-rent, analogous to congestion rent but emission rather than cost

Figure 2: Annual system-wide (a) congestion rent, as reported by the Market Monitor reports[6,7,31–33], and (b) congestion carbon-rent.

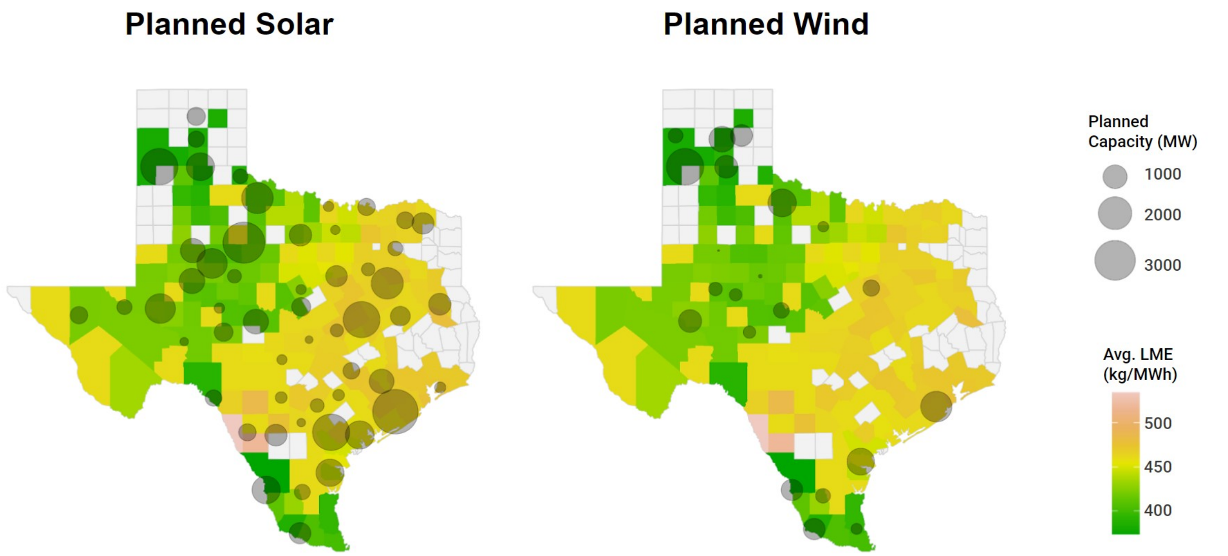
Sub-regional Variation in Emissions Impact

Next, we explore the spatial LME variation driven by congestion across ERCOT and PJM. Figure 3 shows contour maps of the average county LME for 2023 for both ERCOT and PJM. LMEs are mapped onto counties by using generator price node and county data. Counties that do not have at least one generator with a known node associated are filled with the associated hub-level aggregate LME data. Any missing LME values in the plot are due to insufficient data to map nodes to counties, not due to incomplete nodal LME data.

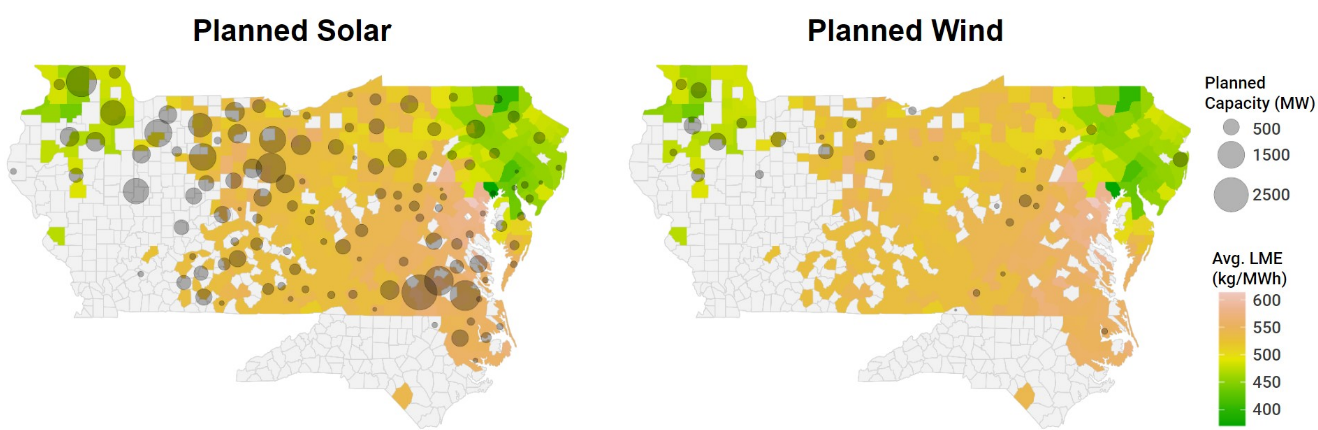
These maps demonstrate the significant variation in marginal emissions rate within each grid-region. In PJM we see that there is nearly a 2x spread in LME across the region. As a result of this variation across the region, a wind farm built in Virginia would have avoided 50% more carbon than an equivalent wind farm in northern Illinois. Similarly, the induced emissions of a newly built load could be reduced by hundreds of kg CO_2/MWh by siting it in eastern Pennsylvania or New Jersey instead of Virginia.

