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Understanding how hourly approaches to emissions accounting and voluntary energy procurement can accelerate the decarbonization of the electric grid

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Understanding how hourly approaches to emissions accounting and voluntary energy procurement can accelerate the decarbonization of the electric grid

By

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ABSTRACT

As the momentum of climate action continues to shift from top-down, nation-state action to decentralized action by corporations, cities, and utilities, these actors are working to decarbonize their energy consumption and help drive the transition to a carbon-free grid. However, the current frameworks and metrics that drive voluntary decision making—GHG inventories and renewable energy procurement goals—do not always reflect the reality of the evolving power system, and thus can lead to decisions that do not effectively reduce emissions or address grid needs. This research seeks to fill the gaps in knowledge about how both regulatory and voluntary approaches to decarbonizing the electric grid can maximize their effectiveness and accurately measure and attribute emissions from electricity consumption. This dissertation draws upon power system engineering and industrial ecology research and applies data science and optimization methods to 1) identify whether there is a need to account for grid carbon emissions on an hourly basis, 2) introduce a comprehensive dataset of validated hourly emissions from the U.S. power sector, and 3) introduce a new modeling tool that enables greater understanding of the role of different voluntary clean energy procurement goals in the broader energy transition.

Acknowledgements

This research would not have been possible without the intellectual and financial support of a wide range of individuals and organizations. (Any opinions, findings, and conclusions or recommendations expressed in this material do not necessarily represent the views of these individuals or organizations)

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Contents

Introduction

In order to avoid global temperatures rising more than 1.5°C, the Intergovernmental Panel on Climate Change (IPCC) has forecasted that renewables will need to generate 37-80% of global electricity by 2030, and 59-97% of global electricity by 2050.[1] However, the main challenge to reliably and cost-effectively integrate high penetrations of renewables on the grid will be managing the temporal variability of renewable resources in order to maintain the real-time balance between electricity supply and demand.[2]

Although climate change is a global challenge, a centralized and coordinated global response has not materialized. Although the success of the 1987 Montreal Protocol limiting ozone-depleting gases seemed to be a model for future top-down policies tackling global environmental problems, a series of failures to replicate it for greenhouse gases (GHGs) has led to a slow but steady shift in the momentum of climate action from nation-states to non-state and substate actors like corporations, utilities, and local governments.[3,4] This shift was enshrined in the 2015 Paris Accord, which recognized that action by nonstate actors would be necessary to achieve the ambitious target of limiting global warming to 1.5°C.[5] The years since the Paris Accord have seen increasingly aggressive commitments and actions from subnational and nonstate actors meant to accelerate the decarbonization of the electric power system.[6,7]

Ensuring that this decentralized and bottom-up climate action can collectively accelerate and sustain the transition to a decarbonized electricity system over the next three decades will require the use of a common framework and set of metrics to inform effective decision-making. Standardized and scientifically rigorous frameworks are necessary to help ensure that these actions are driving real-world emissions reductions and not resulting in double-counting, leakage, or shuffling of emissions. Luckily, there are already two well-established and widely utilized frameworks for guiding this action: GHG inventories and renewable energy procurement goals. GHG inventories, which follow accounting standards such as *The GHG Protocol*, quantify each institution's responsibility for GHGs emitted into the atmosphere, including indirect, or "scope 2," emissions from consuming electricity from the grid. These inventories inform GHG reduction goals or climate action plans, which typically involve a pledge to reduce annual emissions by some percentage below a baseline year, or to eliminate the institution's emissions footprint entirely. Approximately 600 global corporations, 600 U.S. colleges and universities, and 325 U.S. cities have committed to reduce their carbon footprints.[7,8] In addition to these GHG reduction goals, many institutions commit to procuring a certain percentage of their annual energy use from renewable resources. Enabled by restructured electricity markets that allow for consumer access, these institutions can own or contract with renewable energy facilities for power. More than 700 U.S. corporations, universities, and local governments have joined the EPA's Green Power Partnership, and nearly 300 global corporations have pledged to go "100% renewable."[7,9,10]

Despite the successes of these existing frameworks, they are not adequate for guiding decentralized action to achieve a rapid and complete transition to a carbon-free electricity system, as they ignore one of the fundamental dynamics necessary to the success of this transition: timing. More specifically, these frameworks and metrics ignore the temporal variability of renewable resources, and thus provide incomplete information to decisionmakers about how to optimize the impacts of their actions on grid decarbonization. As we are already witnessing in regions such as California, higher penetrations of renewables lead to new operational and reliability challenges which require adding different supply- and demand-side resources with the right operational characteristics in the right locations.[11]

Current GHG accounting protocols only require the use of annual average grid emissions factors for quantifying the scope 2 emissions footprint from consumed electricity. However, these annual averages ignore the fact that emissions intensity can vary significantly throughout the day or seasons with the variability of renewable resources.[12–14] These time-invariable emissions factors not only inaccurately account for emissions, but they make decision-makers blind to the time value of different emission mitigation strategies. Likewise, current renewable procurement goals allow corporations to claim that they are 100% renewably powered, even if they buy renewable energy from a completely different grid at times when they are not consuming energy. This is because these goals only require the total annual volume of electricity generated by contracted renewable projects to equal the total annual volume of electricity consumed. As structured, these goals and metrics provide no incentive for decision-makers to value energy demand flexibility, beneficial electrification, energy storage, or around-the-clock sources of renewable energy, even though these will be critical tools for decarbonizing the electric system.

Thus, the goal of this research is to identify how each of these frameworks need to evolve to effectively guide decentralized action that collectively helps accelerate and sustain the transition to a renewable power system. To do this, the research must evaluate how to align these frameworks with the needs of the evolving electric power system, and how doing so will change the incentive structure and resulting decisions made. The balance that must be struck with this research is on one hand defining metrics that are accurate and lead to real emissions reductions, but on the other hand are simple enough that they remain practical and intuitive to accurately apply to decision making.

This dissertation draws upon theoretical contributions from power system engineering, industrial ecology, and energy economics and applies data science and mathematical optimization methods to answer three main research questions:

1. **Chapter 1**: How would increasing the temporal resolution of attributional grid emissions factors affect the accuracy and practicality of GHG accounting?
2. **Chapter 2**: Is it possible to create a high-quality and comprehensive dataset of hourly generation and emissions data for the U.S. power sector?

3. **Chapter 3**: What are the grid and emissions impacts of time-coincident voluntary renewable energy procurement relative to other types of voluntary goals, and can achieving such goals be practical and cost-effective?

Chapter 1: Hourly accounting of carbon emissions from electricity consumption

Note: This chapter is adapted from Miller, G. J., Novan, K. & Jenn, A. "Hourly accounting of carbon emissions from electricity consumption." *Environmental Research Letters* 17, 044073 (2022), https://doi.org/10.1088/1748-9326/ac6147. This article was published open-access and is reproduced here under a Creative Commons Attribution 4.0 license.

Introduction

Greenhouse gas (GHG) emissions from electricity generation are a significant contributor to climate change and can comprise a large share of the carbon footprint of an individual activity, product, building, company, or city. Accounting and attributing these emissions to specific end-users of the electricity is a common practice and important tool to help understand the sources of climate-changing emissions and enable action to mitigate them. Once limited to academic life-cycle assessment studies and voluntary carbon disclosure initiatives, carbon accounting and disclosure is increasingly being used to guide financial investments, inform policymaking and business decisions, and measure compliance with regulations.

Current GHG accounting protocols account for "scope 2" emissions (those associated with the consumption of grid electricity) by applying an annual-average, attributional grid carbon intensity factor to all electricity consumed by an entity each year. This annual-level accounting represents the carbon intensity of grid-supplied electricity as a single, static value throughout the year. However, because the mix of generators supplying electricity to the grid is constantly changing, grid carbon intensity also varies across seasons and the hours of each day.[12–31] While there are benefits to the simplicity of annual-level accounting, ignoring this hourly heterogeneity may come at the cost of accuracy, which can have real effects both on academic analyses and the effectiveness of our policies in curbing climate change.[14] However, it is unclear from previous studies whether this potential bias is a substantial or widespread problem. Existing studies, primarily in the field of life-cycle assessment, focus on specific building GHG inventories as case studies, demonstrating that annual accounting may bias emission inventories anywhere between 0.2% and 26% when compared to hourly accounting, as summarized in Table 1.1. [17,19–22,28,32,33*]

Table 1.1. *Summary of literature evaluating bias resulting from annual carbon accounting. Bias calculations have been standardized using [(annual – hourly) / hourly] for all papers. The carbon intensity types are defined as: Produced: emissions per unit electricity generated, Delivered: emissions per unit electricity consumed, not accounting for imports/exports of emissions, Consumed: emissions per unit electricity consumed, accounting for imports/exports of emissions, Direct: only considers combustion emissions from the generator, Lifecycle: considers direct and indirect emissions (e.g. mining and transport of fuels) from the generator*

Paper	Geography	Data Years	Temporal Resolutions Analyzed	Carbon Intensity Type	Case Study	Electric demand data	Bias due to annual accounting
Bristow et al. 2011 [17]	Ontario, Canada	2007	Annual Hourly	Produced Direct	Mid-rise residential building with five efficiency scenarios	Simulated, single building	-3.5% to +0.2%
Cubi et al. 2015 [19]	Alberta and Ontario, Canada	2011, 2013	Hourly	Produced Direct	Office and residential buildings with different efficiency variations	Simulated, two reference building types in two regions, with six efficiency variants (36 simulations)	-11% to +6 (one outlier at -44%)
Kopsakangas-Savolainen et al. 2015 [32]	Finland	2011	Annual Hourly	Produced Lifecycle	Two residential buildings in Helsinki	Metered data, two buildings	+1% and +6%
Spork et al. 2015 [20]	Spain	2012	Annual Hourly	Delivered Lifecycle	Generic commercial buildings with constant high load during operating hours and constant low load during non-operating hours	Synthetic data, fifteen operating hour scenarios and different high to low demand ratios	-5% to + 3% (special cases at -6% and -8%)
Roux et al. 2016 [21]	France	2013	Annual Hourly	Delivered Lifecycle	Single family research house in Chambery, France	Metered data, single building	-26%
Vuarnoz and Jusselme 2018 [22]	Switzerland	2015	Annual Hourly	Consumed Lifecycle	Proposed mix-use building in Fribourg, Switzerland	Simulated, single building	+1.9%
Donti et al. 2019 [28]	PJM Inter-connection, U.S.	2017	Annual Monthly Monthly TOD hourly	Produced Direct	Systemwide summer load in PJM	Measured data, aggregate region demand	Underestimated, numerical value not reported
Müller and Wörner 2019 [33]	Germany	2017, 2030, 2050	Annual Quarter-hourly	Delivered Lifecycle	Use phase of residential single-family home	Simulated, single building	-4.2% (2017) -7.7% (2030) -17.9% (2050)

To understand whether annual accounting leads to widespread bias in emission inventories, this study calculates scope 2 GHG emission inventories for approximately 113,000 simulated residential and commercial buildings in fifty-two grid balancing areas across the United States, using annual-average, monthly-average, monthly time-of-day (TOD) average, and hourly grid emission factors. We also

[*] A separate body of literature has focused on comparing the accuracy of using of average, attributional emission factors to marginal, consequential emission factors for quantifying the avoided emissions of grid interventions. However, it is important to note that marginal emission factors are not appropriate for use in attributional carbon footprinting and are thus not relevant to this paper.

examine a specific case study of a high-renewable region in California, utilizing a dataset of actual metered load representing over thirteen million residential, commercial, industrial, and agricultural facilities in the state. Our results suggest that the magnitude and direction of the bias introduced by annual accounting depend on when and how you consume electricity and where you are located: specifically, activities with more variable electric demand located in grids dominated by clean and renewable energy will see a larger relative bias from annual accounting than activities with flat demand in grids dominated by traditional fossil generation. We also find that these biases can only be meaningfully reduced by using emission factors that reflect both the seasonal and time-of-day variation in grid carbon intensity.

Background

The carbon intensity of the grid can vary continuously in response to changes in generation at the minute or second timescale. Thus, even hourly emission factors may not capture the full variability in grid carbon intensity. Indeed, some previous studies evaluating the variability of grid carbon intensity have utilized half-hourly or quarter-hourly emission factors.[12,23,24,33] However, in this study, we use hourly-average carbon intensities as the baseline rather than sub-hourly values, first because hourly grid data is more widely available than sub-hourly data, and second due to the relatively low variation in grid carbon intensity within a single hour. Previous studies note that the variability of wind and solar power, which contribute to the variability of grid carbon intensity, is much less at the hour or shorter timescale than it is across several hours or days.[34] We confirmed this by analyzing a dataset of 5-minute resolution carbon emissions data published by the California Independent System Operator (ISO), finding that even in this renewable-heavy region, the mean coefficient of variation of grid carbon intensity within a single hour was only 2.4%, compared to 31% across the entire year.

Because we calculate actual carbon emissions as the product of hourly energy demand (D_h) and the hourly regional carbon intensity ($C_{r,h}$), the bias resulting from using an averaged carbon intensity value ($\bar{C}_{r,h,l}$) at some aggregation level l is the product of the hourly energy demand and the residual carbon intensity ($\mu_{r,h,l} = \bar{C}_{r,h,l} - C_{r,h}$). Thus, the expected bias introduced into an annual inventory by using an averaged carbon intensity value can also be expressed as the following equation (see the supplementary information [SI] for a full derivation):

$$E\left[D_h \cdot \mu_{r,h,l}\right] = Cov\left(D_{b,h}, \mu_{r,h,l}\right) = \sigma_D \cdot \sigma_\mu \cdot \rho_{D,\mu} \qquad \text{Equation 1}$$

In this equation, σ_D is the standard deviation of hourly energy demand, σ_μ is the standard deviation of the residual hourly carbon intensity, and $\rho_{D,\mu}$ is the correlation coefficient between hourly energy demand and the residual hourly carbon intensity. This relationship suggests that the magnitude and direction of bias is driven by the variability in both carbon intensity and energy demand, as well as the correlation between demand and carbon intensity, and it has three important implications. First, in regions with substantial variation in hourly emissions rates (high σ_μ), there is a potential for larger bias, and vice versa. Second, end-uses of electricity with sizable hourly variation in energy demand (high σ_D) would expect to see larger biases than an end-use with flat energy demand. Finally, the sign of the bias (whether the inventory is over- or under-estimated) will depend on the sign of the correlation coefficient between demand and the residual carbon intensity ($\rho_{D,\mu}$). An end-use whose demand is correlated with times of high carbon intensity (and is thus negatively correlated with the residual carbon intensity), will have their emissions under-estimated by using an averaged carbon intensity value.

As shown in Figure 1.1, hourly consumption-based carbon intensities in certain regions can be highly variable throughout the year, depending on the fuel mix of generated and imported electricity consumed in the region. While production-based carbon intensities only reflect emissions from generators that operate within each region, consumption-based carbon intensities reflect emissions from electricity imported into a region as well. Because imported electricity represents a substantial portion of consumed electricity in many regions and can have a carbon intensity that differs from that of in-region generation, this paper focuses on consumption-based carbon intensity throughout.

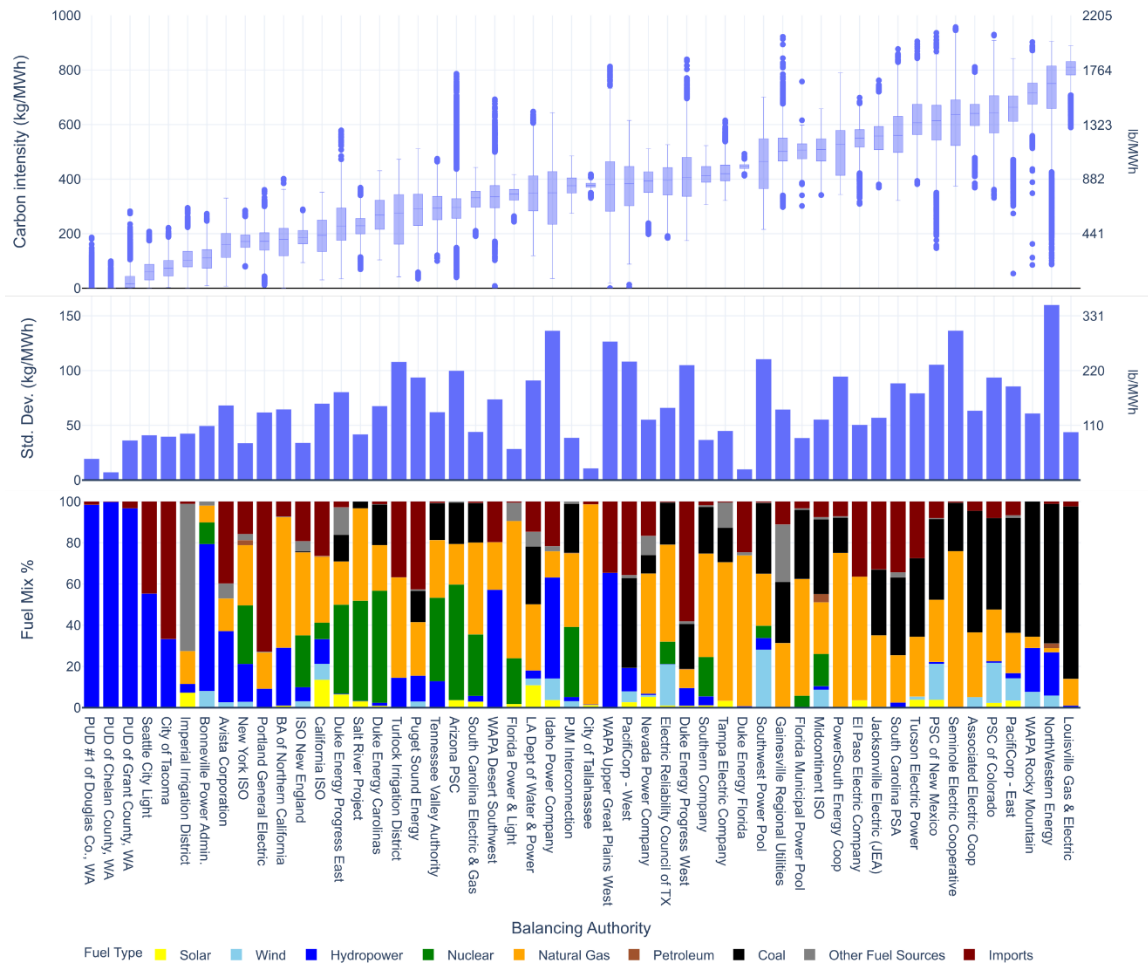

Figure 1.1. *Distribution (top panel) and standard deviation (middle panel) of hourly consumption-based carbon intensities, as well as the source of energy (bottom panel) for fifty-two balancing areas in the U.S. in 2019. Hourly carbon intensities can vary significantly from the annual average value, especially in regions with a diverse mix of resources that include carbon-free generation.*

Data and Methods

This study examines carbon inventories for thousands of building load profiles across the United States at different temporal resolutions. To demonstrate the impact that the intra-regional variability in carbon intensity has on the magnitude and direction of the bias resulting from annual-average accounting, this study first examines annual and hourly inventories for approximately 113,000 simulated residential and commercial buildings across different climate zones in fifty-two different grid regions in the U.S. Then, to demonstrate the impact that variability in electricity demand profiles has on this bias, this study examines inventories for thousands of residential, commercial, industrial, and agricultural building profiles located in the California ISO. Finally, we explore how well the use of monthly and monthly time-of-day average carbon intensity values mitigates the inventory bias compared to using an annual average.

Hourly building demand data.

Although as of 2019, over 60% of all electric meters nationwide included advanced metering infrastructure (AMI), which collect hourly or sub-hourly electricity demand data, wide-scale hourly demand datasets are not publicly available due to privacy concerns.[35,36]

However, NREL recently published a dataset of approximately 900,000 simulated end-use load profiles which have been calibrated and validated using actual meter data and statistically represent the U.S. residential and commercial building stock.[37,38] Each of the fourteen unique commercial building types and 9 unique residential building types (summarized in the SI) are represented by individual building variants with different combinations of physical and operational characteristics that affect the load profile. To keep the volume of data computationally manageable while representing the diversity of actual load profiles that would be found in each grid region, we select a stratified random sample of 10% of the buildings of each type located in each climate zone in each grid region, resulting in a sample of 112,717 unique load profiles.

However, the NREL dataset does not include load profiles for agricultural, industrial, and certain common commercial (e.g., data center) end uses. Thus, for our California ISO case study that examines the impact of different building load profiles on bias, we utilize a dataset from Lawrence Berkeley National Lab (LBNL). This LBNL dataset contains actual hourly AMI data representing over 13.1 million individual residential, commercial, industrial, and agricultural electricity customers (aggregated into

2,766 building profiles) across the three major investor-owned utility territories in the California ISO territory (see SI for details).[39] The choice of CAISO as a case study is also useful because the region is on the vanguard of renewable energy deployment and may be more representative of the carbon intensity variability of more and more grids as the energy transition continues.

Grid carbon intensity data

We source hourly average, consumption-based emission factors for each grid balancing area in the U.S. from Carbonara, a carbon analytics platform developed by Singularity Energy.[40] This study utilizes carbon intensity values for 53 of the 75 grid balancing areas (BAs) in the United States, which represent a spatial resolution that reflect actual power system boundaries and operations.[41,42] To calculate its production-based emission estimates, Singularity uses data on hourly net generation by fuel type for each BA from EIA Form 930, and multiplies it by the fuel-specific, annual-average, adjusted CO_2 output emission rate for that BA, from the EPA's eGRID2019 database.[43] To calculate consumption-based emissions, which account for imports and exports of electricity between BAs, they solve a multi-region input-output model which utilizes hourly BA-to-BA net interchange data from EIA-930.[14] Using these hourly values, we then calculate annual, monthly, and monthly time-of-day averages.

Carbon inventory methodology

A carbon inventory I for each building b in each grid region r is calculated by summing the product of the building's hourly electricity demand D and the actual hourly grid carbon intensity C at each temporal aggregation level for each hour h in year:

$$I_{b,r} = \sum_{h=1}^{8760} D_{b,h} * C_{r,h} \qquad \text{Equation 2}$$

An estimated carbon inventory $\bar{I}$ is then calculated in the same manner, but using an averaged grid carbon intensity $\bar{C}$, which can have one of three levels of temporal aggregation l (annual, monthly, or monthly time-of-day):

$$\bar{I}_{b,r,l} = \sum_{h=1}^{8760} D_{b,h} * \bar{C}_{r,h,l} \qquad \text{Equation 3}$$

The relative carbon inventory bias from using averaged carbon intensity values is calculated as the percentage error compared to the hourly inventory.

$$Relative\ Bias_{b,r,l} = \frac{\bar{I}_{b,r,l} - I_{b,r}}{I_{b,r}} \qquad \text{Equation 4}$$

Results

Regional differences in carbon inventory bias

The results of the 112,717 carbon inventories that we calculated for residential and commercial buildings around the country reveal that the use of annual-average carbon accounting can result in an overestimation up to 33% and underestimation up to 22% when compared to hourly-average accounting, although most bias falls in the range of +/- 5%. Importantly, as Figure 1.2 demonstrates, the magnitude and direction of this bias depends on where you are located and who you are.

In certain regions, clustered near the center of Figure 1.2, annual accounting introduces negligible bias for all inventories. Referring to Figure 1.1, we can see that these low-bias regions tend to rely more heavily on fossil fuel generation and have low standard deviations in their hourly carbon intensity, which confirms what we would expect to see based on Equation 1 (see the SI for a direct visual comparison of these two figures). In a region like Duke Energy Florida, which is supplied mostly by methane gas and has a small standard deviation in carbon intensity, we see a correspondingly low amount of bias, within the range of +/- 0.7%.

In contrast, in regions where the variability in hourly carbon intensity is higher, annual-average accounting results in higher inventory bias, although the magnitude and direction of the bias depends on the variability of the building load, and how highly correlated that load is with periods of high or low carbon intensity on the grid, both on a seasonal and daily basis. If building energy demand tends to peak during seasons or times of day that coincide with peaks in grid carbon intensity, annual accounting will tend to underestimate emissions. For example, in the New York ISO, where emissions peak seasonally in the summer and daily during daylight hours, annual accounting underestimates commercial building emissions because commercial building load follows a similar seasonal and daily pattern.