Wind and solar interconnection queue data for PJM and ERCOT are overlaid onto LME contour map, showing the capacity of wind and solar projects currently planned in each county. We see that, despite the low average LME in Northern Illinois and Western Hub in PJM and the LME in West Texas and South Texas in ERCOT, there is still a large proportion of renewables planned for these regions. More renewable generation build out in these regions, without significant changes to load patterns or substantial transmission upgrades, would most likely further exacerbate congestion in these areas. Any additional renewable energy capacity built in these areas will both add comparatively little to emissions reduction and further suppress the emission impact of existing capacity.

Interconnection queues across US ISOs and RTOs are dominated by wind, solar, storage, and hybrid projects. In recent years, projects have entered queues at faster rates than the queues can be cleared by the ISOs, and the



(a) ERCOT



(b) PJM

Figure 3: Contour map of 2023 average LME by county across (a) ERCOT and (b) PJM, with the capacity of solar (left) and wind (right) in the current interconnection queue (grey circles) overlaid, where the size of the circle represents the total capacity in the queue in that area. Queue capacities for some neighboring counties were aggregated to reduce visual clutter. Incomplete coverage of LME contour map is due to lack of geographic information to associate with nodal data, not due to incomplete LME coverage.

multi-year queue waiting times that now prevail across ISO/RTOs often results in project cancellations.[34] Thus, providing a path to prioritizing the construction projects that are expected to have the greatest carbon impact and suffer the least from congestion could meaningfully expedite the decarbonization of the grid.

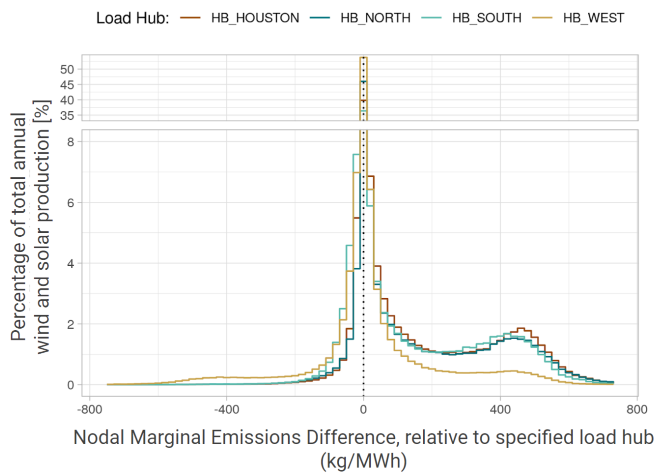
Deliverability Limitations

Many existing and proposed carbon accounting methods, including both annual- and hourly-matching, assume that energy produced anywhere within a grid-region will have an equal and opposite emissions impact as a load consuming an equal amount of energy. This is only true, however, when congestion does not impede generation deliverability across the grid-region[11]. The push toward hourly-matching focuses on high temporal granularity, with minimal locational granularity, assuming perfect deliverability within grid-regions. Thus, a key question to understanding the impact of congestion in designing policy is determining how frequently there are transmission constraints between renewable generation assets and load on the grid, preventing clean power from being delivered to the load. There have been many proposed ways to define 'deliverability', for example based on grid-region[9], spatial proximity, or difference in nodal LMP[10,11]. In this work, we look at the difference in LME, as this directly informs net emissions, rather than serving as a proxy.

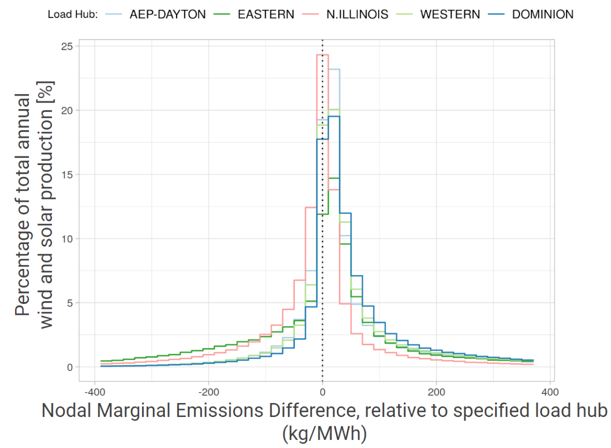
We consider the wind and solar generation from all operating projects in ERCOT and PJM over 2023. For these generators, we calculate the difference in LME between a sample load and the generator node, referred to as 'LME basis'. Using these data, we calculate the total quantity of generation that is produced at each value of LME basis for various assumed load locations, as shown in Figure 4. This is shown for a generic load in four hubs in ERCOT and five hubs in PJM, assuming the hub aggregate hourly LME values for each of the loads. This LME basis can be thought of as the net emissions for hourly-matched generation and load, i.e., when load is matched by an equal quantity of clean generation in the same hour. A positive value of LME basis implies that the emissions produced by the load are greater than the emissions being offset by clean generation, leading to a net increase in emissions.

Tables 1a and 1b take a more granular look at deliverability, showing the total percentage of the wind and solar generation in ERCOT and PJM, respectively, that is generated at a time when the load LME is at least $10\,\mathrm{kg\,CO_2/MWh}$ greater than the nodal LME at the site of generation. Thinking of this metric in the framework of matching load with renewable energy generated in the same hour, this is the percent of generation occurring in hours with greater than $10\,\mathrm{kg\,CO_2/MWh}$ net emissions such that load emissions are not sufficiently offset by renewable generation. This same metric is also shown broken down based on the location of the wind and solar generators, to show the deliverability of different generation zones to different load zones within the same ISO. The $10\,\mathrm{kg\,CO_2/MWh}$ threshold reflects the emission cutoff defined by the proposed '45V' clean hydrogen production tax credit (PTC) of $0.45\,\mathrm{kg\,CO_2/kg\,H_2}$[9]: for an electrolyzer stack efficiency of $50\,\mathrm{kW\,h/kg\,H_2}$ the 45V cutoff corresponds to $9\,\mathrm{kg\,CO_2/MWh}$, which we conservatively round up to $10\,\mathrm{kg\,CO_2/MWh}$. In other words, hydrogen electrolyzers are only eligible for the full PTC if they emit less than 0.45 kg of CO_2 per kg of hydrogen produced, which is roughly equivalent to a net emissions value of $10\,\mathrm{kg\,CO_2/MWh}$.

Figure 4(a) demonstrates that a very large proportion of built renewable generation is not deliverable to ERCOT load outside of ERCOT West, such that the load and clean generation produce net emissions of over $300\,\mathrm{kg\,CO_2/MWh}$. This is largely driven by the high penetration of wind in West Texas that is frequently heavily export-constrained, meaning that there is excess wind power that cannot be delivered to areas outside of ERCOT West due to transmission constraints. The peak around $500\,\mathrm{kg\,CO_2/MWh}$ LME differential coincides with the emissions rate of gas generators in ERCOT and comprised of times when LME is near zero at the site of



(a) ERCOT



(b) PJM

Figure 4: Percentage of total annual wind and solar generation in 2023 that is produced at a particular LME differential, or 'basis', between the point of generation and load, calculated as the LME difference ($LME_{load} - LME_{gen}$). The load location is indicated by the line color, and in all cases the load LME is assumed to be the hub-level LME for the specified load zone to represent a generic load for the region. The data is binned with 20 kg CO_2/MWh resolution.

the clean generation but gas is marginal for most load. This often occurs during periods of high, export-constrained renewable generation, such that renewables are competing with other renewables in the export-constrained area and are unable to serve additional load. As a result, load operating in these hours is being met by gas generators ramping up, despite there being large amounts of renewable energy generation in the same grid-region and at the same time. Overall, load in Houston has the greatest deliverability challenges, with 49.6% of generation across ERCOT being undeliverable to load in Houston, and over half of the wind and solar generation produced in both South and West Texas are not able to meet Houston load. Note that we don't see complete deliverability of generation within the same zone as the load due to intra-hub congestion. The exact intra-hub deliverability is dependent on the specific node where the load is located.

In contrast to ERCOT, PJM has a less pronounced tail at extreme net emissions values (Fig. 4(b)). However, we see that for the generic loads in Dominion Hub, Eastern Hub, Western Hub, and AEP-Dayton Hub, the peak occurs when there is net-positive emissions and the distributions are all skewed toward positive LME differentials, showing a consistent trend of deliverability limitations for renewable generation. Since nodal differences in LME within a grid-region are driven by both congestion and line losses (see eq.2), the LME basis is in part due to losses. The slight positive value of the distributions' peaks is largely driven by small LME differentials due to line losses, showing that these losses are another relevant contributor to increasing the overall net emissions on the grid and impacting the locational sensitivity of energy procurement. However, about 80% of the renewable generation in PJM with over 10 kg CO_2/MWh LME basis is driven by congestion alone.

As shown in Table 1, more than half of all wind and solar generation has limited transmission to supply load sited in any of the zones outside of Northern Illinois. This is driven by the large amount of wind capacity built in Northern Illinois, combined with MISO wind imports and the relatively high proportion of nuclear power in this area, which is both inflexible and non-carbon emitting. Thus, there is excess wind generation that needs to be exported to eastern areas in PJM where demand is higher in order to be consumed. This results in significant transmission bottlenecks to deliver this clean power. Furthermore, Dominion hub has the greatest deliverability limitations, with almost 70% of renewable power with limited deliverability to load in Dominion Hub. This is, in part, due to the high load in Dominion Hub created by the expansion of data centers located in Virginia, thus making transmission infrastructure feeding this region heavily trafficked.

It should be noted that we use modeled generation in PJM that does not account for curtailment. This likely means we are slightly overestimating the percentage of wind and solar generation that is "undeliverable" in PJM since curtailment primarily occurs due to export-constraining transmission congestion, resulting in negative congestion components of both LMP and LME. As a benchmark, we have calculated these metrics for ERCOT using the High-Sustained Limit (HSL) generation data which does not include curtailment and should be most comparable to the modeled generation in PJM, shown in Supplemental Table 1. We see only a few percentage points increase for ERCOT, so assuming curtailment patterns are roughly similar in PJM, this suggests the metrics calculated for PJM in Table 1(b) are likely only a few percentage points inflated.