Because residential building demand profiles can peak at different times than commercial buildings, we see that in some regions annual-average accounting underestimates residential emissions while at the same time overestimating commercial building emissions. This can again be explained using Equation 1, since we identified that the direction of the bias is driven by the sign of the correlation coefficient between demand and the residual carbon intensity.

Re-framing these results in terms of the regional energy supply mix, regions with higher bias tend to have higher shares of renewables, as renewables introduce more variability into the hourly carbon intensity (see figure S9 in the SI). Additionally, emissions from buildings whose demand is positively correlated with the timing of generation from the predominant renewable energy source in the region will be over-estimated using annual-average accounting. For example, for buildings that consume energy more heavily during the day, annual average accounting will over-estimate emissions in solar-dominated regions and under-estimate emissions in wind-heavy regions where wind tends to be stronger at night.

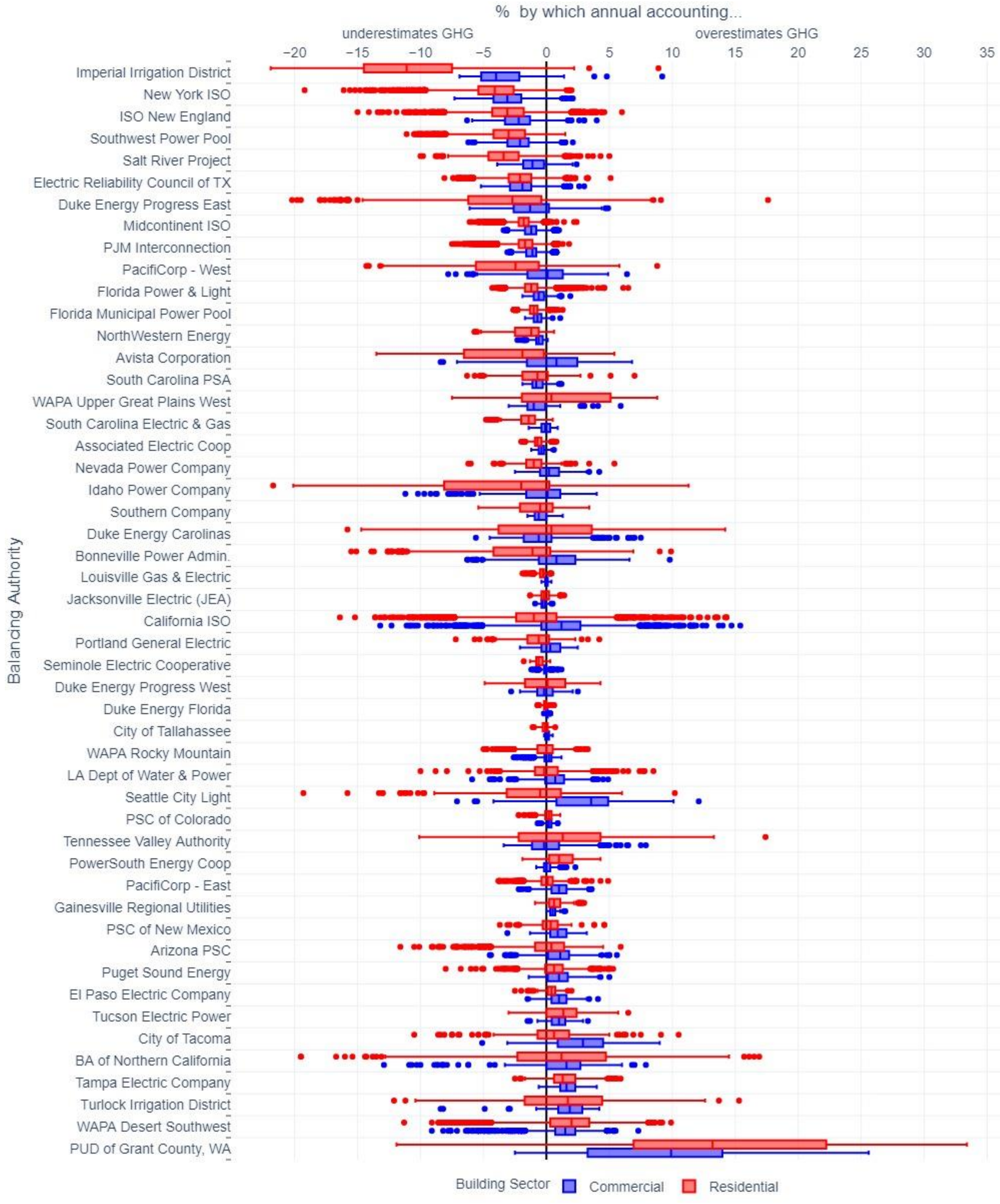

Figure 1.2. *The relative bias that annual-average carbon accounting introduces compared to hourly accounting, for both residential and commercial buildings in each grid region. Each box plot shows the distribution of these biases for all building inventories in each region. The regions are ordered from lowest to highest median bias for all buildings in a region. The results for two regions were omitted from this figure (but can be found in the SI) for the readability of the results, as their relative biases ranged from -29% to +182%.*

California ISO case study

While the national results primarily demonstrate how regional carbon intensity characteristics affect the bias introduced by annual-average carbon accounting, it also showed how the bias can differ for different building types with different energy demand profiles. To further explore these demand-driven impacts for a more complete set of electricity end users (including industrial and agricultural loads), this section focuses on a case study located within the California ISO, using a demand dataset representing millions of actual buildings in the state.

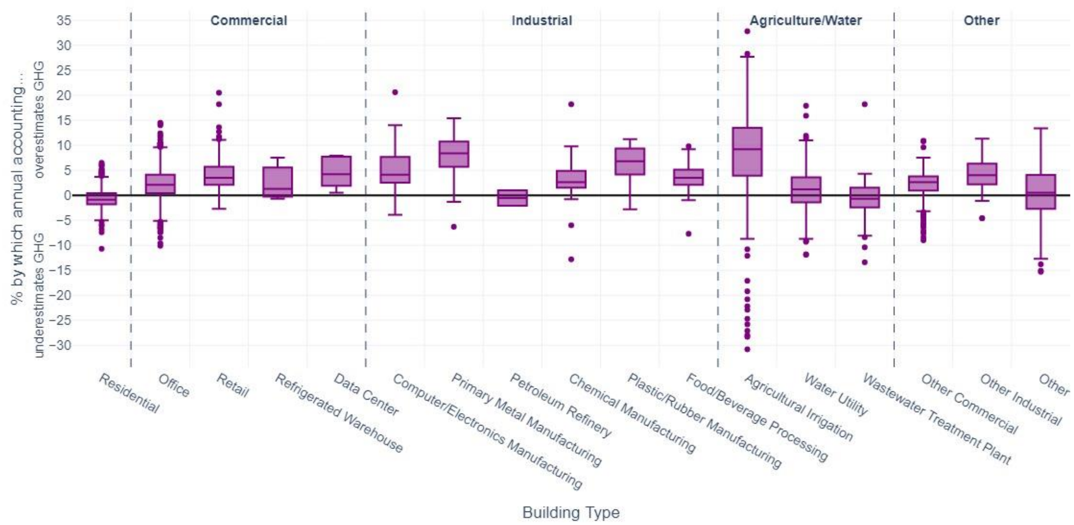

Figure 1.3. *For each of the 2,766 building load clusters in California, we calculated a carbon inventory using both a single annual average emission factor and hourly emission factors and evaluated by what percent the annual average over- or underestimated emissions compared to the hourly resolution inventory. These results are summarized by the box plots of these biases by building category. This shows that even within buildings of a single type in a single region, energy load profiles display large heterogeneity which impact the magnitude and direction of bias in emission inventories.*

From the results presented in Figure 1.3, we can see that the heterogeneity in the energy demand profiles of individual buildings within a single category of buildings means that it is not always possible to generalize conclusions about the magnitude and direction of bias of annual-average accounting. Commercial office buildings, for example, may have their inventories overestimated as much as 15% or underestimated as much as 10%. For data centers in California, we could conclude that annual-average carbon accounting overestimates emissions, although the magnitude of this bias ranges anywhere from 0.5% to 8% for an individual data center.

In the California ISO, which has a high penetration of solar generation, the carbon intensity tends to dip during the mid-day, which shapes the bias trends that we see in Figure 1.3. Most commercial buildings, whose energy demand also peaks during the day, will have their emissions overestimated by annual-average accounting.

Industrial facilities, which can have larger swings in energy consumption between on-shift and off-shift times, and thus larger variability in energy demand (σ_D), tend to have higher emissions inventory bias resulting from annual-average accounting than commercial buildings. The exception is industrial processes which consume energy on a relatively continuous, 24/7 basis, like petroleum refining, for which the inventory bias is much closer to zero. For energy demand that is more intermittent or seasonal in nature, like agricultural water pumping and irrigation, annual-average carbon accounting can introduce much larger biases, in the range of +/- 30%, especially if the carbon intensity during the seasons or times of day when the pumping is occurring do not reflect the annual average, leading to a high correlation between demand and residual emissions ($\rho_{D,\mu}$).

Inventory bias at different temporal resolutions

While hourly accounting using 8,760 unique emission factors for each hour of the year will more precisely quantify the emissions attributable to each end user, it also introduces greater data management complexity for accounting practitioners. Thus, this study also examines whether the use of twelve monthly average emissions factors, which reflect annual seasonality, or 288 monthly time-of-day average emission factors, which reflect both annual and daily seasonality, could improve accuracy while limiting complexity. From a practical standpoint, monthly-average carbon accounting would be convenient because most end-users of electricity are billed monthly and thus have easy access to monthly electricity consumption data.

Figure 1.4 plots the absolute percentage bias resulting from the use of annual average emission factors versus the absolute bias resulting from using twelve monthly average or 288 (12x24) month-by-hour-of-day average emission factors for each end-user in each grid region. Panel (a) shows that monthly-average accounting can reduce bias by over 50% on average for residential buildings, while having no substantial impact on the bias for commercial buildings. Monthly-average accounting does not, however, lead to a systematic reduction in bias: approximately one-quarter of buildings showed no improvement or even an increase in bias when using monthly-average accounting. In panel (b), we can also see that for facilities with highly seasonal energy demands, such as water pumping and irrigation, monthly-average accounting may substantially reduce inventory bias compared to annual-average accounting, because these monthly averages reflect the predominant seasonality of the energy demand. These results suggest that monthly-average accounting could be beneficial for certain types of buildings in certain regions, but it does not represent a substantial improvement on a systematic basis.

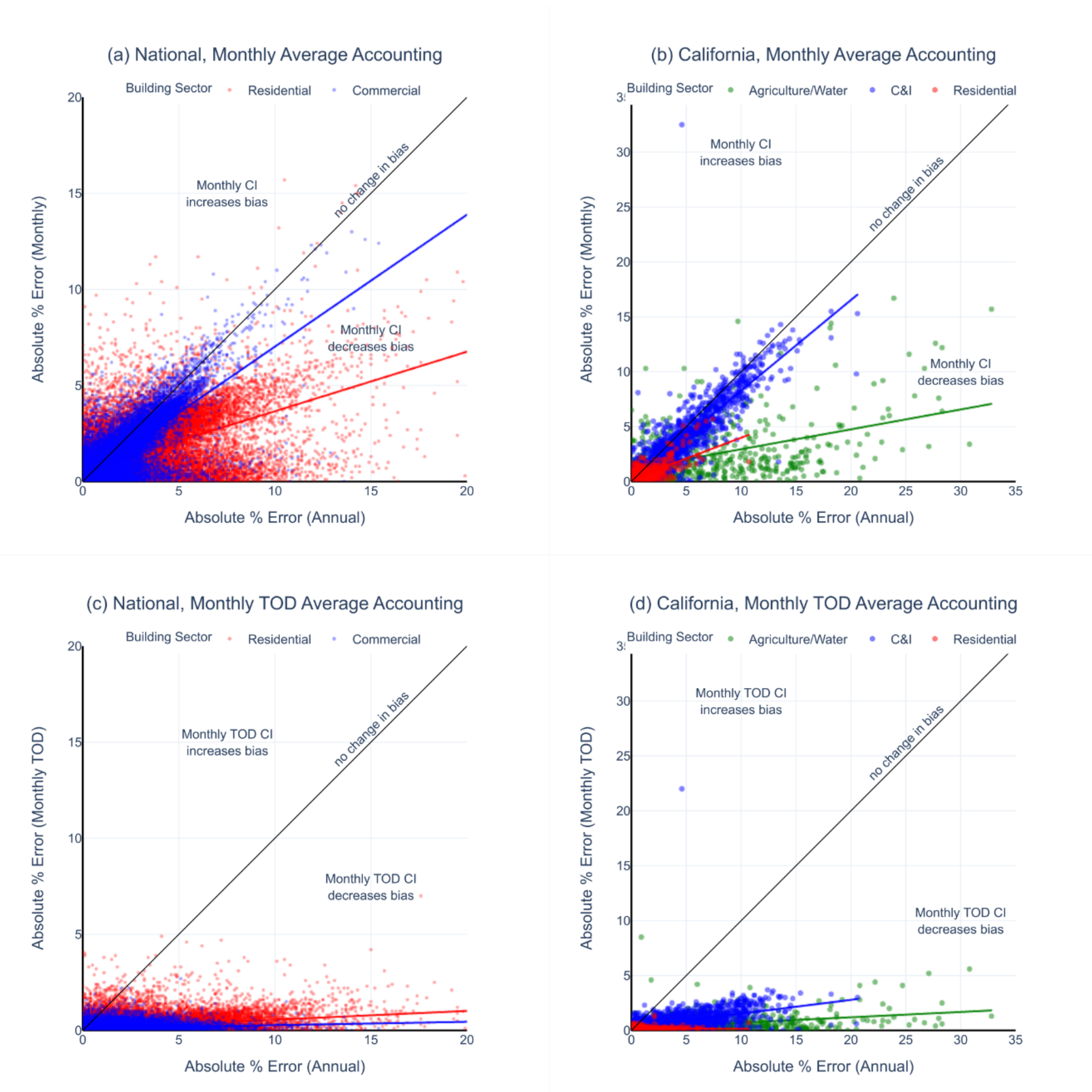

Figure 1.4. *Each plot compares the absolute percentage bias for inventories calculated using monthly-average carbon intensities (top row) and monthly-time-of-day-average carbon intensities (bottom row) compared to the bias from using annual-average carbon intensities for both the national results (left column, N=112,717) and the California case study (right column, N=2,766). Any points below the 45-degree line in each plot mean that the higher resolution carbon intensity decreased bias compared to the annual resolution, and vice versa. For the California ISO case study (right column), the results are broken out by residential loads, commercial and industrial (C&I) loads, and agricultural and water pumping loads.*

The bottom panels of Figure 1.4 demonstrate that monthly time-of-day average accounting substantially reduce, though do not eliminate, carbon inventory bias compared to annual-average accounting for all building types. This is because monthly time-of-day averages reflect both seasonal and daily patterns which are present in most energy demand profiles. These results suggest that the use of monthly time-of-day average emissions factors for accounting may strike a reasonable balance between simplicity and accuracy. However, in practice, monthly time-of-day average data may not be that much simpler to use than hourly emissions factors, because hourly energy demand data would still need to be collected and analyzed to use these emission factors.

Discussion

Recommendations

Accuracy is one of the fundamental GHG accounting and reporting principles described by *The GHG Protocol*. As noted in the Protocol's *Corporate Accounting and Reporting Standard*, "data should be sufficiently precise to enable intended users to make decisions with reasonable assurance that the reported information is credible. GHG measurements, estimates, or calculations should be systemically neither over nor under the actual emissions value, as far as can be judged, and that uncertainties are reduced as far as practicable."[44] The GHG Protocol Corporate Standard suggests as a rule of thumb that an error of 5% or more in an emissions inventory is considered "materially misleading" and would require the organization to recalculate their inventory (and perhaps even their base year inventory) to address the error.[44] As the results of this research show, this 5% materiality threshold may be exceeded in many cases by using annual average emission factors, especially if an organization's emissions inventory is primarily driven by its scope 2 emissions.

As explained through Equation 1, the results illustrate how the bias in carbon inventories is based on a combination of factors including the variability in hourly building demand, the variability in hourly carbon intensity, and the correlation between building demand and grid carbon intensity. If any one of these factors is small (close to zero), whether because building demand is relatively flat, grid carbon intensity is relatively flat, or the variation in either is mostly random and uncorrelated with the other, then the bias introduced by using annual accounting will be small.

However, the results of this study make clear that in today's electricity system, annual-average emissions accounting yields imprecise emission inventories in most regions and for most end-users. In addition, this study shows that monthly average emission factors do not reliably or substantially address this bias. Thus, we recommend that hourly or sub-hourly accounting be adopted as the best practice for attributional GHG accounting of grid-consumed electricity and for location-based Scope 2 GHG inventories.

Implications and urgency

These results have broad implications for many fields including voluntary climate disclosure, building performance regulations, carbon pricing, community-scale climate action planning, climate-based investing, and general business decisions. As emissions accounting is increasingly incorporated into regulations, carbon pricing, and business decisions, the bias from annual-average carbon accounting could have real-world legal and financial implications. For example, New York City's Local Law 97 set a carbon emissions cap (enforced with a substantial fine of $268 per ton in exceedance) for 50,000 buildings in the city and will go into effect in 2024. If this law were to use annual-average grid emissions factors for accounting, the results of this study suggest that the emissions for commercial buildings located in the New York ISO could be underestimated by up to 7%, eroding the efficiency and effectiveness of this law.

These findings are also relevant to crafting effective transportation policies, especially those that require accurately quantifying air pollution related to charging electric vehicles relative to pollution from internal combustion engines. For example, California's Low Carbon Fuel Standard (LCFS), which is designed to decrease the carbon intensity of the state's transportation fuels, currently calculates its base EV charging credits based on annual-average grid carbon intensity, which may be eroding the efficiency of this credit market.[45,46]

This research has several important implications for the academic research community, especially in the fields of lifecycle assessment (LCA), energy and climate policy research, and transportation research. Due to the ubiquity of electricity as an input to the manufacturing and use phase of many products, our findings suggest that hourly emissions factors should be used whenever possible for conducting attributional LCAs, especially when evaluating emissions from individual plug loads or end uses whose demand profile can be more variable than those of entire buildings. Although this study focused on the bias introduced in *carbon* inventories, future research should evaluate whether these biases also translate to other criteria pollutants (such as NO_x, SO_x, and particulate matter), which are also relevant to many LCAs.

Beyond the implications of this bias on scope 2 emissions inventories, these results also have implications for the accuracy of an organization's scope 3 inventory, which focus on upstream sources of emissions, such as the emissions of raw materials or products. Especially for organizations who rely on energy-intensive raw materials such as aluminum, annual-average accounting could lead to inaccurate calculations of the lifecycle emissions associated with those inputs into their products.

Although this study focused on carbon inventories for individual buildings, and thus do not tell us about the annual accounting bias for community-scale or company-wide emissions inventories (which include buildings of many different types, possibly across many grid regions for a company with a national or international footprint), it nonetheless has important implications for how emissions are allocated within the inventory. For example, a community-scale inventory may seek to identify whether residential or commercial buildings represent a larger share of emissions, or a corporate-wide inventory may seek to identify which business region is responsible for the most emissions, so that funding and resources can be allocated to mitigate the largest sources of emissions. These results suggest that the bias introduced by annual accounting could potentially mis-allocate emissions between building sectors or regions, thus mis-informing these types of prioritization efforts.

Annual accounting can also limit effective decision-making about individual carbon-mitigation efforts, such as energy efficiency investments. Using annual-average accounting would lead a decision-maker to believe that whichever project reduces the greatest number of kWh will reduce the organization's carbon footprint most effectively. However, using hourly accounting might reveal that if that project mostly reduces energy consumption when grid emissions are low, then the value proposition of that project would be undermined compared to a project that reduces consumption during hours of high carbon intensity.

The findings of this paper, and in particular the drivers of bias explained through Equation 1, lead us to believe that these annual accounting biases will only get worse, based on current trends in building energy demand and grid carbon intensity. As grids continue to integrate more variable and intermittent renewable energy sources to meet state RPS targets and other climate goals, the variability in hourly carbon intensity will likely increase, increasing σ_μ and inventory bias.[24,33,47] On the demand side, as more and more large end-use loads are electrified, such as vehicle charging, water heating, and space conditioning, building the total facility load profiles may become spikier and more variable, increasing σ_D and inventory bias.[17] Furthermore, efforts such as time-of-use rates, managed charging, and carbon-aware demand response, which seek to shape and shift load to better match the times when carbon-free resources are available, may strengthen the magnitude of the correlation between energy demand and grid carbon intensity ($\rho_{D,\mu}$), also increasing inventory bias. These three trends in combination, suggest that the continued use of annual carbon accounting will lead to inventories that become increasingly biased in the future.

Chapter 2: Modernizing power sector emissions data to inform deep decarbonization of the electric grid

Introduction

Accurate, comprehensive, and high-resolution data for tracking power sector emissions is becoming increasingly important for climate policy and voluntary climate action. An increasing number of policies and regulations, including New York City's Local Law 97 and the U.S. Security and Exchange Commission's proposed rule on climate risk disclosure, are based on accurately tracking the GHG emissions that each end user of electricity is responsible for. Additionally, a record number of actors, including corporations, cities, and other institutions, have made voluntary decarbonization pledges that are informed in part by inventorying and tracking their emissions. However, recent research has shown that the emissions factors that have historically been available to inform these efforts may be inadequate to meet the needs of today's end users. The main public emissions factor datasets for the U.S. include annual-average emissions factors that reflect the emissions intensity of generated electricity, but do not provide any information about how the emissions intensity of consumed electricity (which depends on imports of electricity from other regions) varies across time. The time-varying emissions intensity of consumed electricity is important for accurately describing emissions: recent research has shown imported electricity can account for 20-40% of emissions consumed in a region, and that annual accounting of emissions can significantly over- or underestimate end-use emissions inventories.[14,27,48]

Comprehensive hourly emissions data is also important for academic research. Over the past decade, many of the most prominent studies of the consequential emissions impact of electric vehicles and renewable energy deployment, as well as the broader study of marginal emissions, have relied on hourly generation and emissions data from the EPA Clean Air Markets Division's (CAMD) continuous emissions monitoring system (CEMS) dataset.[28,49–62] The major limitation of this dataset is that it only covers fossil-fueled generators >25MW nameplate capacity, some of which only report data for part of the year. The authors of these studies have generally assumed that generators that did not happen to report data to CEMS could not be on the margin, or represented an insignificant proportion of generation in the regions under analysis, although some authors acknowledge that this is not always an appropriate assumption.[28,54,63] Another limitation of the CEMS dataset is that it only reports hourly *gross* generation, and not *net* generation, which represents the electricity actually injected into the grid and ultimately used by consumers. Many previous studies using this dataset used the gross generation data directly in their calculations of emission factors.[28,50,51,58,59] The continued use of this dataset could be biasing our understanding of the climate impacts of the power sector and electricity end uses.

As of yet, no comprehensive, high-quality, and high-resolution dataset of grid emissions exists. Existing hourly datasets are either incomplete (CEMS) or are estimates that have not yet been validated based on high-quality measured or reported data. Existing comprehensive and high-quality datasets, such as the EPA's eGRID database, only publish low-resolution, annual data. The challenge of producing data that is both comprehensive and high-resolution is that the data source that is used to fill in generation and fuel consumption data that is missing from CEMS, EIA's Form 923, only provides data at the monthly and annual resolutions. Thus, overcoming this challenge requires a robust method for imputing the hourly profile of data that is only reported at the monthly or annual level.

This paper presents a method for estimating hourly generation, emissions, and emissions intensity data for the entire U.S. power sector at the regional and individual plant level, developed as part of the Open Grid Emissions Initiative.[64] The goal is to provide accurate, comprehensive, and high-resolution data that represents both emissions generated by the power sector and emissions from consumed grid electricity. Our method uses publicly available data from the U.S. EPA and EIA and introduces several novel methods and applications of existing open-source methods for working with these data. Our open data, code, and methodological documentation are freely available at the Open Grid Emissions Initiative website.[65] We believe that the OGE dataset is the most comprehensive, most accurate, and highest resolution dataset of historical U.S. power sector emissions and electricity emissions factors available to date.[66] To our knowledge, it is also the first comprehensive hourly dataset of NOx, SO2, CH4, and N2O emissions from the U.S. power sector, and of total CO2 emissions resulting from electricity generation.