These results demonstrate that congestion-driven differences in marginal emissions within the same grid-region occur with high frequency and are affecting a significant proportion of the wind and solar generation produced in both ERCOT and PJM. A blanket assumption of deliverability within a single grid region is not empirically defensible, and will result in significantly higher emissions in reality versus what is assumed under a simplified deliverability assumption.

Impact of Congestion on the Efficacy of Carbon Accounting Approaches

The previous section demonstrated that there are significant intra-regional deliverability challenges in both ERCOT and PJM due to transmission congestion. In this section, we quantify the emissions implications on carbon accounting approaches that do not take intra-regional congestion into account.

In an effort to increase investment in clean energy, government policies and carbon accounting frameworks have been developed to quantify emission reductions achieved by individual organizations. Two dominant carbon accounting strategies are annual energy-matching and hourly energy-matching, the latter of which has been proposed more recently as a solution to shortcomings of annual-matching. In an annual energy-matching framework, the total annual quantity of load added to the grid by a particular entity needs to be met by an equal quantity of carbon-free generation. In an hourly-matching framework, this requirement for clean energy matching becomes more temporally granular, specifying that load should be met by an equal quantity of clean generation in each hour. However, the load and generation are simply required to be located in the same grid-region, without consideration of potential transmission limitations within that grid-region. In the next two sections, we use LMEs to examine the effectiveness and accuracy of hourly-matching and annual energy-matching.

PJM Case Study: Virginia Data Center

Next we examine a generic data center in Virginia, using aggregate LME values for the Dominion hub to represent the load. Since hourly-matching is a commonly discussed carbon accounting framework[3,5,9,35,36], we aim to use marginal emissions data to examine its accuracy. 'Carbon-free energy' (CFE) is a common metric used with an hourly-matching accounting framework[37]. This metric counts all load that is hourly-matched with procured clean generation as carbon-free, as well as a fraction of any unmatched load, set by the percentage of carbon-free generation on the grid in the given time interval. CFE, as a metric, also mirrors the proposed hydrogen PTC emissions requirement which similarly stipulates hourly-matching and bases the emissions of unmatched load on the average grid mix.[9] We calculate the percentage of CFE for a Dominion-based load

Table 1: Percentage of total wind and solar generation from each specified generation zone that is produced in hours with at least 10 kg CO_2/MWh greater marginal emissions at load hub than at generation site. Thinking of this in the framework of matching load with renewable energy generated in the same hour, this is the percent of generation occurring in hours with greater than 10 kg/MWh net emissions such that load emissions are not sufficiently offset by renewable generation.

(a) ERCOT

Loc. of Load	**Location of Wind & Solar Generation**				
	Houston	North	South	West	All
Houston	19.6	33.7	52.9	51.1	49.6
North	24.6	20.5	51.1	46.7	45.2
South	15.1	28.3	44.8	47	44.5
West	16.9	12.2	38.9	21.7	24.6

(b) PJM

Loc. of Load	**Location of Wind & Solar Generation**					
	AEP-Dayton	Dominion	Eastern	N. Illinois	Western	All
AEP-Dayton	43.9	35	52.6	85.1	42.1	61
Dominion	66.8	40.4	58.5	86.1	63.6	69.4
Eastern	46	34.7	44.8	67.4	42.9	52.9
N. Illinois	11.6	21.7	38.8	46.8	23.2	32.6
Western	55.3	38.4	56.1	82	48.3	63.2

with procured clean generation from each operational project in PJM, shown in Figure 5, calculated as:

$$\text{CFE} = \frac{\sum_t \min(E_{load,t}, E_{gen,t}) + (E_{load,t} - \min(E_{load,t}, E_{gen,t}) \times \text{CFE}_{grid,t}}{\sum_t E_{load,t}} \quad (8)$$

where CFE_{grid} is the fraction of carbon-free energy in the electricity grid mix and $E_{load,t}$ and $E_{gen,t}$ are the load and procured clean generation at time t.[37]

To assess the impact of congestion on the accuracy of this metric at quantifying the actual fraction of carbon-free energy, we calculate the percentage of carbon-free energy using an LME-based emissions-matching framework for comparison. The metric used, denoted as CFE_c, is the percentage of induced emissions that is offset by the avoided emissions of procured clean generation, calculated as:

$$\text{CFE}_c = \frac{\text{Avoided Emissions}}{\text{Induced Emissions}} = \frac{\sum_t E_{gen,t} \cdot \text{LME}_{gen,t}}{\sum_t E_{load,t} \cdot \text{LME}_{load,t}} \quad (9)$$

For this analysis, we assume a flat load that is 50% annually energy matched to generation (i.e. annual clean energy produced by the wind or solar project is half the annual load).

Figure 5 reveals that the hourly-matching CFE metric which assuming perfect deliverability over-inflates the percentage of 'carbon-free' hours by as much as 34%, absolute, and 100%, relative, overestimation of how much the load's impact has been offset. The energy-based CFE is greater than emissions-based CFE_c for every operating project in PJM. Of course, when using an hourly-matching approach, procurers of power would develop a portfolio of renewable assets, rather than rely on a single project. However this represents the impact each generator would have in a aggregated portfolio. Generally, we see that for a given capacity of renewable generation, the more the procured renewable portfolio's output aligns with load, the more CFE is an overestimation of the true 'carbon-free' energy. In this case, the clean generation is used more 'efficiently' and exceeds load less frequently. This is why the difference between the energy-based CFE and emissions-based CFE_c is larger for wind than for solar, as solar generation's extreme diurnal profile does not align well with a flat load.

We additionally find that CFE most dramatically underestimates emissions when less renewable generation is procured; as the capacity is scaled up relative to load, the gap between the energy-based CFE and emissions-based CFE_c starts to collapse. This is because the clean generation starts to exceed load more frequently, such that a larger fraction of clean generation is not 'counted'.

In Figure 6, we look at four selected projects in PJM and calculate the net emissions for the Dominion-based load with rigorous energy hourly-matching through load shifting and annual energy matching with flat load. We again find that the wind and solar projects with minimal congestion to the load effectively offset the load emissions and have zero net emissions. However the Camp Grove Wind Farm in Northern Illinois and Frenchtown Solar in New Jersey both fail to fully offset the load's induced emissions, resulting in significant net emissions of 172 kg CO_2/MWh and 109 kg CO_2/MWh, respectively, despite rigorous hourly-matching. Frenchtown Solar and Camp Grove Wind only meet the 10 kg CO_2/MWh basis deliverability threshold to the load 36% and 17% of hours, respectively, which accounts for 35% and 10% of their generation. In contrast, Desert Wind and Grasshopper Solar are deliverable to the load 81% and 82% of the time.

For both solar projects, we see that load-shifting to track with generation actually results in an increase in the net emissions relative to annual energy matching. This is driven by the diurnal profile of the load LME, where operating the load at night when there is no solar generation induces less emissions than during the day when the solar farm is generating power. Grasshopper Solar equally offsets the load's emissions with generation-tracking hourly-matching since there is minimal congestion between the solar project and load. However, while hourly-matching resulted in zero net emissions, not hourly-matching and instead having a flat load would have resulted in negative net emissions, such that the effort of hourly matching actually increases the net emissions.

ERCOT Case Study: Houston Electrolyzer

There has recently been significant interest in investment in hydrogen electrolysis, largely driven by the tax credits introduced as part of the Inflation Reduction Act[9]. The current proposed policy includes a PTC based on hourly-matching, i.e., requiring that electricity load be met by renewable energy generation that is both in the same grid-region, as defined by the Department of Energy[8], and temporally matched to load[9]. However, as demonstrated in the previous sections, clean generation is often not deliverable within a grid-region, meaning that temporally matched load and generation will not necessarily result in zero net emissions.

To explore the impact of congestion-driven deliverability limitations, we quantify the emissions impact a hypothetical hydrogen electrolyzer located in Houston with stack efficiency of 50 kW h/kg H_2 would have had in 2023. We use Houston for this example, as Houston is expected to be a major hub for hydrogen production due to a combination of its infrastructure, natural resources, and economic factors[38].

First, we find the frequency of hours in 2023 for which the net emissions of hourly-matched generation and load meets or is less than than the threshold of 0.45 kg CO_2/kg H_2, shown in Figure 7(a) for every operational wind and solar project location in ERCOT. Figure 7(b) shows the average net emissions per kilogram of hydrogen production, produced with rigorous hourly-matching to each wind and solar project. For the purpose of this analysis, we assume the