Background and literature review

Recent research has demonstrated that as the power sector continues to decarbonize, hourly or higher resolution data is needed to accurately characterize power sector emissions intensity and attribute emissions to end uses of electricity.[48] Previous research has also indicated that consumption-based emissions factors, which account for the interchange of electricity between regions, are increasingly necessary to accurately characterize the attributional emissions of electricity end uses.[14,27]

To date, most publicly accessible datasets of power sector emissions and electricity emissions factors do not include consumed emissions factors or hourly-resolution data. The U.S. EPA’s Emissions and Generation Resource Integrated Database (eGRID) is the oldest and most comprehensive dataset of power sector emissions, primarily relying on measured emissions data from continuous emissions monitoring systems (CEMS).[67] However, the eGRID data is published at the annual resolution. In an attempt to reflect consumption-based emissions, the EPA also aggregates its data into “eGRID subregions”, the boundaries of which are defined to limit the import and export of electricity, but do not explicitly account for power flows between balancing areas.[68] Likewise, the U.S. Energy Information Administration's published "Emissions by plant and region" dataset, which relies on fuel consumption data reported to EIA Form 923, only includes generated emissions factors at the annual resolution.[69] Because of delay involved in collecting and verifying the data that serve as the inputs to these two datasets, another factor that limits their potential usefulness is that they are released on a 1-2 year lag: data for 2021, for example, will not be released until autumn 2022 or winter 2023.[68,69]

Generally, power sector datasets from the EPA and EIA include data for both power plants (which only generate electricity) and combined heat and power (CHP) plants (which produce both electricity and useful thermal output for applications such as district heating or industrial steam). Thus, in addition to reporting total "power sector" emissions, in order to calculate emissions factors for generated electricity, these datasets must adjust their emissions totals for CHP plants, to exclude fuel consumed for non-electricity purposes.

These datasets generally apply an adjustment that treats biomass emissions as carbon-neutral, which means that to date none of these existing datasets include emissions factors that represent all CO2 emissions of generated electricity. This assumption that biomass emissions are carbon neutral has been widely refuted by the academic literature.[70–77] The major flaw of this assumption is that it selectively applies lifecycle accounting to a single fuel source, and also selectively defines the system boundaries and temporal scope of this analysis. The implication of this limitation is that these existing datasets are systematically underrepresenting carbon dioxide emissions in grid that include bioenergy generation.

Several recent academic efforts have improved upon certain limitations of the existing EPA and EIA data. The Power Sector Carbon Index, based on 2018 research by Schivley et al., now publishes monthly-resolution power sector CO2 emissions data on only a 3-6 month lag.[13] Because this dataset is focused on tracking long-term trends in power sector carbon emissions, it does not include consumed emissions factors or data for emissions other than CO2. Work by de Chalendar et al. in 2019 and de Chalendar and Benson in 2021 led to the creation of the GridEmissions dataset, which was the first publicly-available dataset of both generated and consumed, hourly CO2 emissions factors for the U.S., published on only a one-day lag.[14,78,79] Instead of relying on measured emissions data and reported fuel consumption data, the GridEmissions dataset makes use of a relatively new source of near-real-time hourly generation and interchange data available for each balancing authority through EIA Form 930 (published as part of the EIA's "Hourly Electric Grid Monitor").[43] Several additional commercial datasets of hourly, consumed grid emissions factors exist, and are based on similar data sources and methods to the GridEmissions dataset, so are not discussed in this paper.[40,80]

To date, there has been no way to validate how well these real-time estimates reflect actual hourly emissions from the power sector, and there are several factors that may affect the accuracy of these estimates based solely on EIA-930 data. First, the reported EIA-930 data includes multiple known issues with data quality, which while seem to be improving over time, may still affect the accuracy of resulting emissions estimates.[81] These issues include incorrect reporting of the prevailing local time of datapoints, accounting discrepancies in reported interchange values, inconsistent categorization of generation into fuel categories, and missing data. Additionally, the emissions factors used to convert net generation to emissions are generic, historical annual averages and may not reflect the current, time-varying emissions intensity of specific regional fleets. This means that while such datasets might be useful estimates for real-time operational decision making, they might not be of sufficient quality to base accurate emissions inventories on.

The Open Grid Emissions Initiative (OGEI) dataset, introduced in this paper, addresses many of the limitations of these previous datasets by providing hourly, generated and consumed emissions factors for multiple greenhouse gases and air pollutants, as well as generation and fuel consumption data, using primarily measured and reported data. We believe that the OGEI dataset is the most comprehensive, most accurate, and highest resolution dataset of historical U.S. power sector emissions and electricity emissions factors available to date.[66] To our knowledge, it is also the first comprehensive hourly dataset of NOx, SO2, CH4, and N2O emissions from the U.S. power sector, and of total CO2 emissions resulting from electricity generation.

Table 2.1 Comparison of existing publicly accessible sources of power sector emissions and electricity emissions factor data

Dataset:		**eGRID**[67]	**EIA**[69]	**Power Sector Carbon Index**[13]	**GridEmissions**[14,78]	**Open Grid Emissions Initiative**
Temporal Resolution	Hourly				✓	✓
	Monthly			✓		✓
	Seasonal	✓		✓		
	Annual	✓	✓	✓		✓
Emission Factor Type	Generated	✓	✓	✓	✓	✓
	Consumed				✓	✓
Data Sources	CEMS	Annual		Hourly		Hourly
	EIA-923	✓	✓	✓		✓
	EIA-860	✓	✓	✓		✓
	EIA-930				✓	✓
CO2 emissions data	Power sector	Mass				Mass
	Biomass-adj. power sector		Mass & EF			Mass
	Electricity					Mass & EF
	Biomass-adj. electricity	Mass & EF		Mass & EF	Mass & EF	Mass & EF
Pollutants Tracked	CO2	✓	✓	✓	✓ (lifecycle)	✓
	CH4	✓				✓
	N2O	✓				✓
	CO2e	✓				✓
	NOx	✓	✓			✓
	SO2	✓	✓			✓
	Hg	✓				
Spatial Aggregation	Plant	✓	✓			✓
	Balancing Area	✓			✓	✓
	NERC	✓	✓	✓		
	State	✓	✓	✓		
	National	✓	✓	✓		
Approximate Data Release lag		1-2 years	1-2 years	3-6 months	1 day	1-2 years
Historical Coverage as of Sept 2022		1996-2020	2013-2020	2001-March 2022	July 2018 – June 2022	2019-2020

Methods and Data

The Open Grid Emissions Initiative builds on many of the same data sources and methods that have previously been explored in the academic literature for cleaning and analyzing power plant operational data. Many of the underlying assumptions and methods for cleaning the data are adapted from the U.S. EPA's eGRID methodology.[68] The methods for cleaning the EIA-930 data come from Chalendar and Benson 2021 and Ruggles et al 2020.[78,82] The multi-region input output model used for calculating consumption-based emissions come from Chalendar et al 2019.[14] Although this research includes many smaller, incremental improvements to existing methods, the main novel methodological contribution is a method for imputing the hourly profile of monthly-resolution EIA data.

This dataset relies on combining multiple sources of data including the EPA's CEMS data and data from EIA Forms 860, 923, and 930. Because these datasets are released in non-standardized formats, sometimes contain incomplete or anomalous data, and can be challenging to cross-link, we build upon several existing open-source projects for standardizing and cleaning these data. The first of these is Catalyst Cooperative's Public Utility Data Liberation (PUDL) project, which provides standardized and unified relational databases of the raw CEMS, EIA-860, and EIA-923 data, as well as analysis tools for further cleaning and cross-walking the data.[83] Because EPA and EIA datasets do not always use consistent plant identifier codes or units of analysis, we also rely on the EPA's open-source Power Sector Data Crosswalk project, which provides a table for linking these datasets together.[84] Finally, the raw EIA-930 data includes data quality issues that result in the reported demand, generation, and interchange data not obeying energy conservation laws, so we utilize the physics-based reconciliation code as part of the GridEmissions package to produce a cleaned and physically realistic version of the EIA-930 data.[78,79]

The OGE dataset primarily relies on hourly emissions data from the CEMS dataset, and data gaps are filled using monthly and annual-resolution EIA-923 data, which is assigned an hourly profile based on hourly fleet-specific net generation data reported in EIA-930. Whenever emissions data is missing (in the case of individual hours in the CEMS data) or not reported (in the case of the EIA-923 data), it is imputed based on reported fuel consumption, fuel-specific emissions factors, and boiler-specific design parameters and emissions control equipment. Total emissions from both CEMS and EIA data are adjusted for combined heat and power plants to reflect only the portion of emissions associated with power generation. Hourly gross generation data from CEMS is converted to hourly net generation based on the ratio of reported gross generation to net generation (reported in EIA-923) for each subplant (which are described in the next section). Monthly EIA-923 data for subplants that do not report data to CEMS is assigned an hourly profile based on the shape of the residual net generation profile between the total fleetwide net generation in a region reported in EIA-930 and the portion of net generation reported in CEMS for that fleet. Hourly generated emissions factors are calculated by dividing hourly emissions mass by hourly net generation. Consumption based emissions are then calculated using the multi-region input output model introduced in Chalendar et al 2019, based on calculated generation and emissions rates, and reported hourly interchange values between regions in EIA-930.

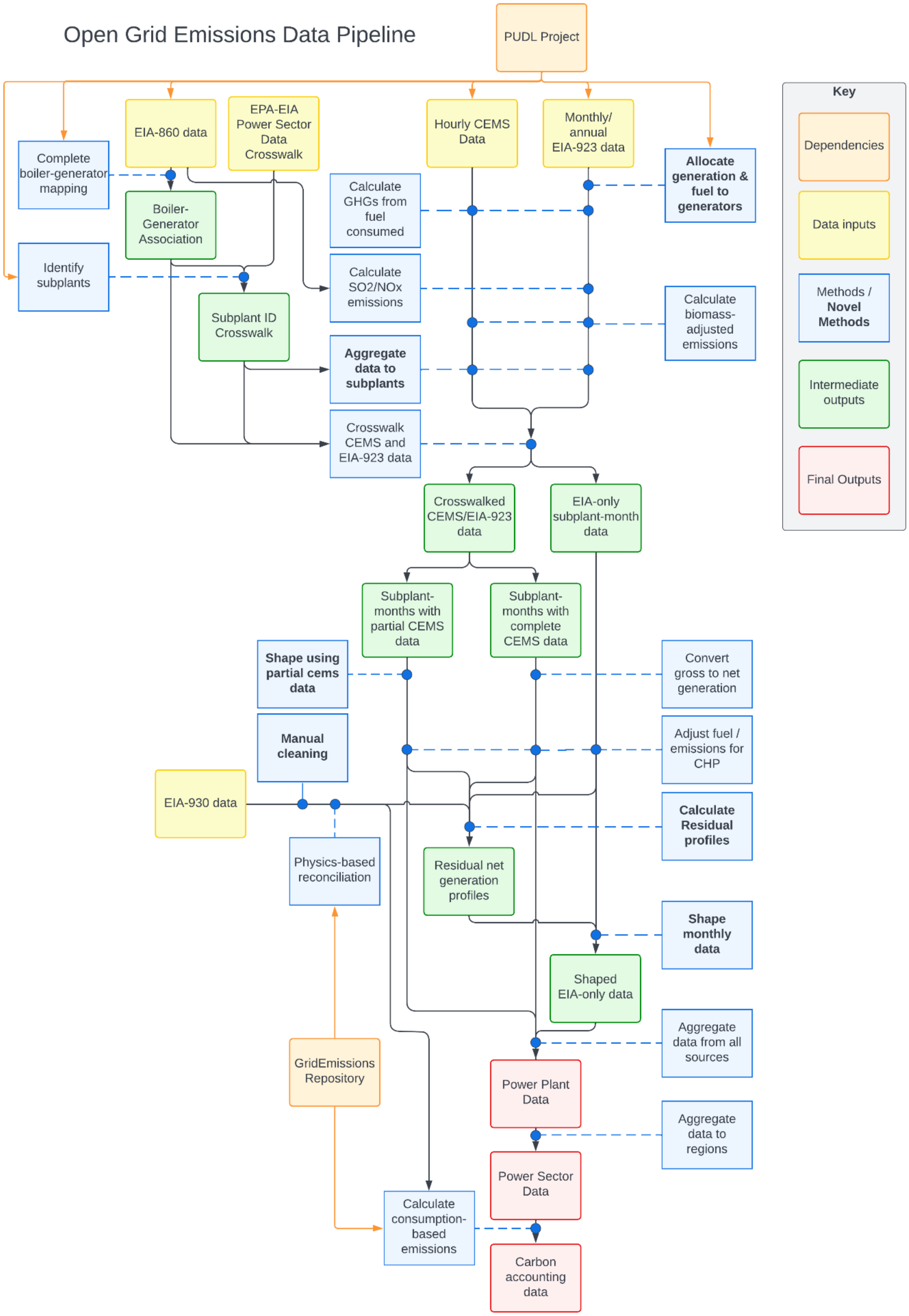

Figure 2.1 Flow diagram of the major steps of the open grid emissions data pipeline

Crosswalking data from multiple sources

Because our emissions calculations rely on data from multiple data sources, matching these data accurately is crucial to identifying data gaps, calculating conversion factors, and ensuring that we are not double-counting data. The main challenge to matching data from each source is that data from each source is typically reported at different aggregations: EIA reports some data at the boiler level (where the fuel is combusted and steam produced) and some data at the generator level (where the electricity is generated), while the CEMS data is reported at the unit level (which represents a collection of boilers and smokestacks). Complicating this is that the EIA also uses the term “unit” to describe multiple generators that operate together. Sometimes boilers, generators, and EPA units are related in simple one-to-one relationships (i.e., a single boiler powers a single generator, and emits pollution via a single stack), but in other cases these units and generators can be configured in complex one-to-many, many-to-one, or many-to-many relationships. To identify these relationships, we use the EPA’s power sector data crosswalk and the EIA-860 boiler-generator association table, supplemented by further associations that the PUDL project added based on string matching and the EIA unit codes.[85] Once all of these relationships were identified, we applied a method developed by Catalyst Cooperative that uses network analysis to create a graph of all connections between boilers, generators, EPA units, and EIA units, and assign a unique “subplant ID” to each connected subgraph. These subplants represent the smallest unit of analysis to which we aggregate data and allows us to accurately identify where data from each source overlaps or is missing.

Hourly Gross to Net Generation

Gross generation represents the total amount of electricity generated as measured at the terminal of a generator. However, the amount of electricity that a plant injects into the power system, referred to as net generation, is lower than gross generation due to parasitic electrical loads at the plant and electrical losses between the generator and the point of interconnection. Net generation is what is used for calculating generated emissions factors. Although EIA-923 reports monthly *net* generation totals, the hourly generation data in CEMS represents *gross* generation, which must be converted to hourly net generation to be used in our analysis. The method that we use to convert gross to net generation involves comparing monthly total gross generation data for each subplant to monthly reported net generation and calculating a gross-to-net ratio.[54,86,87] Wherever monthly reported net generation is negative, we preserve the hourly shape of the gross generation profile but shift it down until the monthly total matches the reported negative total from eIA-923. If plant-specific conversion factors are not available, we use a fuel-specific, national-average gross to net ratio. For year 2020, over 99% of the gross generation data in our dataset was converted using a subplant- or plant-specific gross to net ratio.

Imputing hourly profiles for monthly-reported data

The major novel methodological contribution of this work is a method for imputing the hourly profile of the monthly-resolution data for plants that do not report to CEMS. This method includes a series of three broad approaches that are applied to the monthly data depending on the most specific observed hourly data that is available for each subplant.

The first two approaches apply to plants where only certain units report hourly data to CEMS. If only a subset of units that make up a subplant report hourly data to CEMS, we use the complete monthly data for that subplant from EIA-923 to scale the hourly data from the units that do report to CEMS. If only certain subplants at a plant report hourly data to CEMS, we use the combined hourly profile of all CEMS-reporting subplants to shape the monthly EIA-923 data for the subplant(s) that do not report to CEMS. These two approaches assume that the operational profile of different units within a single subplant, or of different subplants within a single plant will be similar. This assumption may not always be accurate, but it is applied to only a very small segment of the overall data.[88]

For plants that do not report any hourly data to CEMS (which generally includes all clean and renewable generators, as well as any plants less than 25 MW nameplate capacity) or for large emitting plants that only report data to CEMS during ozone season (May-September), we can reasonably estimate their aggregate hourly generation profile using observed fleet-wide hourly generation data. Starting in 2018, the U.S. EIA started collecting hourly net generation data by plant primary fuel type (coal, natural gas, petroleum, nuclear, hydro, wind, solar, and other) for each balancing authority in the U.S. as part of their Hourly Balancing Authority Operations Report (Form 930).

To calculate the hourly net generation profile for all subplants that do not report to CEMS in each month, we subtract the aggregate hourly net generation profile of the CEMS data from the total hourly net generation profile for all plants of that fuel category in each region. This residual hourly profile should represent, in aggregate, the hourly profile of all plants that do not report data to CEMS. This hourly residual profile for each fleet-month is then normalized as a percentage of monthly total net generation for that fleet, and used to shape the monthly total net generation, fuel consumption, and emissions data for all plants in that fleet.

In some regions and periods, the hourly net generation from CEMS exceeds the total reported net generation in EIA-930, due to inconsistencies in which balancing authorities or fuel categories individual plants are assigned to in EIA-930. In the cases where the amount by which the CEMS generation exceeds the EIA-930 generation is small, we shift the CEMS profile down until no hours exceed the reported EIA-930 generation, then calculate the residual. This approach prevents the residual profile from including negative net generation, while preserving residual shape of the two profiles as much as possible.

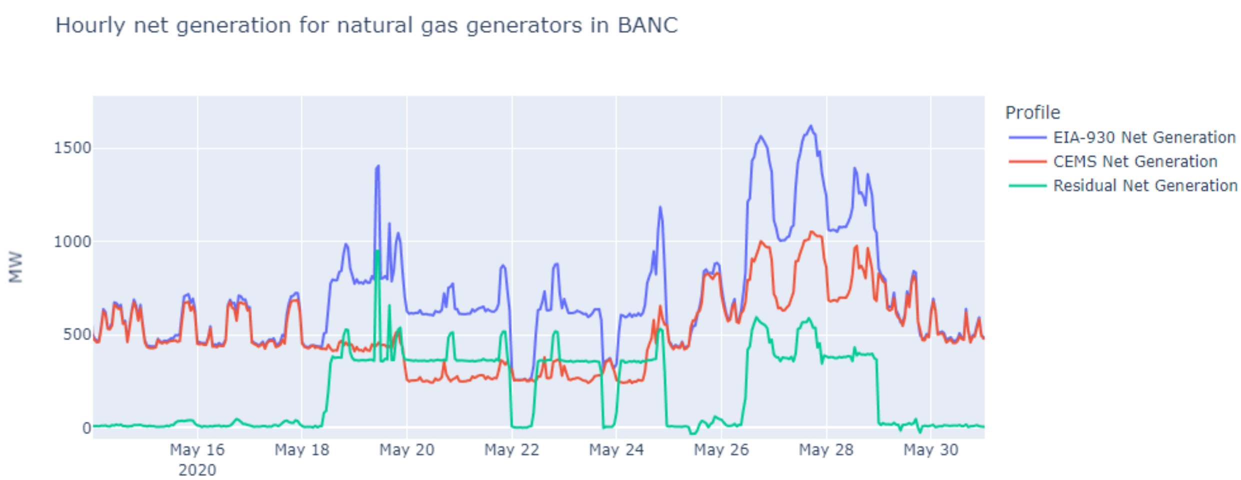

Figure 2.2 Comparing natural gas generation data for the Balancing Authority of Northern California (BANC) reveals that operational patterns for plants that report to CEMS (red line) differ quite significantly from smaller plants that do not report to CEMS (green line). The residual profile shown by the green line was used to shape the May generation, fuel consumption, and emissions totals reported in EIA-923 for the natural gas plants in BANC that did not report data to CEMS.

In the case when a high-quality residual profile cannot be calculated, alternate methods are used to impute the missing hourly profile. If available, the total EIA-930 fleet profile is used, as it represents the generation-weighted average profile of all generators in the fleet. If there is no EIA-930 data, but there is CEMS data that represents at least three different plants in a fleet, the CEMS profile is used as a proxy, even though the generation profile of these larger generators may not necessarily represent the profile of smaller generators. In the case that no hourly data is available for a specific fleet, we apply a flat hourly profile, which is equivalent to using the monthly average value for all hours. This fallback method is only applied to about 2% of the total net generation (see Table 2.5), but for certain types of generation that operate as baseload resource (e.g. nuclear, geothermal, petroleum) this may be a reasonable approximation of their actual hourly profile if there are not significant periods of scheduled maintenance.

If hourly wind or solar net generation profiles for a region are not reported in EIA-930, we impute a profile by averaging the wind or solar profiles for all directly interconnected balancing authorities (BA) located in the same time zone as the missing BA. Solar and especially wind generation tends to vary geographically, so this approach has limitations, but attempts to use wind and solar data from regions that are as geographically proximate to the missing BA as possible to minimize these differences. If data is not available from neighboring regions, we use national-average wind and solar profiles for each local hour. Cross-validating this method for regions where wind and solar data is available reveals that both methods work quite well at estimating the shape of solar generation (median correlation coefficients ~0.9), but as expected perform much worse for estimating local wind generation shapes (median correlation coefficient of 0.45 for the neighboring method and 0.11 for the national method). However, as shown in Table 2.5, this method is used to shape less than 0.5% of all generation data.

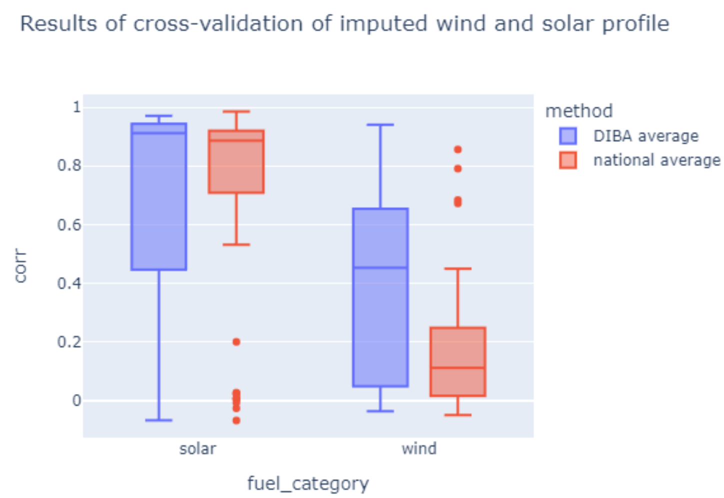

Figure 2.3 Results of cross-validation of our method for imputing missing wind and solar profiles by averaging data from neighboring regions (directly interconnected balancing authorities – DIBA) and the entire country. A correlation coefficient of 1 means that the shape of the imputed profile matches the actual profile exactly.

Results

Validation compared to other datasets

The first data quality metric is how well the magnitude of our annual totals match estimates from other data sources. We expect some differences due to methodological differences between the datasets, but we expect that the order of magnitude should be the same and that results are relatively close, within +/-5% of previous estimates.

We compared the annual total results of the OGE dataset for year 2020 with the results of the other previous datasets. The results in the below table validate that on an annual level, our results are consistent with other previous estimates. The largest differences are in NOx and SO2 emissions outputs, where our NOx totals are 4% higher than eGRID's totals, and our SO2 totals are 13% lower than those in eGRID (although less than 1% different from EIA's totals). These discrepancies in SO2 emissions totals primarily result from the EIA and eGRID using different SO2 emissions factors for coal and landfill gas combustion (OGE uses the EIA factors).

Table 2.2 Comparison of total annual results from each emissions dataset

Metric		OGE	eGRID	EIA	PSCI
	Net Gen (TWh)	4,021	4,021	4,007	4,048
CO_2 (trillion lb)	Power Sector	3.864	3.816	N/A	N/A
	Biomass-adj. electricity	3.290	3.291	N/A	3.276
NOx (billion lb)	Power Sector	2.781	2.636	2.670	N/A
	Biomass-adj. electricity	2.273	2.046	N/A	N/A
SO_2 (billion lb)	Power Sector	2.270	2.595	2.255	N/A
	Biomass-adj. electricity	1.778	1.908	N/A	N/A

Quality of input data

The second data quality metric evaluates what percent of annual total generation and emissions is derived from data from each of our input source, which range in quality. We consider CEMS to be the highest quality because it represents measured data, monthly EIA-923 as the next best because it is based on reported monthly values, and annually reported EIA-923 data as the worst, since although it represents reported data, there is less certainty about how to distribute the data to individual months to ensure that no data is double-counted or under-counted.