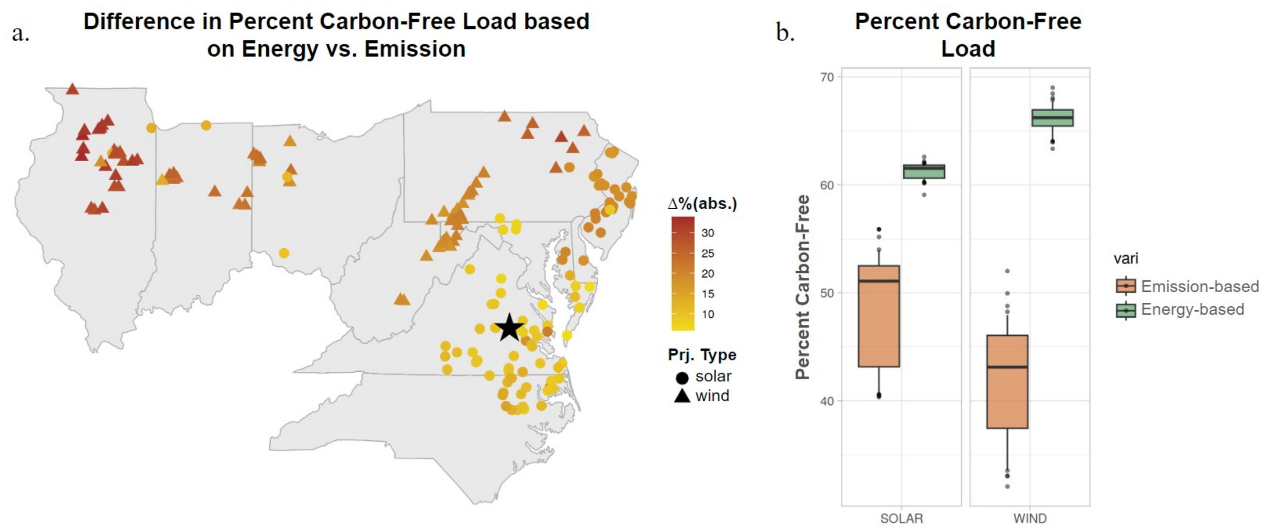


Figure 5: (a) Map of PJM operational wind (triangle) and solar (circle) projects, colored by the differences in average percent of hourly-matched energy and hourly-matched emissions, as defined in equation 9, for 2023 for a generic flat load in Dominion Hub in Virginia (starred). (b) Box plot of project average percent of hourly-matched energy and hourly-matched emissions, broken down by project type. The load and generation are scaled such that the total annual project generation is 50% of the the total annual load.

load is fully flexible and follows renewable generation. This is a simplification of real operation, but represents optimal hourly matching. While we focus on an electrolyzer in this case study, this analysis applies to any load sited in Houston.

We see a large variation in both the fraction of 'green' hours and average net emissions across Texas. For wind and solar projects that are further away from Houston and are behind highly congested transmission constraints, like in the West and South, we see the fraction of hours that meet the 'green' threshold is quite low, around 60% and result in an average net emissions rate of up to 10 $\mathrm{kg\,CO_2/kg\,H_2}$, more than 20 times higher than the 45V threshold. Projects close to Houston, on the other hand, have roughly zero net emissions and almost all hours are deliverable to the load, such that hour-matching is effective. This shows that, without considering the siting of the renewable generation and load and the patterns of transmission constraints, hydrogen production could qualify for the proposed PTC while inducing significant emissions onto the grid in ERCOT.

The variation we see in average net emissions between projects located very close together, as seen in regions with significant congestion in the West and South, is driven by differences in curtailment rather than difference in congestion or LME. Generation is typically curtailed during periods of heavy congestion, causing LMEs to be very low. This causes projects with more curtailment to effectively under-weight those periods of low LME since a lower fraction of their generation is produced at times with very low LME compared to neighboring uncurtailed projects.

Performing a similar assessment to that done for PJM in Figure 6 to examine these trends more closely, we look at four example projects, two wind and two solar, that could be used to offset load in Houston, in Figure 8. South Plain Wind and Lasso Solar both are impacted by transmission constraints limiting their export of power to the rest of Texas. We see, even with rigorous hourly matching, the avoided emissions are significantly less than the emissions induced by the load in Houston during all months for these two projects. Thus, the operation of that load leads to a significant increase in emissions on the grid, despite the seemingly rigor-

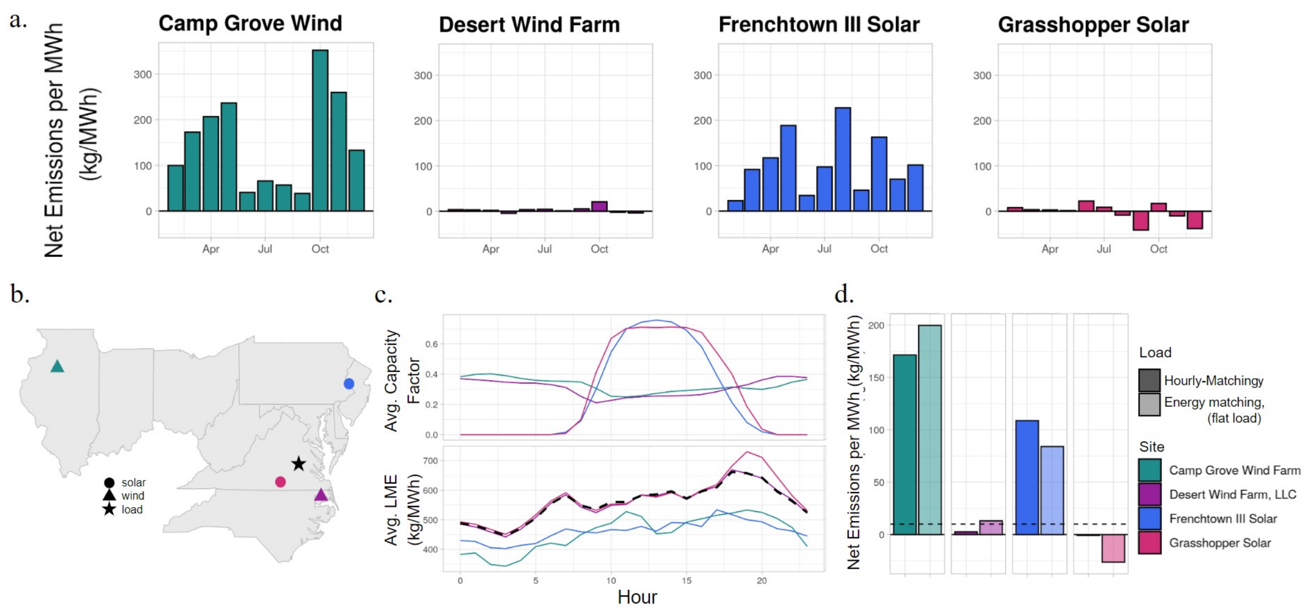


Figure 6: (a) Monthly net emissions of hourly-matched (flexible load) Dominion data center or other load, assuming procurement from 4 different renewable energy projects within PJM; (b) map of PJM wind and solar projects locations and load (starred), (c) diurnal average of LME at each project (solid) and load (dashed) (d) total 2023 net emissions for hourly-matched (variable load) and energy matched (flat load).

ous offset when congestion and variation within the grid-region are ignored as part of an hourly matching framework.

On the other hand, hourly-matching is very effective at minimizing net emissions when congestion is minimal between the clean generation and load, whether due to very close proximity as in the case for Fort Bent Solar, or simply not being impacted by a transmission bottleneck and at a site with similar LME values to the load, like Anacacho Wind. For both of these projects, the monthly and annual net emissions are consistently close to zero.

We see that there is little difference in the net emissions associated with generation-based load shifting to achieve hourly-matching compared with an energy-matched flat load. For both solar projects, generation-based load-shifting (i.e., hourly matching) increases the net induced emissions, since the grid tends to be 'greener' in the evening due to the high penetration of wind in Texas, the diurnal shape of wind generation, and lower ISO-wide demand. Because the load is matching the diurnal solar generation profile for the two solar projects, the load induces emissions during times of day when solar generation is high, which don't correspond to these 'greener' evening periods.

Discussion

This paper demonstrates that in both ERCOT and PJM, there is significant intra-regional congestion, causing large differences in marginal emissions rate at different locations within the same grid-region. Meaningful intra-regional congestion has been occurring frequently over the past five years, and has been shown to have a particularly large impact on renewable generation. This analysis suggests that assuming equal emissions and perfect deliverability within a grid-region misses a major factor in determining the induced and avoided carbon emissions of load and renewable generation. Therefore, by ignoring these effects in any carbon accounting framework, we will continue to misattribute carbon emissions and abatement and allow for taking 'credit' for greater emissions offset than what is reflective of reality.

This work demonstrates that a 100% rigor-

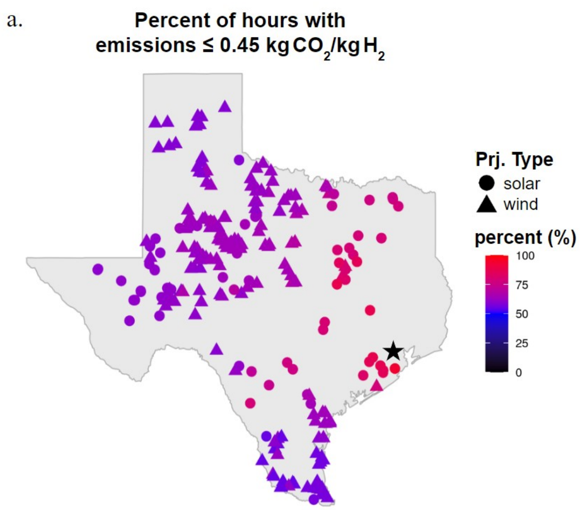


Figure 7: Map of ERCOT operational wind (triangles) and solar (dots) projects in 2023. The star indicates the location of the hypothetical hydrogen electrolyzer facility in Houston. The marker colors indicate (a) the percentage of hours where the net emissions, given the LME basis between generator and load, is below the 45V emissions cutoff, and (b) the average net emissions associated with hydrogen electrolysis for a Houston facility that has procured renewable energy of the wind or solar project indicated on the map, assuming variable load to achieve perfect hourly-matching.