The below metadata for our results indicate that most of the emissions data in the OGE dataset come from measured hourly CEMS data. A smaller but significant portion of the results (one-third of the generation, 7% of CO_2e emissions, and 19% of NOx data) come from monthly EIA-923 records that we have assigned hourly profiles to using the methodology described in this paper. An even smaller portion of the results (9% of the net generation and 17% of the NOx emissions) come from annually reported EIA-923 data.

Table 2.3 Percentage of final OGE data from each input source

	Metric:	Total Net Generation	Combustion Net Generation	Total Emissions			Electricity Emissions		
Quality	**Method:**			**CO2**	**NOx**	**SO2**	**CO2**	**NOx**	**SO2**
Highest ↑ ↓ Lowest	Hourly CEMS	**57%**	90%	84%	55%	70%	**92%**	**64%**	**88%**
	Monthly EIA-923	**34%**	8%	14%	29%	28%	**7%**	**19%**	**10%**
	Annual EIA-923 Only	**8%**	1%	1%	13%	2%	**0%**	**13%**	**2%**
	Mixed CEMS & Annual 923	**1%**	0%	1%	3%	0%	**1%**	**4%**	**0%**

This table also shows why previous academic studies that relied only on CEMS data may be missing a substantial portion of generation and emissions data. While in 2020, CEMS accounted for 92% of all electricity-related CO2 emissions and 90% of all combustion net generation, it only reflects 57% of all net generation, only two-thirds of all NOx emissions. On a regional level, this assumption that CEMS data represents a complete picture is shown to break down further. While in some regions, CEMS represents a nearly complete picture of certain types of GHG emissions and combustion generation, it generally misses a large amount of total generation and air pollution data. In CAISO, for example, CEMS data represents less than two-thirds of CO2 emissions, only one-third of generation, and less than 10% of all NOx and SO2 emissions.

Table 2.4 Percent of data for the seven major ISO/RTOs that is represented in CEMS

ISO	Total Net Generation	Combustion Net Generation	Electricity Emissions		
			CO2	**NOx**	**SO2**
CAISO	**35%**	**69%**	**64%**	**4%**	**7%**
ERCOT	**59%**	**87%**	**92%**	**60%**	**98%**
ISONE	**52%**	**85%**	**70%**	**12%**	**12%**
MISO	**63%**	**89%**	**93%**	**69%**	**88%**
NYISO	**41%**	**90%**	**82%**	**30%**	**50%**
PJM	**57%**	**96%**	**95%**	**67%**	**94%**
SPP	**57%**	**94%**	**97%**	**83%**	**97%**

Quality of hourly profile

The final data quality metrics evaluates the quality of the hourly values, based on the source and method used to identify the hourly value. The highest quality hourly profile data is represented by a measured hourly value from CEMS, while the lowest quality hourly datapoint represents a monthly average value assigned to each hour.

A majority of the hourly data represent actual measured values from CEMS, or values derived from hourly CEMS data (in the case of net generation). The next most used method is the residual EIA-930 profile. While this value is not necessarily accurate for a specific, individual plant, it should be relatively accurate at the fleet level since it is derived from subtracting two observed hourly values. Based on this metric, the quality of hourly CO2 values is the highest, followed by SO2, and the quality of specific hourly NOx values is lowest quality.

Table 2.5 Percentage of hourly data that was shaped using each method.

	Metric:	**Net Generation**	**Total Emissions**			**Electricity Emissions**		
Quality	**Method:**		**CO2**	**NOx**	**SO2**	**CO2**	**NOx**	**SO2**
Highest	CEMS reported	**57%**	84%	54%	69%	**92%**	**64%**	**88%**
	Partial CEMS	**1%**	1%	3%	2%	**1%**	**3%**	**1%**
↑ ↓	Residual EIA-930 profile	**38%**	6%	18%	6%	**3%**	**12%**	**3%**
	EIA-930 profile	**2%**	0%	1%	0%	**0%**	**1%**	**0%**
	CEMS-avg profile	**0%**	3%	8%	8%	**1%**	**7%**	**3%**
Lowest	Imputed wind/solar profile	**0%**	N/A	N/A	N/A	**N/A**	**N/A**	**N/A**
	Assumed flat (monthly avg)	**2%**	7%	16%	14%	**3%**	**13%**	**6%**

Comparing non-biogenic electricity emissions to total electricity emissions

Nationally, our results show that excluding biomass underestimates total electricity-related emissions from the U.S. power sector by 3%. However, the impact of excluding biomass from CO2 emissions factors has an even bigger impact at a regional scale. One extreme example is the emissions factor for Alaska Municipal Light and Power (AMPL), which at 0.701 lb/MWh (in eGRID) makes it among the lowest-carbon balancing areas in the county (the national average, according to eGRID, is 818 lbCO2/MWh). The biomass-adjusted electricity emissions factor in OGEI is similarly low (0.645 lb/MWh), but if you consider the carbon emissions from biomass combustion, the AMPL emission factor increases over 2000% up to 1,319 lb/MWh, making among the dirtiest regions in the country. This is likewise a significant issue in some of the largest balancing areas in the country: we found that the use of a biomass-adjusted emissions factors would underestimate CO2 emissions in ISONE by 22%, in CAISO by 14%, and in NYISO by 8%.

Table 2.6 Comparison of biomass-adjusted generated electricity emissions factors to total electricity-related emissions for four grid regions

Balancing Area	Electricity CO2 EF (lb/MWh)	Biomass-Adjusted electricity EF (lb/MWh)	% by which adjusted EF underestimates emissions
Alaska Municipal Power & Light	1,319.3	0.7	100%
ISO New England	671.7	526.8	22%
California ISO	487.8	419.6	14%
New York ISO	489.4	449.6	8%

Discussion

The research presented in this paper has potentially far-reaching implications for future academic research, GHG accounting, policymaking, and voluntary decarbonization efforts.

The Open Grid Emissions Initiative dataset includes hourly, monthly, and annual-resolution data for each of its three outputs types which cover a wide variety of potential use cases: consumed emissions factors, regional power sector generation and generated emissions, and individual power plant data. The consumed hourly emissions factors are applicable to scope

2 GHG accounting, attributional lifecycle assessment studies, and validation of near-real-time estimates of consumed emissions factors. The regional power sector emissions and generation data can be used by policymakers and regulators to track progress toward climate goals, for calculating state or national emissions inventories, or as part of next-generation energy attribute certificates. Finally, the individual power plant data can enable more complete academic research and modeling of the power sector, and could be useful to environmental justice advocates for pinpointing hourly point sources of air pollutants in local communities across the country.

Our results suggest that lifecycle assessment studies and studies of marginal emissions may be mis-representing impacts if they rely solely on CEMS data in their analyses. As shown in Table 2.3 above, although CEMS data covers over 90% of CO2 emissions nationally, it represents less than 60% of total generation, and only about two-thirds of all NOx emissions. In specific regions, such as CAISO, ISONE, and NYISO, the coverage of CEMS is even less representative of the entire regional power system. Previously, studies of marginal emissions that relied only on CEMS data assumed that generators that did not report to CEMS were unlikely to be on the margin. However, data from ISOs suggests that non-combustion fuels that don't report to CEMS are increasingly marginal resources.[89–93] Furthermore, we found that over half of all combustion-based generation not represented in CEMS has a capacity factor less than 0.25, suggesting that these resources are likely operating in a peaking capacity on the margin. In the future, we recommend that such studies incorporate complete hourly emissions and generation data into their analyses.

Our results also suggest that the use of biomass-adjusted CO2 emissions factors from existing datasets may significantly underestimate the emissions intensity and impact of electricity end uses in certain regions. Besides being widely used in the academic literature, biomass-adjusted emissions factors are ubiquitously used for policies, markets, and emissions tracking systems. These uses include the ENERGYSTAR Portfolio Manager (the most-used energy tracking tool for commercial buildings), fueleconomy.gov (the official U.S. government source for vehicle fuel economy information), and any GHG inventory that follows The Climate Registry or the Greenhouse Gas Protocol recommendations.[68] Our results, in combination with the existing academic literature on biomass emissions, suggest unless there is a specific policy need to treat biomass emissions as carbon-neutral, CO2 emissions factors that represent total electricity-related emissions should be used.

Although recent research on carbon accounting and time-coincident electricity procurement has driven much interest from stakeholders in understanding grid emissions on an hourly basis, there have been four primary barriers to the wider adoption of hourly accounting of emissions, three of which we believe the research presented in this paper helps address: 1) the availability of hourly electricity metering data, 2) the availability of high-quality hourly grid emissions data, 3) the lack of guidance on standardized approaches for performing hourly accounting, and 4) the real and perceived complexity of working with hourly data. While this research does not affect the first barrier, this barrier is slowly being removed with the growing deployment of advanced metering infrastructure (AMI), which is capable of hourly or sub-hourly readings, from 39% of all meters in 2013 to 65% of all meters in 2020.[35] This paper directly removes the second barrier by making high-quality, hourly consumed emissions factors publicly and easily available. We believe that this work will also make an especially timely contribution to addressing the third barrier around lack of standardization. The Greenhouse Gas Protocol has announced that it will begin a stakeholder process to revise the scope 2 GHG accounting guidance starting in late 2022 or early 2023, and by making these data available, we believe that it reframes the discussion of hourly GHG accounting from a theoretical exercise to a practical discussion of how to implement it. Finally, the increased complexity of working with hourly data suggests that third party software platforms and inventory tools will become increasingly necessary to help users manage the data. By releasing our code and data under a permissive, open-source MIT license, we hope that this will enable this data to be widely integrated into these software tools.

Another implication of this work is how it might enable higher-quality, real-time estimates of grid emissions. One factor that limits the relevance and usefulness of the Open Grid Emissions data is that because it relies on the same high-quality, validated data inputs as eGRID, it is subject to the same 1–2-year lag in releasing data. However, the OGE data presents a novel opportunity to validate real-time emissions estimates, and refine the methods used for estimating real-time emissions. Once validated and determined to be of high enough quality, these real-time estimates could enable more timely analysis, reporting, and regulation of consumed emissions from electricity consumption.

Limitations

Although we believe that the Open Grid Emissions Initiative dataset represents the most comprehensive and accurate dataset of hourly generation and emissions data for the U.S. power sector available to date, it is still far from perfect. A complete list of known issues and future work can be found on the online code repository (https://github.com/singularity-energy/open-grid-emissions/issues), but some of the largest limitations are discussed briefly here. The OGEI data does not yet include a methodology for estimating hourly charge and discharge patterns from energy storage, nor a method for accounting for emissions from stored electricity. Second, when residual net generation profiles cannot be calculated from the EIA-930 data, we impute generation profiles for wind and solar, and assume flat generation profiles for all other resources. This may result in reasonable approximations of the hourly shape in some cases but is not necessarily robust in all cases. Finally, in some limited cases, only annually reported data is available, which increases the chances of double-counting or under-counting data if used in combination with partial-year data from other sources. As an active open-source initiative, we expect that these limitations will be improved upon over time.

Chapter 3: Evaluating the cost and impact of voluntary renewable procurement goals using the MATCH model

Introduction

Voluntary renewable energy procurement by corporations, municipalities, and utilities makes up over one-third of total renewable energy procurement in the United States.[94] Over the past decade, much of this procurement has been driven by voluntary goals that seek to procure a certain percentage of the entity's annual electricity consumption from clean or renewable generation sources. This annual volumetric based procurement has been effective at adding new renewable energy capacity to grids. However, the challenge of fully decarbonizing the electric grid is not only a matter of how much clean and renewable energy is built, but when it is available to meet load. In recent years, the concept of "24/7" or "time-coincident" clean energy procurement has gained significant attention as a way to help ensure that voluntary procurement leads to around-the-clock availability of clean energy that matches the times when electricity is consumed. Another "next-generation" voluntary procurement approach that is sometimes framed as a competing approach to time-coincident procurement is emissions-optimized procurement, which seeks to procure generation from any global location that displaces the greatest amount of carbon emissions.

Previous studies and reports have hypothesized that time-coincident procurement can result in several types of benefits for energy buyers and the broader clean energy transition. These purported benefits include acceleration of clean energy deployment, incentivization of new clean energy technology, improving the long term affordability of the energy transition, increasing the grid's carrying capacity for renewable energy, and mitigating certain types of procurement risk.[95–99] However, some of these same studies have also called into question whether achieving time-coincident goals are practical, cost-effective, or effective at decarbonizing the electric grid as quickly as possible.[95,96,98,100] There are also open questions about how exactly to define a time-coincident procurement goal.

Although several previous studies have attempted to start answering these questions, these efforts have been limited by the lack of modeling tools that can be used to simulate the resource portfolios that would be selected, and the costs faced by voluntary buyers of energy under each of these different types of procurement goals. This will be explored further in the literature review, but in general existing models are tailored to simulating an entire regional power system or optimizing capital and operating costs faced by owner-operators of power plants, rather than to voluntary buyers of energy, which typically contract for energy using physical or virtual power purchase agreements.

This paper introduces a new model called MATCH ("**M**atching **A**round **T**he **C**lock **H**ourly energy"), which can be used to identify the most cost optimal portfolio of contracted resources that can meet an organization's energy procurement goals. In addition to this model's focus on the voluntary procurement context and ability to optimize the dispatch of generation and energy storage resources to match load on a time-coincident basis, it is also novel in its ability to identify and compare the impacts of multiple types of procurement goals, including annual renewable energy targets, 24/7 procurement, or emissions-based procurement.

This paper introduces the MATCH model as both a decision-making tool for voluntary energy buyers and as a tool for further research of questions surrounding the cost and impact of different types of voluntary clean energy procurement. Using the case study of a community choice aggregator (CCA) in California, this paper then illustrates the use of the MATCH model to answer questions about the cost and impact of 24/7 procurement strategies.

Literature Review

There are many existing studies that examine 100% renewable or clean energy pathways for states, utilities, and grid regions, but very few that focus on time-coincident procurement by voluntary buyers.[101–104] For utilities and grid regions, any renewable or carbon-free goal is inherently a time-coincident goal since these entities are responsible for maintaining reliable, around the clock delivery of electricity to their service territories. However, focusing on voluntary buyers of clean and renewable energy enables us to evaluate several unique aspects of this energy transition that have not already been explored in utility and regional-focused studies. The primary difference is that voluntary buyers have a choice in how and where they procure energy to meet such targets: generally, they can choose to procure renewable energy (or renewable energy attributes) from anywhere in the world that isn't necessarily generated at the same time as they consume electricity. Thus, the potential set of resources available to voluntary buyers, the costs of those resources, and the impact of their procurement can be dramatically different from the geographically and temporally constrained set of resources available to meet utility or state goals. Second, utility-focused modeling is often constrained by a number of regulatory, reliability, and physical power system constraints that voluntary buyers are often not subject to. Third, the costs faced by voluntary buyers are different. As opposed to many pathways studies which focus on the capital and O+M costs of generation and transmission infrastructure, voluntary buyers often procure electricity via virtual power purchase agreements, which represent contracts for difference between the fixed PPA price per MWh and any wholesale electricity market revenues that the project earns. Finally, many system-level pathways studies that use optimization are generally seeking to minimize system-level costs rather than the costs of individual actors, and thus may not accurately represent the behavior of any individual actor very well.

There have been three previous studies that focus on modeling time-coincident procurement by voluntary buyers, all published in 2021. In general, the limitations of these previous studies for understanding voluntary procurement fall into one or more of the following categories: they fail to represent realistic portfolio optimization based procurement strategies, they tend to assume non-economic dispatch of energy storage resources, use unrealistic hourly load profiles, do not consider a geographically or technologically diverse set of potential generation resources, or do not represent the complete or relevant set of costs faced by voluntary energy buyers. Many of these limitations spring from the lack of existing models tailored to exploring voluntary energy procurement.

The first is a 2021 study published by RMI that evaluated the cost and emissions impact of pursuing time-coincident procurement for a single commercial building or flat 1MW load in seven different U.S. and European electricity markets.[98] This study found that time-coincident procurement can create demand for emerging technologies, but it only modeled up to 90% time-coincident procurement because they found that beyond that, hourly matching became “impractically costly” (more than double the cost of a 100% annual target). However, this study has several important limitations that affect the relevance of its results. First, it uses a simple portfolio selection model that iteratively optimizes the cost serving each incremental MWh of time-coincident facility load, rather than optimizing the total portfolio costs. Second, the study only considered wind, solar, and batteries, and only considered a wind and solar profile for a single location, which ignores the role that technological and geographic diversity of resources can play in matching load. Second, the only costs the model considered were the levelized costs of each resource, which does not always reflect actual PPA pricing, and ignores wholesale market revenues earned by the projects. The model also only dispatches batteries based on facility load, and not economically based on any market signals. Finally, most of the results focus on the case of data center load, which the study models as a flat load with no hourly or seasonal variation, which is not necessarily a realistic approximation of datacenter end use load profiles.[105–108] Due to these limitations, this study likely does not provide a representative picture of the practicality, cost, or impacts of time-coincident procurement.

The second is a 2021 study published by researchers at Princeton that evaluated the system-level impacts of 24/7 carbon-free electricity procurement.[96] This study used a more sophisticated modeling approach, using an open-source electricity system planning model (GenX), which optimizes investment and operational decisions while meeting all relevant power system and policy constraints. The key findings of this study were that time-coincident procurement drives investment in advanced and clean firm resources and reduces system-level emissions more than annual procurement when the target was more than ~90% carbon-free energy. This study also found that achieving a 100% time-coincident portfolio was 39-54% more expensive than 100% annual goals when considering a full portfolio of clean resources, but that this premium increased to 64-139% when only considering wind, solar, batteries, DR, and geothermal (as opposed to the RMI study, which found > 100% cost premiums just to achieve a 90% match). Despite the sophistication of this study and the insights that it provides about system-level costs and impacts, this study does not answer important questions about the cost-effectiveness and practicality of time-coincident procurement for individual voluntary buyers. Instead of simulating cost-optimal time-coincident portfolios for each voluntary buyer, this modeling assumes that system level resources would be used to match the time-coincident load of a certain percentage of all C&I customers on the grid, and optimizes that portfolio to minimize system-level, rather than buyer costs.

The third is a 2021 preprint by NREL that introduces a new model called Vapor that can be used to estimate the grid impacts and costs of corporate renewable energy procurement.[109] However, this study, and the model it is based on, include major limitations that affect the relevance of the results for understanding the costs and impacts of voluntary procurement. The main limitation is that the Vapor model is designed to optimize the siting, technical design parameters, and battery size of a single PV+storage or wind+storage project based on the net cost of the system to the project offtaker. The model also assumes that any storage included in the project would only be dispatched to follow net load, rather than be economically dispatched in response to market signals. Thus, because this model is not designed to model a portfolio-based approach to voluntary procurement, the relevance of the Vapor model is limited to cases where voluntary buyers are seeking to only procure energy from a single generation project.

The modeling methodologies used in these previous studies illustrate the gap in available modeling tools for understanding real-world voluntary energy procurement. On one end of the spectrum are tools like GenX that are sophisticated but tailored to optimizing system-level costs that are not faced by voluntary buyers of energy. On the other end of the spectrum are tools that have been specifically designed to study voluntary procurement (Vapor and RMI's model) but do not realistically represent the ways that voluntary buyers make procurement decisions.

Methods and Data

The MATCH Model

This paper introduces a new voluntary energy portfolio planning and optimization model called MATCH ("**M**atching **A**round **T**he **C**lock **H**ourly energy"), which was developed in collaboration with an actual voluntary renewable energy buyer to plan their time-coincident renewable energy procurement strategy. As opposed to previous models, MATCH realistically reflects the objectives, cost structures, and constraints of voluntary renewable energy buyers and is able to select a diverse portfolio of resources that can be economically dispatched while meeting the buyer's voluntary procurement target. This model offers the flexibility for a buyer to consider any level of annual, time-coincident, or emissions-optimized procurement, or any combination of these three goals. The model balances sophistication with ease of use, configurable primarily using an excel spreadsheet and able to be run by any user who can run simple Python code in Jupyter notebooks.

The MATCH model is built upon the architecture of the “Switch 2.0” model, an open-source platform for planning high-renewable power systems.[110] Switch is a Python package which uses the Pyomo optimization framework to define models, load data, and solve instances. While built on the same architecture as Switch, the MATCH model substantially modifies the formulation and user interface of Switch to tailor it to the needs of modeling voluntary energy procurement. While Switch already offered users features such as flexible timescales, spatially and temporally resolved balancing constraints, modeling of inter-hour relationships, and modules for building and dispatching any generation or storage technology, MATCH adds several important capabilities, including:

- The ability to flexibly define annual, time-coincident, or emissions-optimized procurement targets, including the ability to specify different types of limits on excess generation.
- The ability to optimize PPA and storage capacity contract costs, nodal wholesale market revenues, load costs, and hedge contract costs, rather than the capital and O+M costs of generation infrastructure.
- The ability to automatically simulate location and project-specific expected hourly wind and solar generation profiles for each project using a python-based implementation of NREL’s System Advisor Model (PySAM)
- The ability to model hybrid (co-located generator + storage) projects in addition to standalone storage
- The ability to automatically evaluate the grid and emissions impacts of the selected portfolio’s dispatch based on region-specific data from NREL’s Cambium model
- The ability to dispatch economic curtailment of renewable resources

Because the MATCH model is being released under an open-source license, we hope this allows the functionality of model to be expanded in the future to explore a broader set of questions about voluntary procurement.

MATCH Model Overview

This section provides a qualitative description of the model features and formulation. For a detailed mathematical description of the model, see the supporting information.

Objective. Given a set of possible generation and storage projects, MATCH selects the least-cost portfolio of these resources that can be dispatched to meet three different voluntary procurement targets: annual renewable % targets, time-coincident renewable % targets, or emissions-optimized renewable energy targets.

Costs considered. MATCH minimizes the total annual cost of a contracted energy portfolio, which may include PPA contract costs, wholesale generation revenues and energy storage arbitrage at each LMP node, wholesale and/or retail cost of electric load, cost premium of hedge contracts for any load not matched by PPA contracts, cost of economic curtailment of renewable generators, the resale value of excess RECs or RA capacity value, and the cost of meeting any resource adequacy requirements. In addition to optimized costs, the model can also add into the final cost of power any fixed or non-power costs.

Voluntary procurement targets. MATCH can attempt to meet any hourly or time-coincident clean energy target between 0-100% of annual or hourly load. All targets must be met by generation and storage contracts inputted into the model.

MATCH can also select an emissions-optimized portfolio that maximizes the avoided emissions impact of the portfolio. The user inputs a direct CO_2 emission rate for each generator, and CCS information if applicable, and the indirect avoided emissions impact is estimated using the month-hour average Long Run Marginal Emission Rates (LRMER) for a given year and grid region from NREL's Cambium model. Users also specify which resources are "additional" (generally new resources that do not already exist), and thus which resources may have an avoided emissions impact. The avoided emissions impact in each hour is calculated by multiplying the additional dispatched generation and storage by the LRMER and adding that to any direct generated emissions net CCS. Because MATCH optimizes portfolios based on cost, the avoided emissions impact must be converted to dollars so that it can be optimized. To do this, the user specifies an internal carbon price, which is then multiplied by the avoided emissions impact to allow the model to co-optimize the actual financial costs with the financial value that the user assigns to avoided carbon emissions.

Load. MATCH uses an 8760 hourly load profile to optimize resource selection and dispatch based on the type of target selected.

Generation Technologies. MATCH can model any dispatchable, variable, or baseload generators, as well as standalone or hybrid storage technologies.

Generation profiles. MATCH can automatically simulate wind and solar generation profiles using PySAM, the Python version of NREL's System Advisor Model, based on the project's coordinates, system design, and a selected resource year. Users can also enter manual 8760 profiles for any variable or baseload resources.

Wholesale market prices. MATCH can use hourly locational marginal prices for each generator and load node to simulate wholesale market costs and revenues.

Storage Dispatch. Storage assets are dispatched to maximize wholesale price arbitrage revenue while meeting the specified renewable target, assuming perfect foresight across the whole year, and considering roundtrip efficiency losses, hourly leakage (self-discharge) losses, and cycling constraints. Storage is allowed to discharge whenever it is economically advantageous, even if, in the case of a time-coincident renewable target, there is already enough generation to meet load in a specific hour.