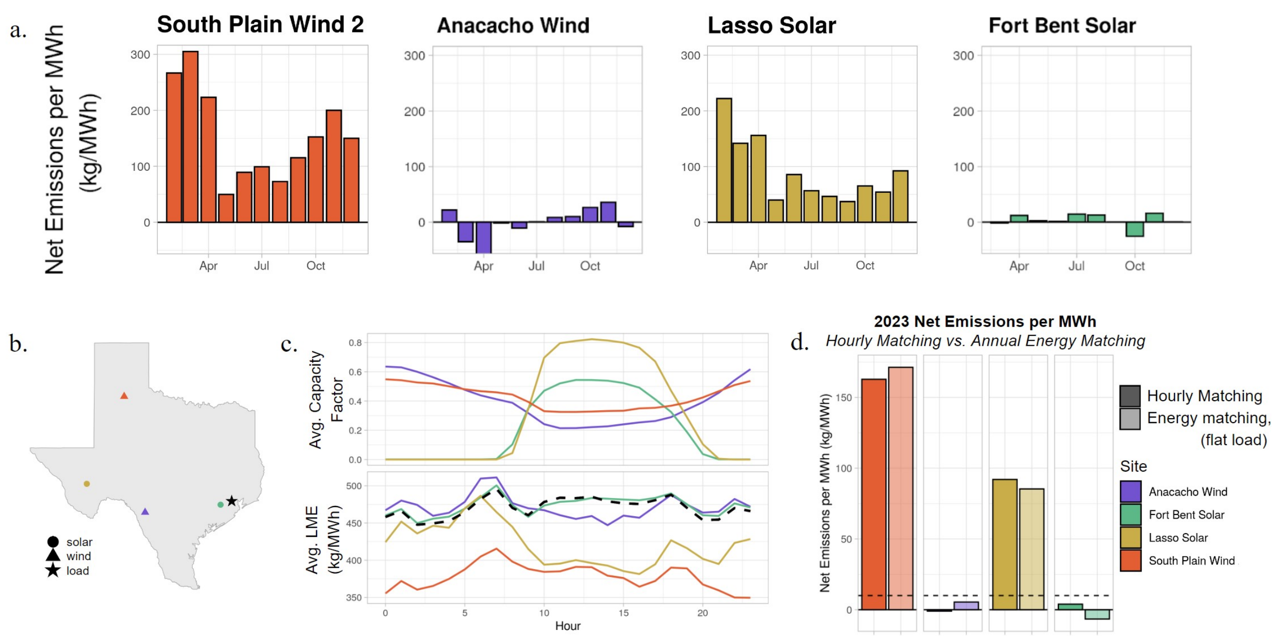


Figure 8: (a) Monthly net emissions of hourly-matched (flexible load) Houston electrolyzer assuming procurement from 4 different renewable energy projects within Texas; (b) Map of renewable project locations and load (starred), (c) average diurnal values of nodal LME, (d) total 2023 net emissions for hourly-matched (variable load) and energy matched (flat load). The black dashed line indicates 10 kg/MWh.

ous hourly-matched load, when not considering deliverability or the local variation in marginal emissions impact within a grid-region, will often still result in significant net induced emissions in both ERCOT and PJM. Similarly, potential new hydrogen production that would qualify for the proposed hydrogen PTC could likely meaningfully increase the net emissions on the grid, despite strictly abiding by the proposed hourly-matching PTC requirements. Carbon accounting frameworks that require a tight definition of temporal matching (e.g., hourly) but allow for a loose definition of deliverability (e.g., grid-regions) will result in increased costs of operations, due to the need to load shift to match CFE generation, while having limited real world carbon benefit, as a result of intra-regional transmission congestion that limits or even reverses the benefits of temporal matching.

The choice for where to site load and clean generation within a given grid-region, alone, can have a sizable effect on emissions, resulting in a change to carbon emissions on the order of 10s to 100s of $\mathrm{kg\,CO_2/MWh}$. Building a wind farm in Virginia is equivalent in avoided emissions to building a wind farm in Northern Illinois that has 50% more capacity. At a time when we need to decarbonize the grid as quickly as possible, it is vital to prioritize investment in the construction of projects that will maximize the carbon impact, and avoid suffering from or exacerbating the effects of transmissions congestion.

Decisions for renewable energy investment and procurement are based around carbon accounting frameworks or other relevant policy (e.g., hydrogen PTC). It therefore seems less likely that carbon accounting frameworks that ignore the emissions impacts of intra-regional transmission would drive emissions-sensitive procurement and investment demand towards projects and strategies where the impacts of congestion are lower. Not incentivizing a buyer of clean power toward procuring energy to maximize emissions reduction and avoid congestion-effects will most likely result in new clean energy investment continuing to exacerbate existing problems as current trends continue, as we see from the location of wind and solar projects in the current PJM and ERCOT interconnection queues. We would expect this to result in more extreme congestion, increased curtailment of renewables, and a reduction in the potential carbon impact of new and existing projects, unless there are other structural changes on the grid.

Similarly, siting load in export-constrained areas when possible has great potential system-wide benefits to not only reduce carbon emissions but alleviate existing strain on transmission. As transmission is built, some effects of congestion will be mitigated. However the rate of growth of renewables has and is expected to continue to outpace investment in transmission. Neither ERCOT nor PJM had more than 500 circuit-miles of transmission on average per year built or upgraded over the past 5 years.[8] It is estimated that, to mitigate congestion, transmission would need to be built at a much faster rate than this or than what is planned.[8] This suggests that even if transmission buildout is prioritized, the rate of development is unlikely to keep pace with renewable growth enough to address worsening congestion, if trends continue. This is also a reason that static grid-regions are flawed, since the behavior within regions is dynamic and evolves with changes to the grid.

This work focuses on operating emissions impacts, and thus does not consider long-run structural changes to the grid. For example, if the growth of congestion limiting the export of renewable generation continues, that would exacerbate the problems highlighted in this study in the near to medium term but could also signal that more transmission capacity is needed in the long run. This signal could incentivize policy reform and investment to expand the transmission grid, mitigating some of the effects of transmission congestion. A carbon accounting framework that accurately reflects the emissions impacts of transmission congestion could also induce additional transmission expansion. These long-run effects are out of scope for this study, but would be valuable to explore in future work.

Conclusion

This work demonstrates the high frequency of intra-regional transmission congestion and the large effect of the emissions of renewable generation. We see that nearly half of ERCOT wind and solar generation and the majority of PJM wind and solar generation is not deliverable to much of the rest of the grid. This results in large variation in the avoided and induced emissions across the grid, causing large discrepancies between the induced emissions of a load and avoided emissions of procured renewable energy. Without accounting for intra-regional congestion, carbon accounting methods like hourly-matching or annual energy matching, significantly underestimate the net induced carbon emissions on the grid.

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