Standalone energy storage charges from the grid but is required to charge only when there is renewable energy being generated by generators selected by the model. This is done to simplify accounting and ensure that all discharged storage energy can be considered "renewable" (at least on an accounting basis). Hybrid energy storage is required to charge only from the paired generator, and combined discharge and generator dispatch must be less than the project's interconnection limit (which is assumed to be the nameplate capacity of the generation resource).

Excess Generation. MATCH allows for excess generation (defined as any generation that exceeds load in each hour). Excess generation is assumed to be delivered to the grid but does not count toward meeting any time-coincident goals. Excess generation may be limited either by setting a $/MWh financial penalty, or by setting an explicit constraint that specifies that generation cannot exceed a certain percent over total annual or hourly load.

Economic Curtailment. Variable generators such as wind and solar may be economically curtailed by the MATCH, which means that the model chooses not to dispatch some portion of available variable generation. MATCH may only dispatch economic curtailment when the generator's nodal wholesale electricity price is negative. Curtailed energy still costs the normal PPA contract rate, unless there is a free curtailment allowance specified for a generator.

Carbon intensity and emissions impacts. The CO2 intensity of delivered electricity is based on direct carbon emissions from selected resources (such as from geothermal or biogas) and based on the carbon intensity of any system power that is used to meet load in each hour. System unspecified carbon intensity is calculated based on the hourly average carbon intensity for all fossil generation in a region, based on forecasted values from NREL's Cambium model. This approach essentially approximates the system "residual mix" or "null" power that does not include any zero-carbon energy attribute certificates.

Resource adequacy (RA). MATCH includes an optional module that can model the cost of meeting system and flexible RA requirements based on the RA structure in California as of 2022. Users specify the system and flexible RA requirement for each month, as well as the cost of procuring RA on the market. Users can also specify the monthly ELCC and production factor values for each type of resource and specify whether each resource qualifies for RA. Users can also specify a requirement for a minimum capacity of firm or long-duration energy storage resources that must be included in the portfolio.

Case Study of a California CCA

In order to demonstrate the capabilities of the MATCH model and advance the state of knowledge on voluntary time-coincident procurement, this study seeks to answer several research questions by examining a specific case study:

- How practical and cost effective are time-coincident procurement goals to achieve?
- Does time-coincident procurement incentivize greater investment in firm, flexible, and emerging technologies that can increase the grid's renewable carrying capacity?
- How well can time-coincident procurement reduce GHG emissions relative to other procurement goals?
- Does time-coincident procurement address system peaking and ramping challenges better than other procurement approaches?
- What is the role of excess generation in cost-effectively meeting time-coincident procurement targets?

To answer these questions, we examine the case study of a hypothetical Community Choice Aggregator (CCA) in California that is seeking to procure a cost-effective portfolio of resources that matches at least 100% of their customer load on an annual basis by the end of 2025. This CCA wants to maximize the grid and emissions benefits of their portfolio, so they are considering three different strategies to meet this goal: a traditional annual 100% goal, an emissions-optimized goal, or a time-coincident goal that matches either 90%, 95%, 99%, or 100% of their load on an hourly, time-coincident basis. Because this CCA is a load serving entity in California, it is only considering PPAs for projects that exist in the state, or which can deliver into the state.

In order to evaluate the real-world feasibility and cost-effectiveness of these options, this study makes use of actual project and pricing data for 59 projects which includes a mix of generation projects, standalone storage projects, and hybrid projects offered to Peninsula Clean Energy, the CCA for San Mateo County, between 2020 and 2021. This is supplemented by fifteen additional projects that represent emerging technologies or hypothetical projects. These projects are primarily located in (or off the shore of) California, but some are also located in other parts of WECC, including Arizona, New Mexico, Nevada, and Idaho (we assume that the hypothetical CCA has transmission rights that enable them to procure energy from resources outside of the CAISO footprint). Thus, the generator input data for all but the five offshore wind projects modeled came from proprietary and/or confidential sources. While the use of this data limits the reproducibility of this specific case study, it offers a unique opportunity to explore the real-world, rather than hypothetical cost effectiveness and feasibility of these procurement goals.

Besides the resource and cost input data, all other model inputs were derived from public sources and created as generic examples for this case study so that the results could be more generalizable to CCAs in California. The load profile used, for example, represents a 1% share of the total California hourly net demand for 2025 forecasted by NREL's 2021 Cambium model.[111] A full description of the assumptions and inputs into our case study are included in

Table 3.7.

Although the results of this case study may not be generalizable to all voluntary energy buyers, the main intention of this case study is to illustrate the robustness of the MATCH model for future research related to voluntary procurement. In the first real-world application of the MATCH model, a separate study that applies the MATCH model and other proprietary stochastic modeling tools to evaluate Peninsula Clean Energy's specific time-coincident is also currently under development.

Grid Impact Metrics

Due to the focus of this case study on California (and the fact that the development of the model was originally funded to explore voluntary procurement in California), the grid impact metrics included in the current version of the model are specific to some of the grid and renewable integration challenges in CAISO. These challenges, described by CAISO's "duck curve," include the magnitude of evening net peak demand and maximum daily ramping needs.[11]

The California Independent System Operator (CAISO) has described two primary challenges to reliably integrating increasing amounts of renewable energy into the California grid: the need to keep fossil generators online to meet peak demand and the need for more natural gas to meet system ramping needs in the afternoon.[11] Ideally, we would want our portfolio to help reduce the magnitude of the evening peak and decrease the steepness of the evening ramp. These three metrics are calculated using the system net demand profile, which traditionally is defined as the systemwide demand minus systemwide wind and solar generation and is a heuristic for what is required from the fossil gas generation fleet. However, due to the increasing role of energy storage in CAISO (and the role it plays in our modeling), we also calculate these metrics using a net demand profile that nets wind, solar, and batteries from total demand, in order to reflect the requirements put on the natural gas fleet.

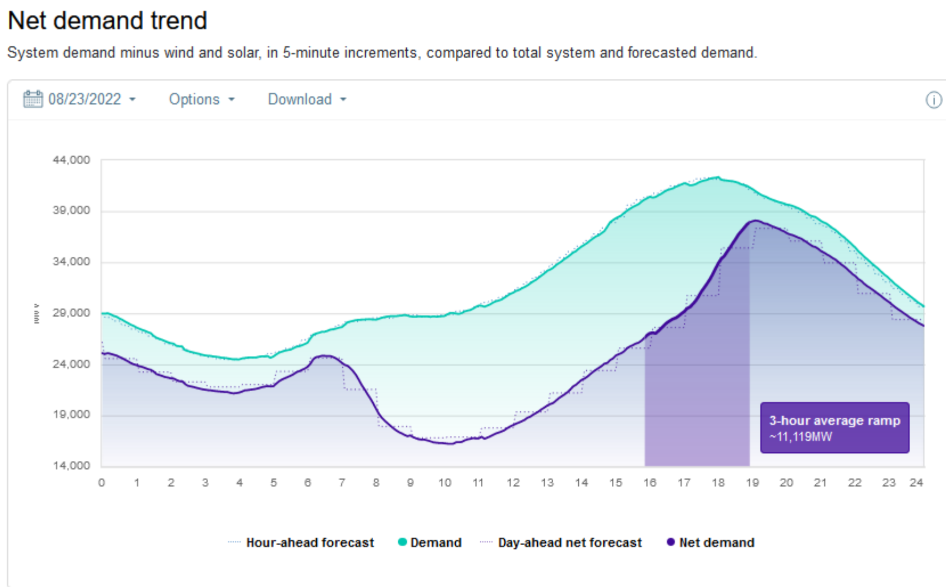

Figure 3.4 This screenshot from CAISO's "Today's Outlook" page illustrates several of the grid challenges faced in CAISO, including the daily ramping needs between 4-7pm, and the maximum daily peak at 7pm.[112] These ramping and peaking needs are currently for the most part met by natural gas generators.

While the curtailment of renewable energy has traditionally been framed as a negative grid impact, recent research has suggested that renewable energy curtailment actually contributes to grid flexibility and reliability.[11,113–115] Thus, we also examine how each procurement target contributes to renewable curtailment.

Table 3.7 Model inputs and assumptions for the California CCA case study

Topic	Inputs for Example
Costs considered	We use actual PPA contract prices that were offered to Peninsula Clean Energy, a California CCA, between 2020 and 2021. The hedge premium cost is modeled as 10% of the hourly forecasted LMP value at the NP15 hub. Resource adequacy costs and the resale value of excess RECs were not optimized.
Wholesale market prices	We use forecasted 2025 hourly day-ahead market LMP values for 20 different nodes from Ascend Analytics.
Renewable Targets	Because all of the generation resources we modeled are renewable, all of our modeled goals are "renewable" targets rather than "clean energy" targets. We tested a 100% annual renewable target, as well as a 90%, 95%, 99%, and 100% time-coincident renewable target.
Emissions-optimization targets	Our emissions-optimized scenarios assume that a buyer is attempting to optimize the emissions of a 100% annual renewable energy portfolio. We test two different internal carbon prices, one set at \$63.36/ metric ton CO_2 (representing the inflation-adjusted 3% social cost of carbon used by the federal government), and one set at \$191.21/metric ton CO_2, which is the social cost of carbon for the 95th percentile of damages based on a 3% discount rate.[116] We also test three different forecasted LRMERs based on different Cambium future scenarios (Mid Case, high RE cost, and low RE cost scenarios), in order to represent the future uncertainty about LRMERs.[111] LRMERs for each resource are based on its location, which for this study included the CAMXc, AZNMc, and NWPPc grid regions.
Load	We created a synthetic hourly load profile that represents 1% of the total California demand net behind-the-meter solar, forecasted for 2025 by NREL's Cambium model. This load represents about 2.7 TWh of annual load, or an average of 308 MW in each hour.
Generation Technologies Assessed	We include both commercial and emerging technologies located around California and adjacent states including utility-scale solar PV, utility-scale hybrid solar + storage, onshore and offshore wind, geothermal, run-of-river hydro, biogas, solar thermal, and wave energy. Commercial project characteristics were taken from PPA offers, and data for offshore wind came from a 2020 NREL study.[117]
Variable resource profiles	We calculate expected wind and solar profiles by averaging multiple simulated profiles based on three different years (2008-2010) of historical resource data. All other variable and baseload resources (small hydro, geothermal, wave) use a manually inputted 8760 profile based on historical or modeled data from third party sources.
RA	We do not model any resource adequacy in this case study.
Storage Dispatch	We model both short-duration (<= 4 hours) and long-duration (>= 8 hours) standalone storage from multiple technologies, including lithium-ion batteries, chemical batteries, compressed air storage, pumped storage hydro, and gravity storage. We also model multiple hybrid solar + storage projects.
Excess generation	Our modeled time-coincident scenarios are allowed to include any volume of excess generation that is cost-optimal. For each of our time-coincident renewable targets, we also model scenarios that limit the volume of annual excess generation to 20%, 10%, and 0% of load. Setting the constraint to 0% for a 100% time-coincident target means that the portfolio must be exactly balanced in each hour.
Economic Curtailment	Many of the forecasted wholesale prices we use include negative prices during some hours, so economic curtailment is possible for these variable generators.
Carbon Emissions	All model resources except biomass and certain geothermal generators have no direct emissions. The system carbon intensity is based on 2025 forecasted values for the CAMXc region from Cambium.

Results and Discussion

Next generation procurement can be economically feasible

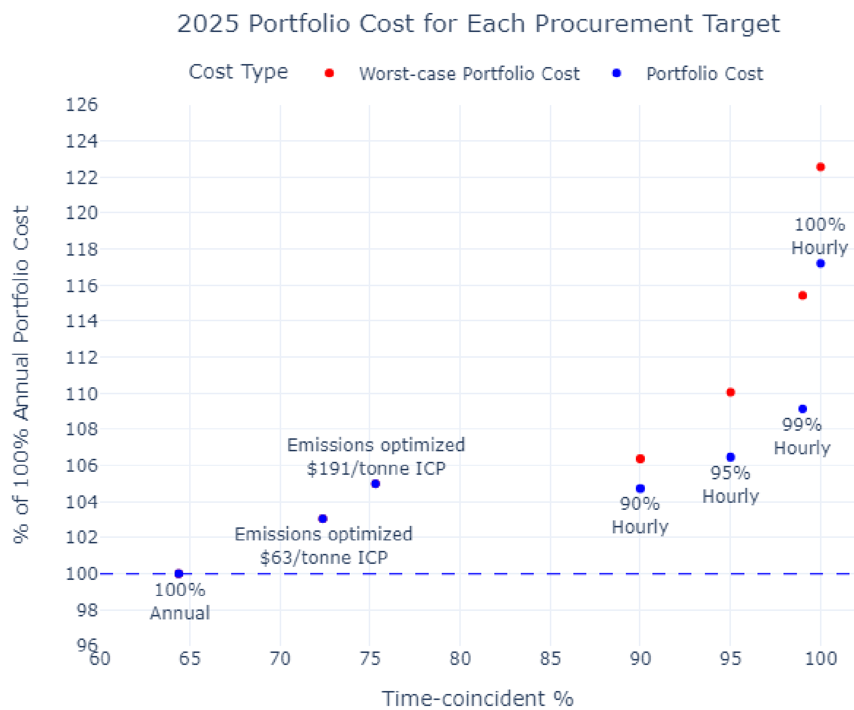

Figure 3.5 The total cost of energy for each portfolio as a percentage of the cost of a 100% Annual portfolio, compared to the time-coincident renewable percentage achieved by each goal. The "worst-case" costs in red represent the energy cost if no RECs from excess generation can be sold to other buyers. Dollar per MWh results from the model were normalized by the annual portfolio cost to protect potentially sensitive input data.

In contrast to previous studies, the results of our modeling suggest that high levels of time-coincident procurement (90-100%) can be achieved for only a 5-17% cost premium over 100% annual procurement. Consistent with previous studies, we find that the marginal cost of achieving the last 1% of time coincident matching, from 99% to 100% time-coincident, is significant, jumping from a 9% cost premium for 99% time-coincident to a 17% cost premium for 100% time-coincident. All of these time-coincident portfolios include some volume of excess annual generation, and the portfolio costs shown in blue in Figure 3.5 assume that all excess RECs could be sold to other buyers. To be conservative, we assume that these excess RECs could be sold at approximately 70% of their market value. As a worst case, we also calculated the portfolio cost assuming that none of the excess RECs could be sold (shown in red in Figure 3.5). In this case, the premium of achieving a 90-100% time coincident porfolio ranges from 6% to 23%.

We also find that our two emissions-optimized scenarios could be achieved at a 3-5% cost premium over a 100% annual goal. The high internal carbon price emissions optimization achieves approximately 75% time-coincidence for about the same cost as the 90% time-coincident scenario.

Time-coincident procurement encourages greater investment in firm, flexible and emerging (FFE) technologies

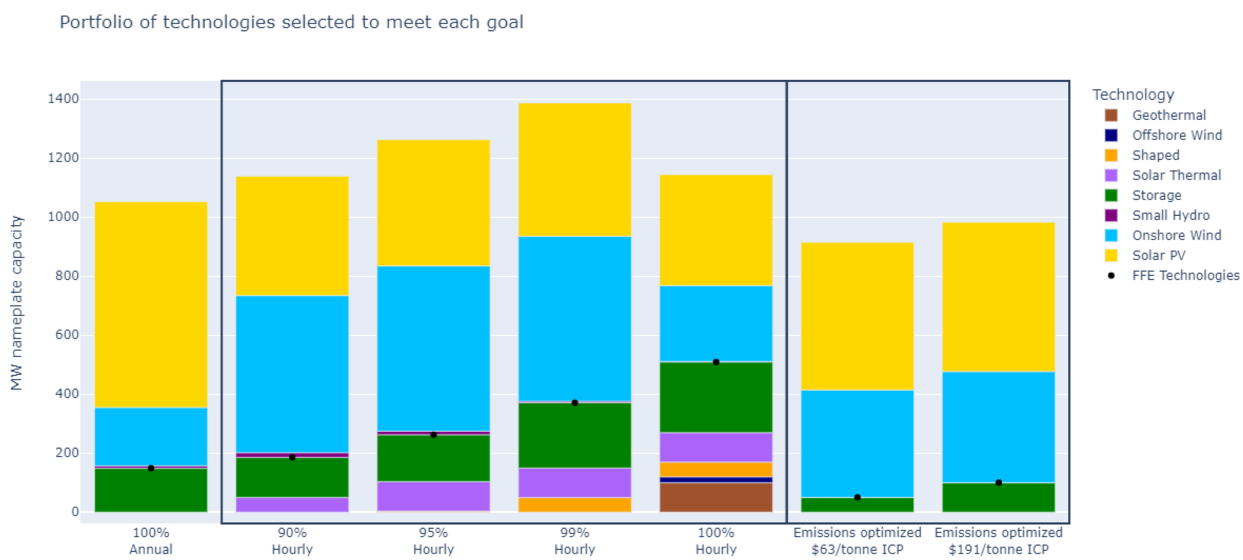

Figure 3.6 The portfolio composition in MW of nameplate capacity selected under each goal by technology type. The black dot represents the total amount of firm, flexible, and emerging technologies selected under each scenario.

Our results confirm that time-coincident procurement encourages greater investment in firm, flexible, and emerging technologies than annual procurement or emissions-optimized procurement. Firm and flexible resources, like geothermal and energy storage, generally increase the grid's carrying capacity for additional renewable energy, which enables broader adoption of clean energy.[95] We also found that time-coincident procurement encouraged investment in new and innovative technologies like offshore wind, innovative shaped products, and dispatchable solar thermal. Our results suggest that generally higher time-coincident targets better incentivize investments in these types of technologies than lower targets (our 100% time-coincident model selected over twice as much of these technologies as the 90% time-coincident target).

These results also illustrate that higher levels of time-coincident procurement generally result in larger amounts of generation and storage capacity being procured overall. The exception to this is the drop in procured capacity from 99% to 100% time-coincidence, due to the inclusion of geothermal in the 100% portfolio, which has a much higher capacity factor than variable resources.

Time-coincident procurement can result in emissions reductions comparable to emissions-optimized procurement

One previous criticism of time-coincident procurement is that it may not maximize GHG emissions reductions compared to emissions-optimized procurement.[96,98] However, the results of our modeling suggest that high-levels of time-coincident procurement can reduce GHG emissions just as effectively as emissions-optimized procurement, on an absolute and per $ basis. In this case study, the avoided emissions impact of the 100% time-coincident scenario performed worse than all of the other next-generation goals (and about the same as the 100% annual goal) due to its reliance on non-additional geothermal generation with non-zero direct carbon emissions.

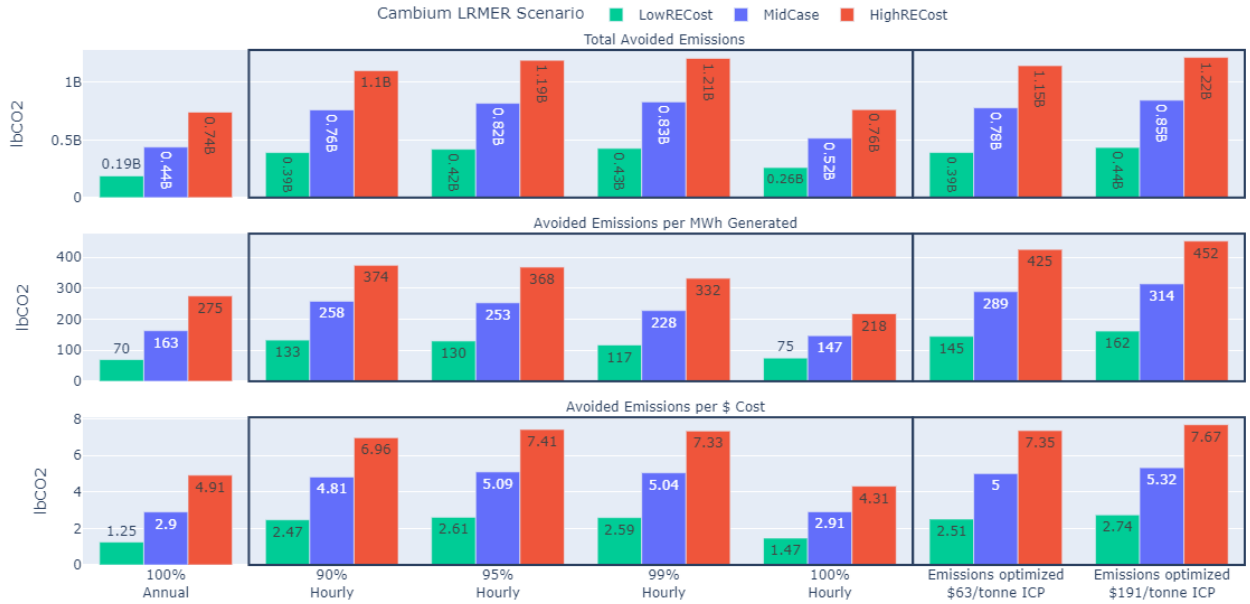

Figure 3.7 Avoided emissions impacts for each scenario on an absolute, per MWh, and per $ basis. Each of the three bars shows the avoided emissions results based on the long-run marginal emission rates forecasted under three different future scenarios in Cambium.

While emissions-optimized procurement with the high $191/metric ton internal carbon price performed the best on all three metrics, our results show that 95%-99% time-coincident procurement actually performed better than emissions optimized procurement on an absolute and per $ when the lower $63/metric ton internal carbon price was used. These results suggest that when emissions-optimized procurement is used, unless a buyer sets a relatively high internal carbon price, this procurement strategy may not always maximize emissions reductions once weighted against the other financial considerations that go into energy procurement decisions. For reference, a 2019 survey of 2,600 global companies found that for most sectors, the median internal carbon price was under $30 per metric ton, with the highest prices hovering around $100 per tonne.[118]

We note that one limitation of this case study in examining the relative effectiveness of time-coincident and emissions-optimized procurement in maximizing emissions reductions is that the buyer in our case study was only allowed to procure resources from within a limited geographic boundary, including California, the Northwest, and the Southwest. If a voluntary buyer's load is located in a relatively low-carbon grid region, and the buyer was able to procure generation from anywhere in the world, it is likely that an emissions-optimized approach could more effectively maximize emissions reductions than a time-coincident approach, since it could choose from resources in much dirtier grid regions.

Time-coincident procurement results in greater grid benefits than other goals

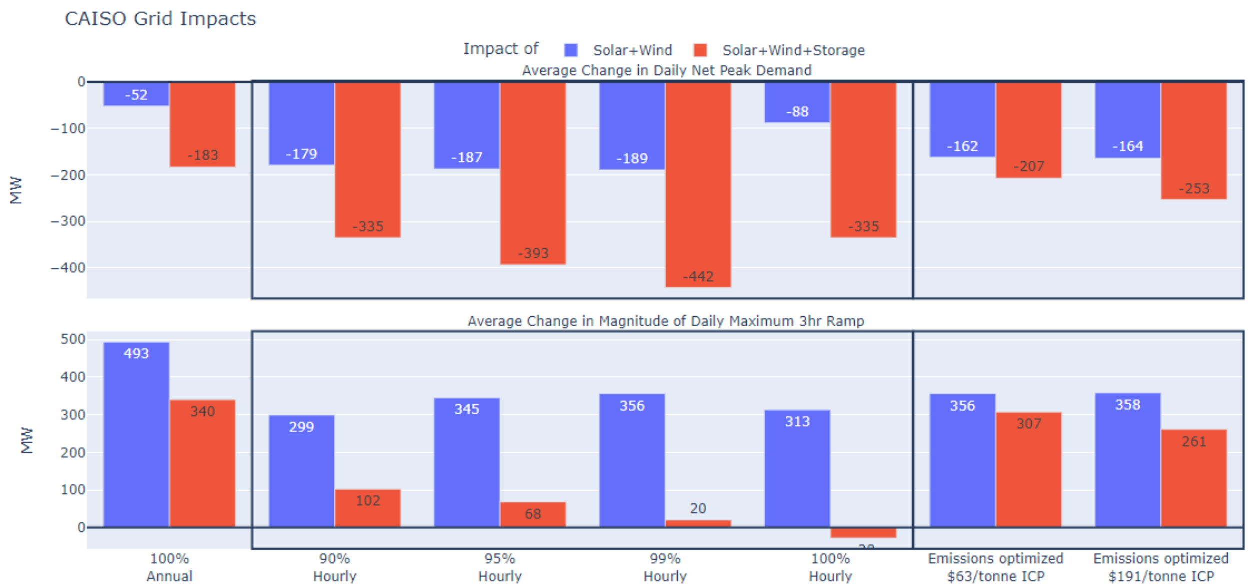

Figure 3.8 The change in system-wide (CAISO) net peak demand and maximum 3-hour ramping needs due to the contribution of additional wind, solar, and energy storage dispatch from each portfolio.

Our results suggest that in California, time-coincident procurement can help address the duck curve better than other approaches by reducing the net system peak the most and contributing the least to increasing the steepness of the maximum daily 3-hour ramping needs. Time-coincident procurement and emissions-optimized procurement perform about equally as well when only considering the impact of additional wind and solar on the net demand curve. However, if the impact of storage is also considered, time-coincident procurement does much better than both annual procurement and emissions-optimized procurement. For example, while both next generation procurement strategies increase ramping needs between 300 and 360 MW, when considering how storage is dispatched, time-coincident procurement has the potential to have negligible impact on ramping needs, or even slightly decrease ramping needs.

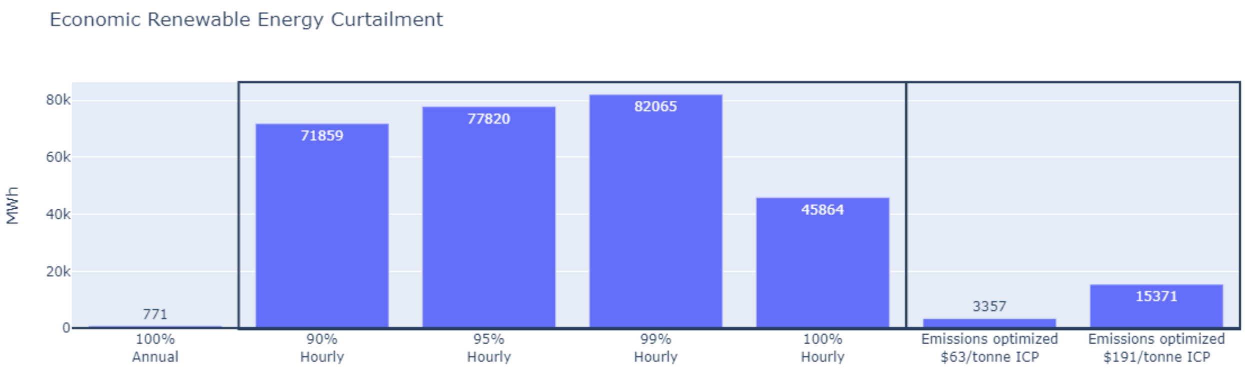

Figure 3.9 Total annual MWh of economically-curtailed renewable energy from contracted projects in each portfolio.

Our results show that time-coincident procurement results in a much greater annual volume of economic curtailment being dispatched than either annual procurement or emissions-optimized procurement. This suggests that in this case, time-coincident procurement results in the deployment of more renewable energy in areas where there are a greater number of hours of negative LMP pricing. Despite this, these resource's inclusion in the cost-optimal portfolio indicate that it was still more cost effective for the model to build resources that are curtailed more often. While curtailment is not necessarily a desired outcome of time-coincident procurement, research suggests that it also represents a ”new normal” that does not necessarily have a negative grid impact and may, in fact, contribute to grid flexibility and reliability.[113–115]

Excess generation is currently a necessary feature of cost-effective time-coincident procurement

Our modeling suggests that practically achieving a cost-optimal time-coincident portfolio will require some volume of annual excess generation – that is, generation that not only exceeds the load being matched in some hours, but generation in excess of the annual volume of load. This excess generation ranged from 9% of the annual load in the 90% time-coincident scenario, to 35% of the annual load in the 99% time-coincident scenario.

Table 3.8 As the amount of excess generation is limited in each of the time-coincident portfolios, the portfolio cost increases, and several scenarios become infeasible.

Goal	Excess Generation Limit	Annual Renewable %	Cost Premium over no limit portfolio
90% Hourly	No limit	109%	N/A
	No excess	100%	+2.7%
95% Hourly	No limit	120%	N/A
	10% excess	110%	+2.6%
	No excess	Infeasible	
99% Hourly	No limit	135%	N/A
	20%	120%	+3.4%
	10%	Infeasible	
	No excess	Infeasible	
100% Hourly	No limit	130%	N/A
	20%	120%	+1.7%
	10%	Infeasible	
	No excess	Infeasible	

We also found that attempting to limit excess generation negatively impacts the feasibility and cost-effectiveness of achieving a time-coincident target. Every 10% decrease in the amount of annual excess generation led to a 2-3% increase in portfolio cost. In addition, the model was unable to find feasible portfolios that could achieve above a 95% hourly match with no annual excess generation.

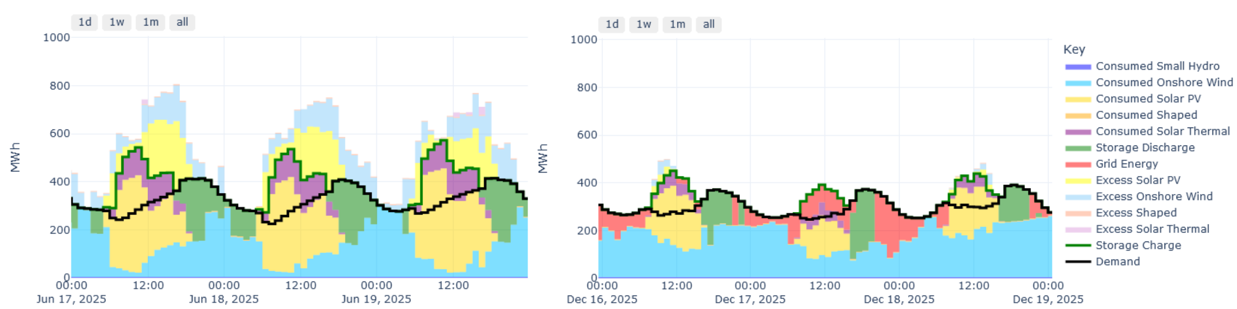

Figure 3.10 In a 95% time-coincident portfolio, there is a large amount of excess generation in the summer, while in the winter, almost all generation is stored or consumed, and there is a greater reliance on unspecified grid energy (shown in red). In contrast to previous models, note that MATCH allows storage to economically dispatch, charging even when there is not enough generation to meet load, and discharging even when there is excess generation.

As shown in Figure 3.11, we found that attempting to achieve exactly time-coincident portfolios leads to mixed positive and negative grid and emissions impacts relative to not limiting excess generation. Our results suggest that limiting excess generation helps address system ramping needs better than non-limited time-coincident portfolios, but reduces the system peak less, increases the amount of economic renewable curtailment dispatched, and leads to lower and less cost-effective avoided emissions impacts. This suggests that limiting excess generation may not always be desirable.

Figure 3.11 The impact of limiting excess generation on CAISO system peak and ramp needs (A), economic renewable energy curtailment (B), and avoided emissions (C).

Sensitivity Analysis: Real-time performance of time-coincident portfolios

The optimal time-coincident portfolios selected by MATCH for our case study are based on how well expected wind and solar generation (based on an average of three historical resource years), assisted by energy storage that has perfect foresight, could match forecasted load. In real-life, however, the ability of a portfolio to meet real-time demand, when faced with the uncertainty of variable resources and load, and energy storage with limited foresight, is likely to underperform compared to the optimal modeled scenario. Completely understanding the impact of such uncertainty on the performance of a time-coincident portfolio would require stochastic analysis that could vary resource profiles, loads, and wholesale market prices.

While MATCH is not a stochastic model, it does conduct a sensitivity analysis after the optimization is complete to attempt to understand how the real-time performance of a selected portfolio would compare to the optimal performance. To do so, when exporting model results, MATCH loads historical wind and solar resource data from each of the years used to create the expected value and simulates the generation of the selected portfolio based on these single-year weather profiles. In addition to using a single weather year, this analysis uses a "greedy" storage dispatch algorithm that attempts to fill the batteries whenever there is excess hourly generation and discharges them whenever generation drops below hourly load, until empty. These results will not be as accurate as a full stochastic analysis but can help illustrate the limitations of MATCH as a planning tool.

The results of this sensitivity analysis, shown in Figure 3.12 below, suggest that real-time performance of the selected portfolios is generally 1.5-3% below the planning target. The exception is the 100% time-coincident target, where the sensitivity results are all within 1% of the planning target, likely due to the volume of excess generation available and the increased reliance on firm, rather than variable resources relative to other scenarios. These results suggest that achieving a specific time-coincident percentage in real-time will likely require planning to achieve a time-coincident goal that is several percentage higher than the real-time goal.

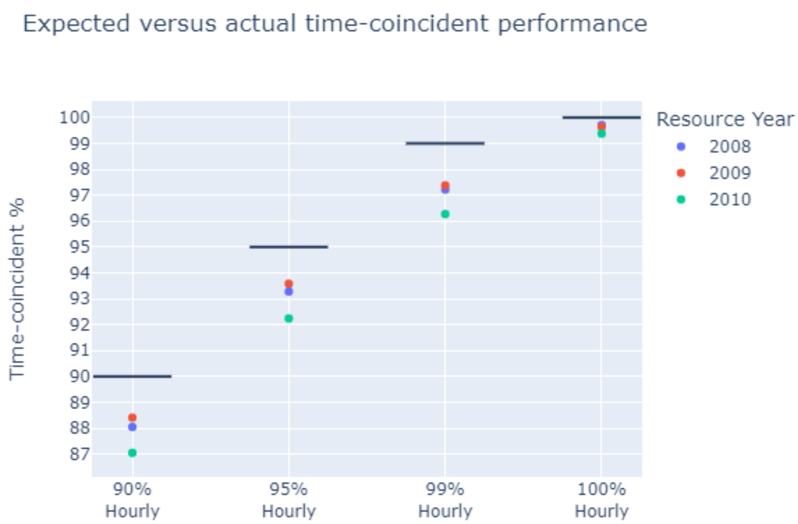

Figure 3.12 The selected portfolios generally underperform compared to the time-coincident target (shown by the black line) when simulated using single-year weather resource data and a greedy storage algorithm.

Discussion

The work presented in this study significantly advances the state of knowledge about and set of tools available to understand voluntary energy procurement. The MATCH model represents the first open-source model that has been developed to model portfolio-based voluntary energy procurement behavior under several types of procurement goals. The results presented here confirm several findings of previous studies, including that time-coincident procurement encourages greater investment in firm, flexible, and emerging technologies than other procurement goals, and that time-coincident procurement generally involves a cost premium over annual procurement targets. However, our results demonstrate that the cost premium of achieving time-coincident procurement may be much lower than previously estimated, at only a 5-17% premium over a 100% annual goal. Although previous studies have discussed the role of excess generation in voluntary time-coincident procurement, this study was the first to quantify the financial, grid, and emissions benefits of excess generation in time-coincident procurement. Our results also confirm the benefits of considering technologically and geographically diverse portfolios of generation and storage technologies for cost-effectively achieving voluntary time-coincident procurement. Our results also show that both types of “next-generation” procurement approaches (time-coincident and emissions optimized procurement) result in higher grid and emissions benefits than “traditional” annual procurement targets.

Another significant and unexpected finding relates to the assumption that time-coincident procurement may not maximize emissions reductions compared to emissions-optimized procurement. Our findings suggest, however, in that some cases, time-coincident procurement can actually reduce emissions more effectively than emissions-optimized procurement on an absolute and per $ basis (while emissions-optimized procurement reduces more emissions per MWh). Another significant finding is that the effectiveness of emissions-optimized procurement at maximizing emissions reductions is dependent on the internal carbon price used by a buyer to value avoided emissions. We found that at least in this case study, the internal carbon price used by most organizations would be too low to allow for emissions-optimized procurement to effectively maximize emissions reductions.

Finally, our results suggest that 100% time-coincident targets may not be the optimal target for organizations to pursue in all cases. Our results suggest that instead, setting time-coincident targets between 90%-99% may much more cost effectively achieve the same or better emissions and grid benefits as a 100% time-coincident target. The emissions benefits of time-coincident procurement, in particular, are eroded if achieving them relies on procuring generation from existing (non-additional) sources of firm generation. Additionally, our results suggest that allowing for excess generation in a time-coincident portfolio (rather than attempting to exactly “balance” supply and demand in each hour) leads to better outcomes.

Future work

While we believe that the results of this study present the most realistic picture of time-coincident procurement based on the most sophisticated modeling of individual voluntary procurement conducted to date, our results are still subject to several limitations that may affect the generalizability of the results. As previously mentioned, the choice to use an hourly load profile that is 1% of the system load profile means that the time-coincident procurement of the case study buyer will align with system needs better than a buyer whose load is not correlated or anti-correlated with system demand. While this choice may over-estimate the beneficial grid impacts of our results compared to some users, we feel that this choice of load profile is more realistic in many respects than the completely flat load profile used by previous studies, which is almost never observed for real-life end loads.[†] Another limitation is the fact this this study does not consider how different types of demand response, such as load shaping or load shifting, may contribute to meeting a time-coincident target. A third limitation is that the PPA prices and market forwards used in this study were current as of late 2021, but there have been significant disruptions to the market in 2022 that have increased energy development costs across the board. While the future trajectory of these disruptions and their effects on prices are uncertain, if these disrupted prices come to represent a new normal, these results would need to be updated to remain relevant. Finally, as opposed to some previous studies, this modeling does not count existing grid-mix renewables toward meeting the procurement goals. Because we were modeling a CCA, which is a load serving entity responsible in part for establishing the "grid mix," it was not appropriate to count renewables not directly procured by our hypothetical CCA toward meeting its goal. However, in the case of corporate or other end-use voluntary procurement, including existing supplier-provided renewables

[†] These flat load profiles used in previous studies are intended to represent data center load profiles, since many of the leading organizations implementing 24/7 procurement operate data centers. However, even individual data centers exhibit some hourly and seasonal variation in loads, and if considered in aggregate as a fleet, aggregate data center load will vary with variable compute needs by society.

toward a goal would further increase the cost-effectiveness of time-coincident procurement, meaning that our cost results are likely on the conservative side.[98]

There are many avenues for future research using the MATCH model to explore the implications of voluntary procurement. The biggest opportunity not addressed in this study would be to evaluate the costs and impacts of different voluntary procurement strategies for corporate buyers, whose procurement considerations may differ from those of the hypothetical CCA in this case study.[119] Other opportunities include outstanding questions about the impact of different realistic load shapes, regional availability of resources, inclusion of standard-delivery carbon-free energy toward meeting a goal, and the inclusion of renewable versus carbon-free resources in the goal definition. Future opportunities to further improve the MATCH model include addition of a module for dispatching demand-side resources, validation of the modeling performance of multi-regional loads, expanding the grid impact metrics to ensure relevance to a broader set of grid regions, and building out a dataset of standard inputs using public data sources.

Conclusion

As the electric power system continues to rapidly transform, the state of knowledge about power sector emissions and the impacts of voluntary action to decarbonize the electric grid has not always kept pace. Today, the common metrics used to define the electric grid in policy, regulation, business, and the academic literature largely treat it as a mostly static system. The use of static, annual metrics seems to be a vestige of the power system as it existed a decade ago, before the growth in deployment of utility-scale renewables, and before higher-resolution data existed. The research presented in this dissertation shows that today, however, understanding the temporal variation in power system operations and emissions is critical for effective climate policy and action. This research leverages the unprecedented access to high-resolution data that is now available about the power sector, as well as the proliferation of open-source data cleaning and modeling tools to help modernize our understanding of power sector decarbonization.

This research is important for advancing the academic literature in a wide variety of research areas, including the study of marginal emissions from the power sector and attributional and consequential life-cycle analyses of a wide range of electricity end uses such as electric vehicles, heat pumps, and buildings. Chapter 3 especially contributes to advancing the relatively nascent body of literature on voluntary clean energy procurement. In addition to advancing the state of knowledge on these topics, this research contributes two new open-source projects that can be used for the continued study of these topics by other researchers. Chapter 2 introduces the Open Grid Emissions Initiative, which includes a dataset and open-source data pipeline that can be used to study hourly grid emissions and serve as a repository on the best available knowledge related to grid carbon emissions. Chapter 3 introduces the MATCH model, an open-source voluntary procurement portfolio planning model that can be used to model individual buyer procurement behavior and understand the tradeoffs of different voluntary procurement goals.

This research also makes several practical and timely contributions for shaping the conversation about effective grid decarbonization policy, regulation, and action. Recently there have been numerous policy developments that depend on accurate accounting of grid emissions and can benefit from the new knowledge generated by this research:

- In late 2021, President Biden signed an executive order requiring the federal government to procure 100% time-coincident carbon-free electricity by 2030.[120]
- Over the past few years, several major cities in the U.S., including New York City and Boston, have introduced new regulations mandating the disclosure and reduction of building-related GHG emissions.[121,122]
- The 2022 Infrastructure Investment and Jobs Act passed by Congress mandated that the U.S. EIA begin publishing temporally-granular electricity emissions rate data by the end of 2022.[123]
- The 2022 Inflation Reduction Act (IRA) includes funding for the EPA to analyze the life-cycle emissions of different transportation fuels (including electricity and hydrogen), as well as for the White House CEQ to collect data on which communities are disproportionately harmed by negative environmental impacts (such as air pollution from the power sector).[124]
- In 2022, the U.S. Securities and Exchange Commission proposed a new rule that would require all publicly-traded companies in the U.S. to disclose, among other climate risk metrics, an inventory of its scope 2 emissions.[125]
- In 2022, the World Resources Institute began preparing for a multi-year process to update the GHG Protocol Scope 2 Guidance.
- In 2022, California passed Senate Bill 1158, which requires all California retail electricity providers to report carbon emissions data on an hourly basis.[126]

Chapter 1 establishes a case for the growing necessity of accounting for scope 2 emissions on an hourly, rather than annual basis. Especially in many of the grid regions where the most progressive carbon regulations are being introduced, we found that annual accounting introduces substantial bias in scope 2 emissions inventories, which can not only erode the effectiveness of these regulations, but also have important implications for the equitable allocation of responsibility for carbon emissions. We found that annual accounting can cause accounting errors up to 35% in some regions and for some end-uses, which is substantially higher than the 5% error threshold above which the GHG Protocol defines an emissions inventory to be "materially misleading."[44] Especially as existing trends such as variable renewable energy deployment, electrification, and carbon-aware demand response become more widespread, the bias introduced by annual accounting will only continue to grow.

Chapter 2 introduces a new open-source dataset of power sector emissions which for the first time makes complete electricity-related emissions data (including emissions from biomass combustion) publicly available, as well as complete hourly GHG, NOx, and SO2 emissions factors for generated and consumed electricity. We find that existing emissions datasets that treat biomass combustion as carbon neutral are substantially underestimating power sector GHG emissions in certain regions, up to 14% in the California ISO and 22% in ISO New England. We also find that the existing academic literature that relies exclusively on hourly CEMS data to represent power sector operations and emissions may be using substantially incomplete data, especially in certain regions. For example, the CEMS data is missing over 90% of SO2 and NOx emissions in the California ISO, and over 50% of these emissions in the New York ISO. In addition to introducing several new methods and applications of existing methods for estimating hourly emissions from power generation, this research also synthesizes and introduces a number of open questions for future academic research in this field.

Chapter 3 introduces a new open-source model that can be used to understand the cost and implications of voluntary energy procurement under several types of procurement goals. This is the first voluntary procurement model that considers the full range of costs and constraints optimized by voluntary renewable energy buyers and takes a portfolio optimization approach to modeling voluntary procurement. By representing voluntary procurement more realistically than has been done in previous studies, we showed that existing studies may have significantly over-estimated the costs and under-estimated the practicality of achieving voluntary time-coincident procurement goals. This research also shows that both forms of "next-generation" procurement approaches (time-coincident and emissions-optimized) lead to greater grid and emissions benefits than traditional annual procurement goals. Finally, this research suggests several practical directions for how time-coincident procurement goals should be designed to maximize cost-effectiveness, grid benefits, and emissions reductions.

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Appendices

Supporting Information for Chapter 1

Code Repository

The code repository for this research can be found at

https://github.com/grgmiller/hourly_carbon_accounting or

https://zenodo.org/badge/latestdoi/461343198

Expanded Literature Review

In addition to the studies summarized in Table 1 in the main text, the studies summarized in Table S2 have explored the temporal variation of grid carbon intensity.

Table S1. Expanded literature review. In addition to the studies summarized in Table 1 in the main text, the following studies have explored the temporal variation of grid carbon intensity.

Paper	Geography	Data years	EF Temporal Resolutions	EF Type
Gordon and Fung 2009, 2011[15,16]	Ontario, Canada	2004-2006	Annual Seasonal Seasonal TOD Monthly TOD Hourly	Produced Direct
Stoll et al. 2014[18]	Great Britain Ontario, Canada Sweden	2011-2012	Hourly	Consumed Lifecycle
Schivley et al. 2018[13]	U.S. (8 NERC Regions)	2001-2017	Annual Quarterly Monthly	Produced Direct
Khan 2018a, 2018b, 2019[12,23,24]	New Zealand Bangladesh	2015	Annual Monthly Daily Half-hourly	Produced Direct
Marrasso et al. 2019[26]	Italy	2016-2017	Hourly	Produced Direct
Tranberg et al. 2019[27]	Europe (27 countries)	2017	Hourly	Produced and Consumed Lifecycle
de Chalendar et al. 2019[14]	U.S. (66 Balancing Areas)	2016	Hourly	Produced and Consumed Direct
Pereira and Posen 2020[29]	Ontario, Canada	2010-2018	Annual Monthly Hourly	Consumed Lifecycle

Analysis of 5-minute resolution carbon intensity data from CAISO

The background section of the main text explains that this study uses hourly average carbon intensity values as the baseline rather than sub-hourly values, partially due to the relatively low variation in grid carbon intensity within a single hour. We confirmed this finding, by analyzing a dataset of 5-minute resolution carbon emissions data published by the California ISO, finding that even in this renewable-heavy region, the mean coefficient of variation of grid carbon intensity within a single hour was only 2.4%, compared to a 31% coefficient of variation across the entire year.

In Figure S1 we show that the mean coefficient of variation of grid carbon intensity within a single hour in CAISO in 2019 was only 2.4% when utilizing a dataset of 5-minute resolution emissions published by the California ISO [127,128]. This suggests that the hourly resolution reflects most of the 5-min variation in emissions, and that there are diminishing returns from using sub-hourly resolutions. Although these data represent a single grid region, we believe that these numbers represent the high end of sub-hourly carbon intensity variation, as CAISO has a relatively high percentage (~30%) of generation coming from variable and intermittent wind and solar resources.

To calculate these values, we downloaded 5-minute resolution data from CAISO's "Today's Outlook" website on carbon emissions rate (mTCO2/h) and generation (MW). We divided the carbon rate by generation to get carbon intensity (mTCO2/MWh). We then aggregated these data to different temporal averages (quarter-hourly, half-hourly, hourly, monthly, quarterly, and annual) and calculated the mean coefficient of variation within each period.

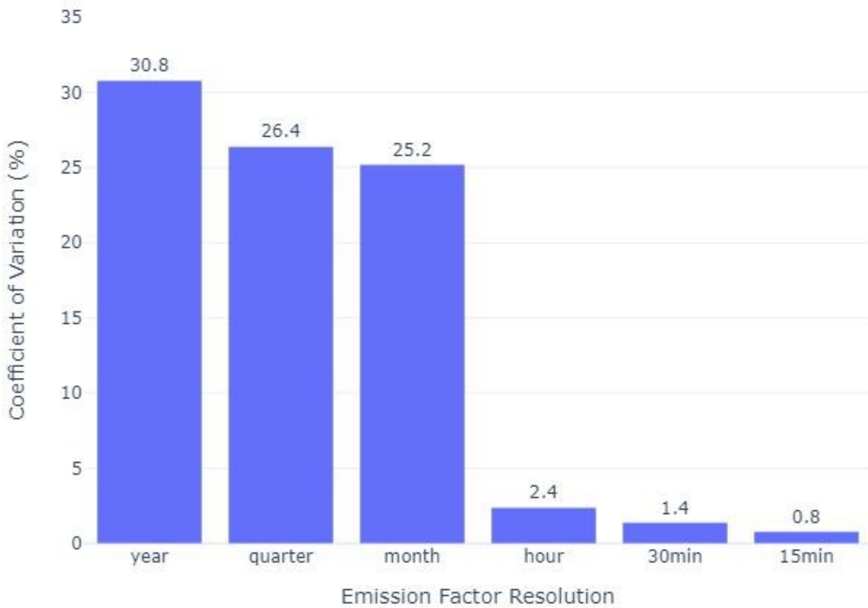

Fig. S1. The mean coefficient of variation (relative standard deviation) of 5-min carbon intensity within each aggregation period in CAISO in 2019, based on data published directly by CAISO. The hourly resolution already captures most of the 5-min variation, and there are diminishing returns to using sub-hourly temporal resolutions.

Full Derivation of the bias expression (Equation 1)

Notation:

$I_h = inventory\ of\ carbon\ emissions\ caused\ by\ consumption\ in\ hour\ h$

$D_h = Demand\ (consumption)\ of\ electricity\ in\ hour\ h$

$C_h = Actual\ average\ emission\ rate\ in\ hour\ h$

$\bar{C}_h = Estimated\ average\ emission\ rate\ in\ hour\ h$

$\mu_h = \bar{C}_h - C_h = Error\ in\ estimated\ average\ emission\ rate\ in\ hour\ h$

$\sigma_D = Standard\ deviation\ of\ Demand$

$\sigma_\mu = Standard\ deviation\ of\ errors\ emission\ rate\ estimates$

$\rho_{D,\mu} = Correlation\ coefficient\ between\ D_t\ and\ \mu_t$

We can write the carbon emissions inventory in a single hour (I_h) as a function of the emission rate and demand:

$$I_h = D_h \cdot C_h$$

Re-writing this expression for the actual emissions in terms of the averaged emissions ($\bar{C}_h \cdot D_h$) and the errors:

$$I_h = D_h \cdot (\bar{C}_h - \mu_h) = D_h \cdot \bar{C}_h - D_h \cdot \mu_h$$

Now reorganizing the above expression, we can see that the difference between the estimated emissions and the actual emissions is the product of the demand and error:

$$D_h \cdot \bar{C}_h - I_h = D_h \cdot \mu_h$$

So the "bias" in the estimated emissions is dictated by the sign and magnitude of the $D_h \cdot \mu_h$ term. Taking the expectation of this term:

$$E[D_h \cdot \mu_h] = E[D_h] \cdot E[\mu_h] + Cov(D_h, \mu_h)$$

We can simplify this because the $E[\mu_h] = 0$ assuming that the estimated emission rate and the actual emission rate are, on average equal (for example, if you use the annual average emission rate as a constant value for $\bar{C}_h$, then the differences between the actual hourly emission rates and the annual average emission rates will all sum to zero over the course of a year).

Rewriting the expression above given that the $E[\mu_h] = 0$:

$$E[D_h \cdot \mu_h] = Cov(D_h, \mu_h) = \sigma_d \cdot \sigma_\mu \cdot \rho_{D,\mu}$$

This expression above highlights that the sign of the bias will be determined by the sign of the correlation coefficient – if hourly demand and the hourly errors are positively correlated, the predicted emissions using $\bar{C}_h$ will be overstated (or vice versa if the sign of the correlation coefficient is negative). The magnitude of the bias is jointly dictated by the variation in the hourly levels of demand, the variation in the "errors" (or the differences between $\bar{C}_h - C_h$), and the correlation between these errors and the demand. For example, for a demand profile that doesn't vary dramatically across hours (i.e. σ_D is small), then even if there is a great deal of variation in the actual emission rate around the predicted emission rate, and even if there is a correlation coefficient that is large in absolute value (i.e. close to -1 or 1), the bias will be small.

Expanded discussion of the limitations of this study

In addition to the limitations discussed in the main text, the authors highlight the following limitations of the current study:

The building energy timeseries data and the carbon intensity data are not from the same years, so weather-driven correlations between building load and grid carbon intensity will not be reflected in the results. The grid carbon emissions data is from 2019, while the national results use simulations of buildings based on TMY3 weather data, and the California case study represents "1 in 2" (typical year) building load in 2014. Given that correlation between hourly demand and hourly carbon intensity is one of the factors that influences inventory bias, we believe that the results in this paper may underestimate bias, due to the weaker correlation between demand and carbon intensity resulting from the use of different years. In practice, carbon intensity data used for accounting should always match the timeframe of the energy demand being analyzed. However, the point of this paper was to illustrate bias rather than to measure contemporaneous historical emissions.

The carbon intensity data used in this study also has several potential limitations. First, it relies on self-reported data from balancing authorities about generation, load, and interchange. As noted by the EIA, there are known data quality issues with some of these data that have yet to be addressed [129]. Although this methodology captures temporal variation in emissions based on the changing resource mix in each hour, there are additional sources of variation in carbon emissions that these data do not currently capture, including:

- Resource mix of specific fuels in each hour (the EIA-930 data reveals how much generation came from "coal" for example, but not the mix of coal generators that were burning bituminous vs subbituminous coal, for example, in each time period.
- Fleet composition in each hour. Each generator that burns a specific fuel can have different heat rates based on factors such as its age, size, the specific generation technology used, emission control equipment, parasitic loads, etc. These factors are captured in the annual average fleet-specific fuel rate from eGRID, but this method does not consider which specific generators were online in each hour.
- Heat rate fluctuations. The heat rate of each individual generator changes over time depending on its current capacity factor, ramping, temperature, and how long it has been online.

These factors may only result in a small difference in calculated carbon intensities, but further research is needed to fully understand the impacts of these factors.

Grid balancing areas excluded from this study

Of the 75 balancing areas (BAs) identified in eGRID2019, 23 were excluded from this analysis.

Eight BAs were excluded because they are not located in the continental United States, which is the geographic availability of data from EIA-930:

- Anchorage Municipal Light & Power
- Chugach Electric Assn Inc
- Constellation Energy Control and Dispatch, LLC
- Hawaiian Electric Co Inc
- Alaska Miscellaneous
- Hawaii Miscellaneous

- Puerto Rico Miscellaneous
- New Brunswick System Operator

Two BAs were excluded because they were retired in 2018:

- Gila River Power, LLC (GRMA)
- Ohio Valley Electric Corporation (OVEC)

Ten BAs were excluded because they are generation-only BAs that do not directly serve retail customers:[81]

- Avangrid Renewables LLC (AVRN)
- Arlington Valley, LLC – AVBA (DEAA)
- Electric Energy, Inc. (EEI)
- Griffith Energy, LLC (GRIF)
- Gridforce South (GRIS)
- NaturEner Power Watch, LLC (GWA)
- New Harquahala Generating Company, LLC – HGBA (HGMA)
- Southeastern Power Administration (SEPA)
- NaturEner Wind Watch, LLC (WWA)
- Alcoa Power Generating, Inc. - Yadkin Division (YAD)

Two BAs were excluded because they are limited-generation BAs which did not report any net generation by fuel type data to EIA-930:

- City of Homestead (HST)
- New Smyrna Beach, Utilities Commission of (NSB)

One BA was excluded because no GIS shapefile of its boundaries was available, which was necessary for sampling buildings from the NREL End-Use Load Profile dataset:

- Southwestern Power Administration (SPA)

Example load shapes for NREL demand dataset

The NREL End-Use Load Profile dataset contains simulated load profiles for 14 unique commercial building types and 9 unique residential building types. Table S3 summarizes these types and how we assigned them to categories and sectors for this research.

Table S2. Summary of DOE reference building types and how they were categorized for this study.

<table>
<tr><th>NREL Building Type</th><th>Assigned Category</th><th>Assigned Sector</th></tr>
<tr><td>Full Service Restaurant</td><td rowspan="2">Restaurant</td><td rowspan="14">Commercial</td></tr>
<tr><td>Quick Service Restaurant</td></tr>
<tr><td>Hospital</td><td>Hospital</td></tr>
<tr><td>Large Office</td><td rowspan="4">Office</td></tr>
<tr><td>Medium Office</td></tr>
<tr><td>Small Office</td></tr>
<tr><td>Outpatient Health Care</td></tr>
<tr><td>Large Hotel</td><td rowspan="2">Hotel</td></tr>
<tr><td>Small Hotel</td></tr>
<tr><td>Primary School</td><td rowspan="2">School</td></tr>
<tr><td>Secondary School</td></tr>
<tr><td>Standalone Retail</td><td rowspan="2">Retail</td></tr>
<tr><td>Retail Strip Mall</td></tr>
<tr><td>Warehouse</td><td>Warehouse</td></tr>
<tr><td>Mobile Home</td><td>Mobile Home</td><td rowspan="9">Residential</td></tr>
<tr><td>Single-family attached</td><td rowspan="2">Single Family</td></tr>
<tr><td>Single-family detached</td></tr>
<tr><td>2 Unit</td><td rowspan="2">Small Multifamily</td></tr>
<tr><td>3 to 4 Unit</td></tr>
<tr><td>5 to 9 Unit</td><td rowspan="3">Medium Multifamily</td></tr>
<tr><td>10 to 19 Unit</td></tr>
<tr><td>20 to 49 Unit</td></tr>
<tr><td>50 or more Unit</td><td>Large Multifamily</td></tr>
</table>

Figures S2 and S3 show the month-hour average load shapes for commercial and residential buildings (respectively) in a representative cooling climate (Arizona Public Service). Figures S4 and S5 show the month-hour average load shapes for commercial and residential buildings (respectively) in a representative heating climate (ISO New England).

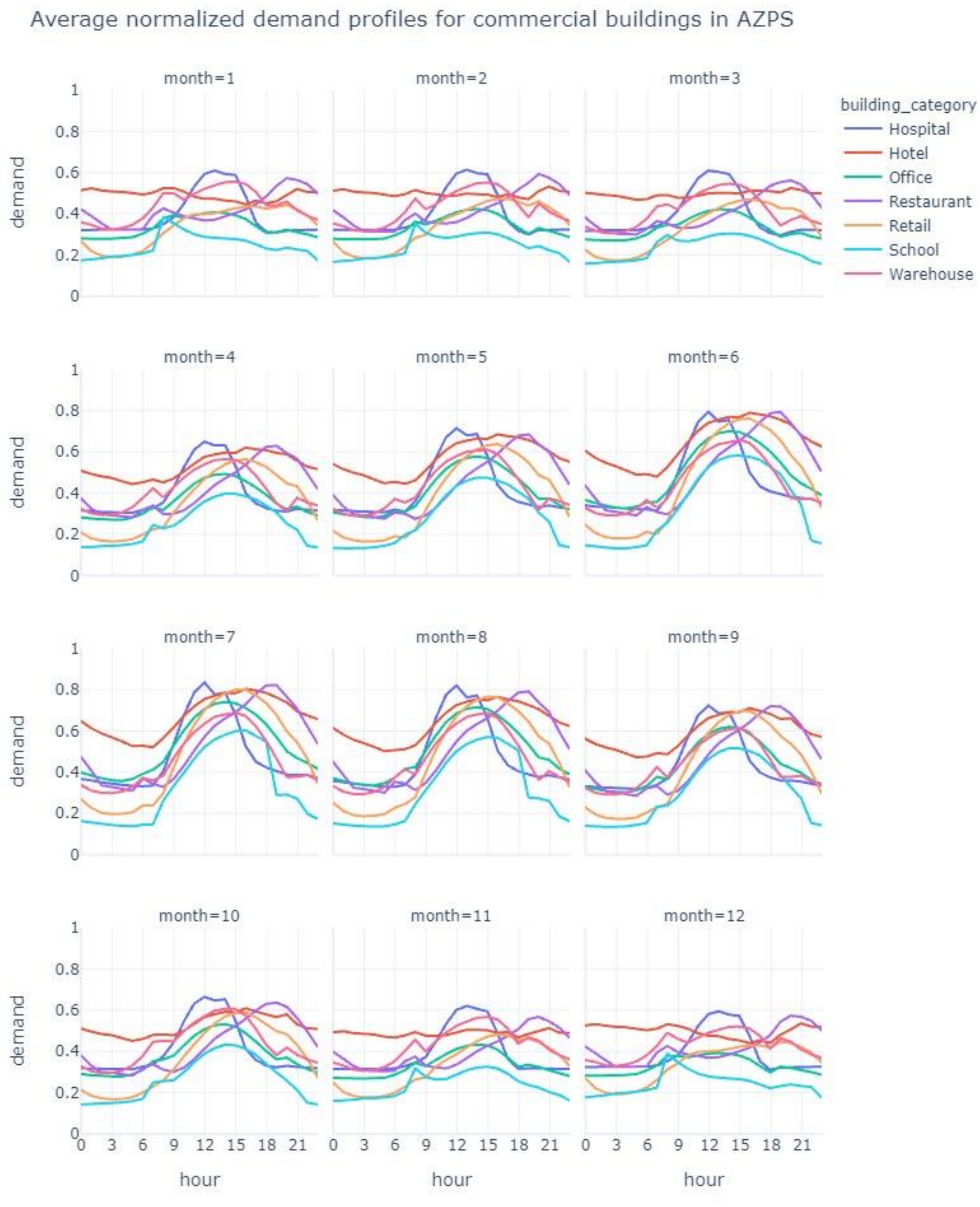

Fig. S2. Month-hour average load shapes for each commercial building type in AZPS, normalized as a percentage of maximum hourly demand in the year.

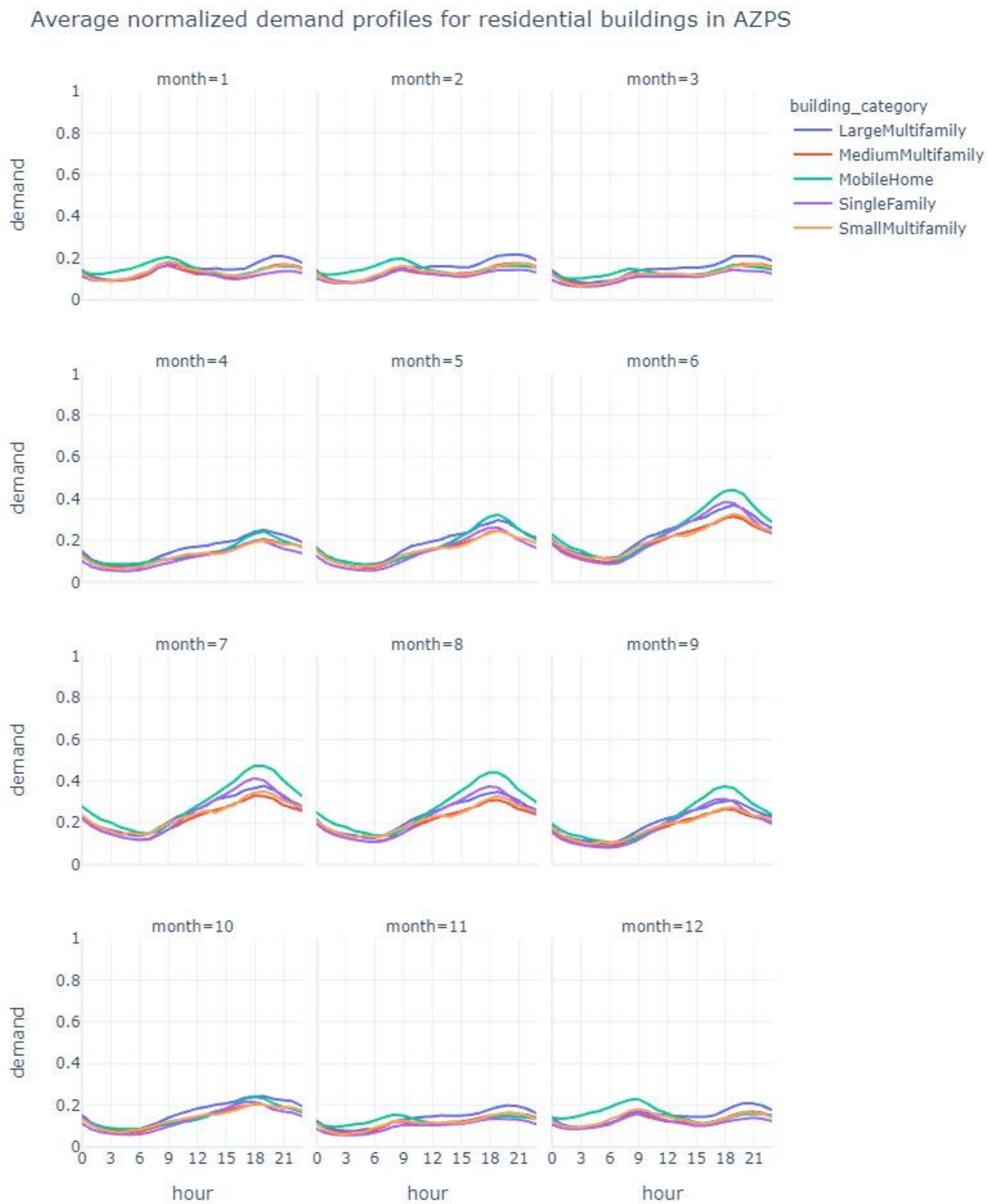

Fig. S3. Month-hour average load shapes for each residential building type in AZPS, normalized as a percentage of maximum hourly demand in the year.

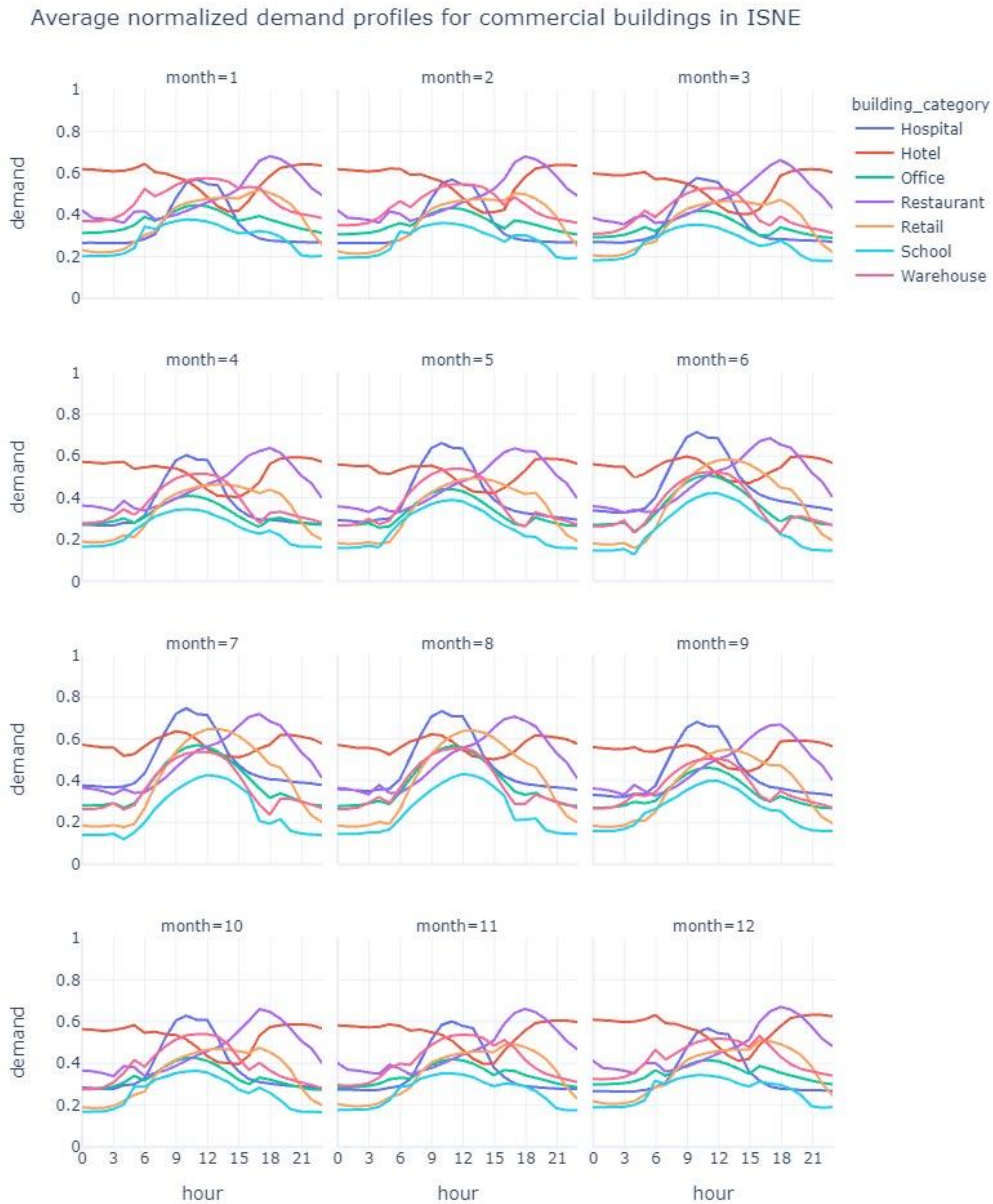

Fig. S4. Month-hour average load shapes for each commercial building type in ISNE, normalized as a percentage of maximum hourly demand in the year.

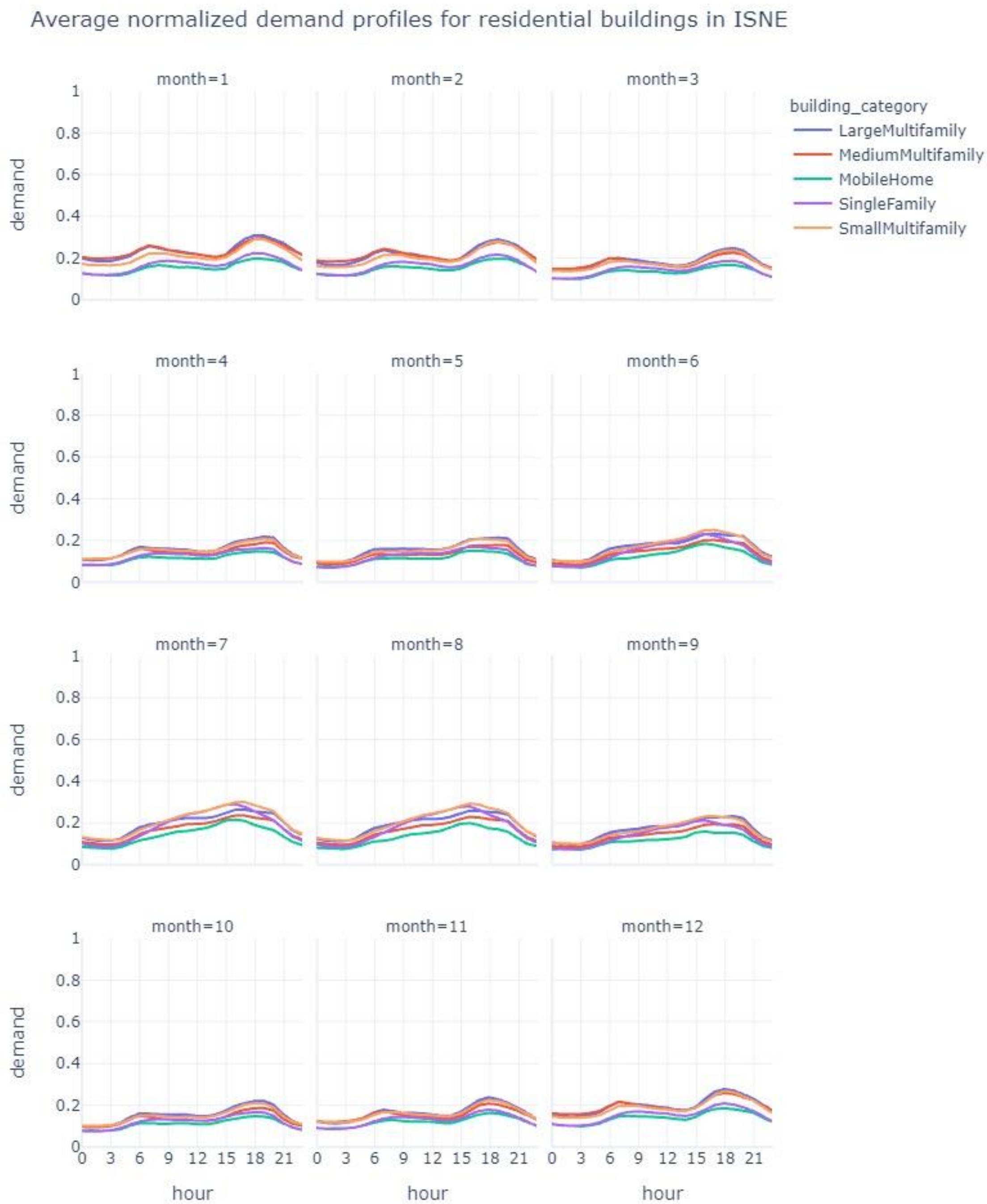

Fig. S5. Month-hour average load shapes for each residential building type in ISNE, normalized as a percentage of maximum hourly demand in the year.

Metadata for LBNL energy demand data

The dataset used for the California ISO case study was developed by Lawrence Berkeley National Lab (LBNL) as part of their 2025 California Demand Response Potential Study.[39] Utilizing the state's Energy Data Request Program (EDRP), LBNL researchers were able to request and collect actual hourly AMI data representing over 13.1 million individual electricity customers from each of the state's three major investor-owned utilities (Southern California Edison, San Diego Gas and Electric, and Pacific Gas and Electric). In order to maintain the privacy of individual electricity customers, the researchers aggregated these 13.1 million timeseries into 2,766 representative profiles. LBNL categorized these load profiles into 17 facility types, which we categorized into five broader categories, which is summarized in Table S3.

Table S3. Metadata for the hourly demand profile data included in the LBNL dataset, and how we assigned each building type to categories for this study.

Study-assigned Category	LBNL Building Type	# of aggregated Profiles	# of end Customers
Residential	Residential	493	10,652,391
Commercial	Office	467	415,895
	Retail	452	192,621
	Refrigerated Warehouse	7	1,158
	Data Center	6	164
Manufacturing	Computer/Electronics	68	5,087
	Primary Metals	113	15,438
	Petroleum Refining	2	71
	Chemical	18	1,417
	Plastic/Rubber	28	2,166
	Food/Beverage Processing	121	7,185
Agriculture and Water Pumping	Agricultural Irrigation	275	147,742
	Water Utility	253	50,576
	Wastewater Treatment	104	21,487
Other	Other Commercial	266	602,685
	Other Industrial	72	102,666
	Other	21	904,342
	Grand Total:	**2,766**	**13,123,091**

Full national results for each building type in each grid region

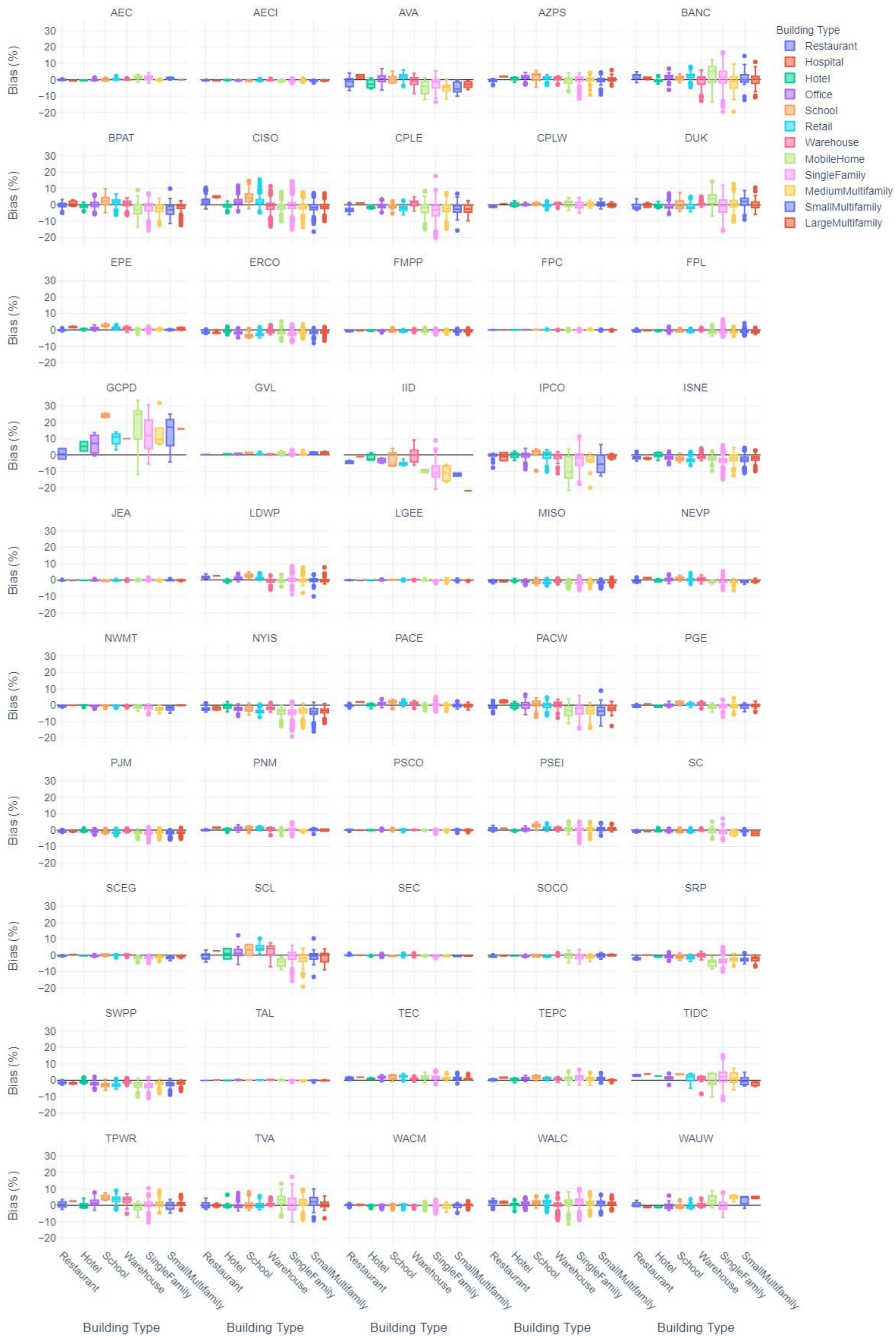

Fig. S6. Distribution of biases for the national results broken out by balancing authority (facets) and building types (x-axis)

Results for regions omitted from the main text (CHPD and DOPD)

As mentioned in the results section of the main text, the results for two regions were omitted from Figure 2 for the sake of readability. These two regions, PUD No. 1 of Douglas County (DOPD) and PUD of Chelan County (CHPD), are two hydro-only balancing authorities in Northeast Washington State.

As shown in Figure S7, the carbon intensity in these two regions is typically zero and is intermittently higher when importing fossil-fuel-based electricity from other regions. Due to this, the annual average value will significantly misrepresent the actual carbon intensity in each hour, which leads to inventory biases that range from 20% to 106%, as shown in Figure S8. Although these relative biases are large, the absolute biases are relatively small due to the low average emission rate for these regions.

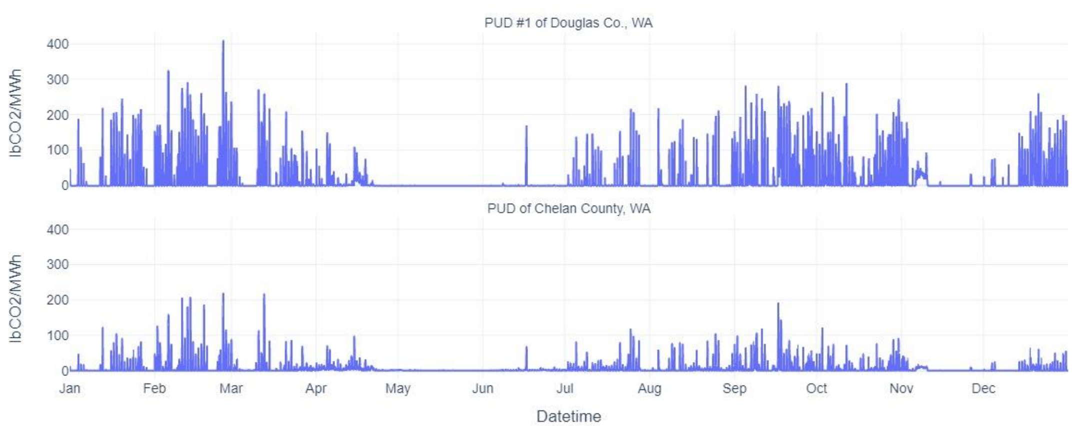

Fig. S7. Hourly carbon intensity values for DOPD and CHPD in 2019.

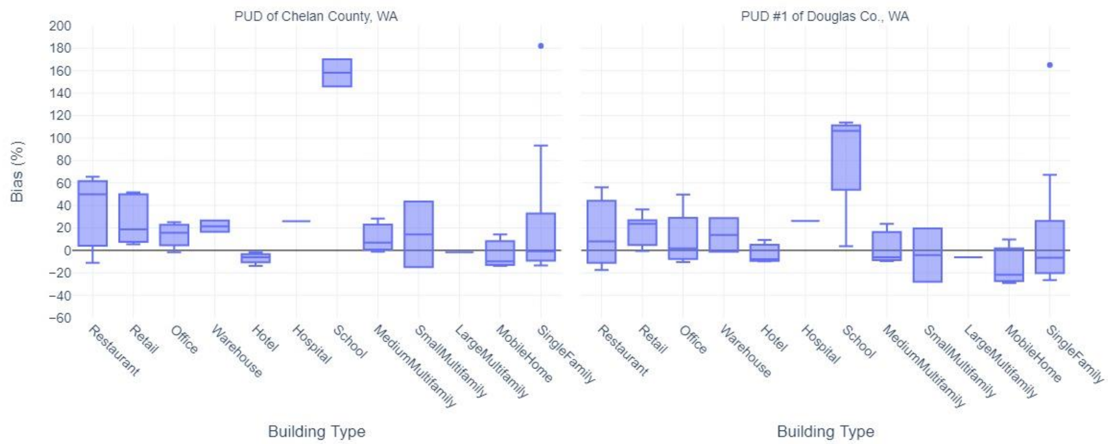

Fig. S8. Bias introduced by annual carbon accounting for each building type in CHPD and DOPD.

Comparison of Inventory Bias and regional fuel mix and CI variability

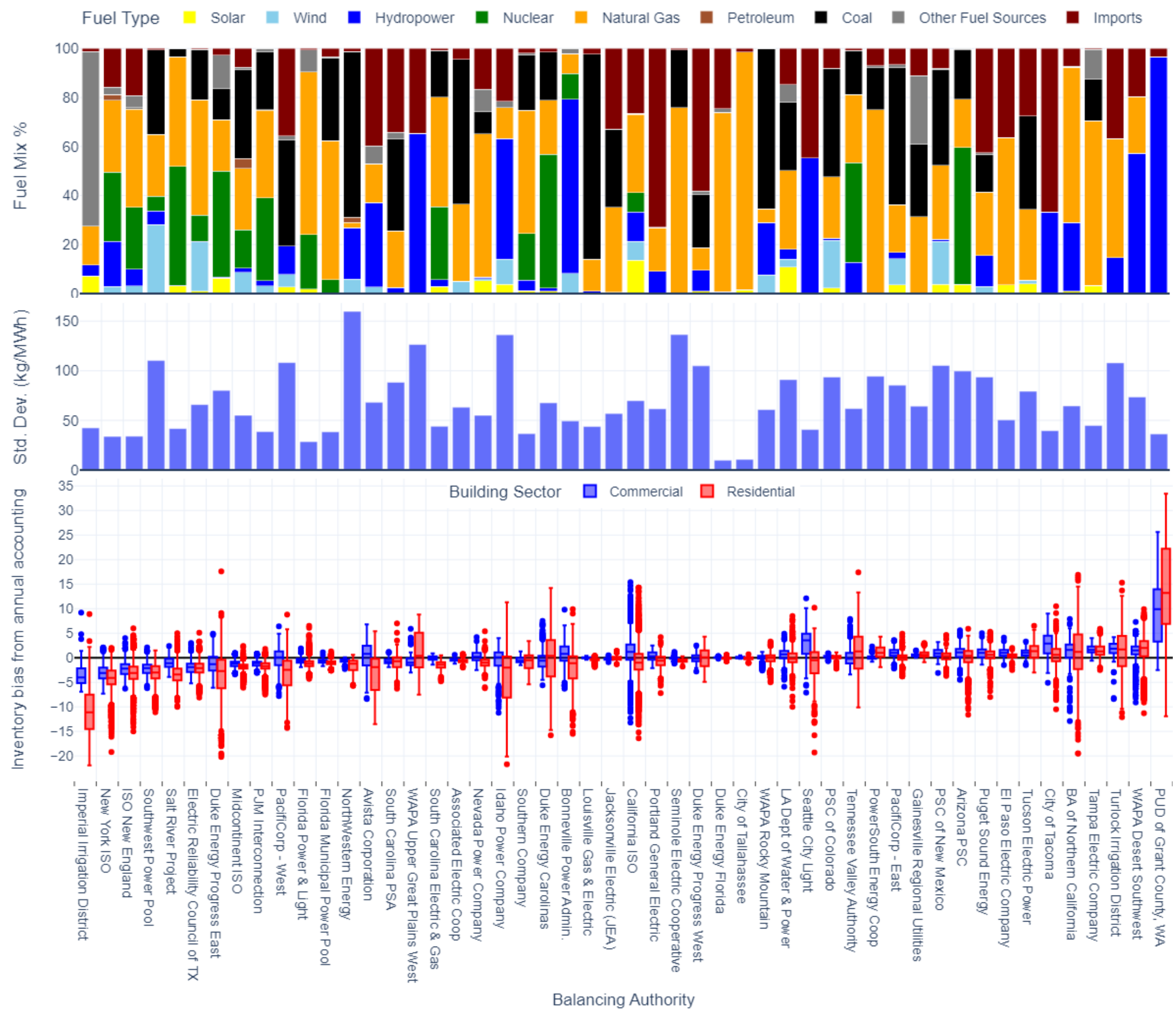

Fig. S9. Comparison of inventory bias, variability of carbon intensity and regional fuel mix.

Supporting Information for Chapter 2

Documentation

Detailed documentation of the data inputs, assumptions, and methodologies used to produce the Open Grid Emissions dataset can be found online at https://docs.singularity.energy/docs/open-grid-emissions-docs. This documentation contains a step-by-step overview of the data pipeline, description of the data cleaning steps, the methodologies used to calculate and adjust emissions, the gross-to-net generation conversion, how data were aggregated, and the methodology for assigning an hourly profile to monthly data.

Code Repository

The code repository can be found at https://github.com/singularity-energy/open-grid-emissions and is archived at https://doi.org/10.5281/zenodo.7062460

Dataset download

The dataset is available to download at https://singularity.energy/open-grid-emissions/ and is archived on Zenodo at https://doi.org/10.5281/zenodo.7063072 . These datasets include regional consumed emissions factors, regional power sector data, and power-plant level data, as well as a complete set of data quality metrics.

Supporting Information for Chapter 3

Code Repository

The MATCH model can be found online at https://github.com/grgmiller/MATCH-model.

Model use case

The MATCH ("Matching Around The Clock Hourly energy") model for planning 24/7 energy portfolios is a derivative of the open-source SWITCH 2.0 power system planning model.

This model is intended to model a renewable energy portfolio for an entity that primarily procures power using virtual power purchase agreements. This could include a load-serving entity such as a Community Choice Aggregator, or a large end-use customer of electricity, such as a corporation. This user should be a "small" user of electricity within the balancing authority(s) within which it operates (< 5-10% of total balancing authority load). This assumption is important because this model does not consider the impact of the portfolio on physical system stability (system frequency, voltage, etc.), and it is assumed that any power that is not generated by contracted generation will be sourced from "system power" which is always available from other resources on the system.

Model Overview

This model is a mixed-integer linear program that selects the lowest-cost portfolio of renewable and carbon-free resources to meet a time-coincident renewable or carbon-free energy goal in a single target year. The model both selects the capacity of each resource that should be included in the portfolio, and is able to dispatch each resource in each hour throughout the year.

The model is coded in Python and uses the Pyomo optimization modeling language. It may be used with multiple different optimization solvers, including the open-source CBC, or commercial solvers such as Gurobi or CPLEX.

The model is based on the architecture of an open-source power system planning model called "SWITCH 2.0," although has been heavily modified to simulate time-coincident ("24/7") renewable energy procurement goals by entities that primarily buy energy through power purchase agreements (PPAs) and wholesale electricity markets. The current version of the model has been built and tested for use by Community Choice Aggregators (CCAs) in California, although the model is also flexibly designed to be used by large corporate energy buyers (although adjustments may need to be made in future versions to ensure full compatibility with this use case).

The model is capable of modeling renewable energy goals for load centers and generators located in multiple grid regions, although to date, all of the testing has been done on single-region models, as this corresponds to the initial use case of CCAs.

Model Inputs

Model Timescales

The model is currently configured to model all 8,760 hours in a single target year (the model treats all years as a non-leap year).[‡] For example, if the user has a 100% renewable energy target that they are trying to achieve by 2030, they would be modeling the single year 2030. The target year may be interchangeably referred to as the "model year" or the "period." Each of the 8,760 timepoints [t] in the target year are part of a single continuous timeseries spanning the entire period, each representing a single, unique hour. Each of the timepoints are treated as consecutive, and "wrap" around the end of the year (I.e. timepoint 1 is preceded by timepoint 8760). Each hour of input data should be entered in local standard time (not prevailing time, which shifts for daylight savings time).

There is only a single build decision per generator for the modeled period. If the generator is selected/built, the model assumes that its commercial operation date (COD) is on or before the first

[‡] Any leap years that are modeled should be fit to an 8760 timeseries by removing the 24 timestamps on February 29 from all timeseries inputs. This is consistent with how NREL's System Advisor Model handles leap years.

timepoint of the period, meaning that the generator is available to be dispatched in every timepoint of the model year.

Because we are modeling a single year, the costs that are being optimized only represent the costs that occur in the single model year, rather than the lifetime costs of the generator.

Because of the way the model is currently configured, it is useful for identifying what an optimal portfolio would look like in the target year, but not what the investment pathway would look like (for example, between now and the target year, in which years should the user invest in each resource). Such pathways could be simulated using this model by modeling several years independently using interim targets along the way. For example, a user could model a 50% target in 2025, and then use the outputs from that model as the predetermined generator portfolio in a subsequent model of a 100% target in 2030.

Because each timepoint is 1 hour, any power units occurring in a single timepoint (measured in MW), can also be interpreted as a unit of energy (measured in MWh): 1MW for 1 hour is 1MWh.

Terminology

- A "generator" is any generation or storage asset that can be built in the model. Specific subsets of generators will be qualified such as "storage generators," "variable generators," "non-storage generators," "baseload generators," etc.
- The term "generation" or "total generation" refers to all energy output from a non-storage generator, not including any curtailed energy. "Dispatched generation" refers to the portion of total generation that is used to match time-coincident load. "Excess generation" refers to the portion of total generation that is generated in excess of time-coincident load.

- “Capacity” refers to any quantities related to generator build decisions (quantified in MW), while “energy” refers to any quantities related to generator dispatch decisions, generation, charging, or discharging (quantified in MWh)
- Generators can be interchangeably “built” or “contracted,” which refers to the amount of capacity from each generator that will be included in the optimal portfolio. Regardless of whether the actual generator is being physically built as a results of the decision, we generally refer to a decision about how much capacity to contract as a “build decision”. In other words, there is no meaningful difference in the model between a resource being “built” and a resource being “contracted.” It is assumed that signing a contract will lead to the resource being built, or else that the contract is for an existing resource.
- Throughout the document, the main policy goal is generally referred to as a “renewable energy goal”, although in this document, “renewable” can be interpreted interchangeably with “carbon-free” or “clean” energy goals. The model itself can model any type of renewable/clean/carbon-free energy target, as long as all of the generators included in the model meet the user’s definition of a renewable/clean/carbon-free resource.

A note on notation

- Decision variables are represented by names that capitalize each word in the variable name (e.g. BuildGen). Set names are indicated in all capitals with underscores between words (e.g. GENERATION_PROJECTS). Parameters are indicated with all lower-case letters, with or without underscores between the words (e.g. predetermined_build_capacity or predeterminedbuildcapacity).
- All variables and parameters can be indexed by one or more indexes. These indexes are either represented in a subscript following the variable name, or in square brackets after the variable

name (e.g. $BuildGen_g$ or BuildGen[g]). If the variable is indexed by more than one value, these will be separated by commas (e.g. zone_demand_mw[z,t]).

- The following single letters are commonly used to represent elements in sets:
  - "g" represents a generator in GENERATION_PROJECTS or any subset
  - "z" represents a load zone in LOAD_ZONES
  - "t" represents a timepoint in TIMEPOINTS
  - "mo" represents a month in MONTHS
  - "req" represents a resource adequacy requirement in RA_REQUIREMENTS

Decision Variables and associated constraints

Generator Build Decisions

$BuildGen_g$ is a decision variable for the capacity of each generator that should be built/contracted and included in the optimal portfolio. Generator build decisions can be constrained by the following constraints:

- BuildGen must be positive
- A "**predetermined build capacity**" can be specified for each generator, which requires $BuildGen_g \geq predetermined\_build\_capacity_g$. This is useful for specifying generators that are already an existing part of the portfolio.
- A **maximum build capacity** can be specified for each generator, which requires $BuildGen_g \leq gen\_capacity\_limit\_mw_g$
- A **minimum build capacity** can be specified, which requires the minimum amount that must be built if the generator is built at all. This creates a binary decision variable $BuildGenMinCap_g$, which is activated using a linking constraint $BuildGen_g \leq BuildGenMinCap_g * gencapacitylimitmw_g$. This constraint is enforced by $BuildGen_g \geq BuildGenMinCap_g * genminbuildcapacity_g$

- Multiple generators can also be specified as **mutually exclusive variants** of each other. This is useful if a generator has an offer price curve (e.g. if more capacity is built, the PPA cost is lower), or if there are different configurations of the same project being offered. This creates a binary variable $BuildVariants_g$ for each project, which is activated with a linking constraint $BuildVariants_g * gencapacitylimitmw_g \geq BuildGen_g$. This constraint is enforced by $\sum_g BuildVariants_g \leq 1$ for all g in each generator variant group.
- The user can optionally specify that a generator be **built in discretely-sized units**, such as 10MW increments. If this build behavior is desired, the model includes a new integer decision variable $BuildUnits_g$, and BuildGen is constrained as $BuildGen_g == BuildUnits_g * genunitsize_g$. Introducing an integer decision variable makes the model a mixed-integer linear program and can slow down the model solve time.

Storage Build Decisions

Each storage generator consists of two components that must be built: the power capacity (MWac) and the energy capacity (MWh). The power capacity build decision shares the same decision variable $BuildGen_g$ with non-storage generators, though with additional constraints specific to storage. The energy capacity build decision uses a decision variable $BuildStorageEnergy_g$. All storage generators are contained in the set STORAGE_GENS, which is a subset of GENERATION_PROJECTS. Furthermore, the storage component of a hybrid/co-located resource are contained within the set HYBRID_STORAGE_GENS, which is a subset of STORAGE_GENS. HYBRID_STORAGE_GENS have additional constraints on the build decisions, in addition to those for all STORAGE_GENS. The following decision variables apply to all STORAGE_GENS:

- $BuildGen_g$ is subject to all of the same constraints as normal generation projects: it must be positive, and less than $gen\_capacity\_limit\_mw_g$, if specified. A predetermined build capacity, minimum build capacity, and variant group can also be specified for all STORAGE_GENS.
- $BuildStorageEnergy_g$ must be built in a fixed ratio with $BuildGen_g$, as specified through the energy-to-power ratio specified as an input. This ratio represents the number of hours of storage that the battery has (i.e. a "4-hour battery" would have an energy-to-power ratio of four. This constraint is: $BuildStorageEnergy_g == storageenergytopowerratio_g * BuildGen_g$
- **Hybrid storage** can also be required to be built in a specific ratio with the paired hybrid generator capacity. The user must specify a minimum and maximum capacity ratio between which the storage capacity must fall. If the storage should be built in a fixed ratio with the paired generator, the user can set minimum = maximum. This constraint is: $storagehybridmincapacityratio_g * BuildGen_{storagehybridgenerationproject[g]} \leq BuildGen_g \leq storagehybridmaxcapacityratio_g * BuildGen_{storagehybridgenerationproject[g]}$

Generator Dispatch Decisions

Generator dispatch decisions apply to all NON_STORAGE_GENS, which is a subset of all GENERATION_PROJECTS. However, the specific constraints and decision variables used depend on which specific subset of NON_STORAGE_GENS the generator belongs to. A generator can belong to BASELOAD_GENS if the generator is a baseload resource that must be dispatched at its full capacity in each timepoint. A generator can belong to VARIABLE_GENS if it is a variable renewable resource such as wind or solar. If a generator belongs to neither BASELOAD_GENS nor VARIABLE_GENS, it is assumed to be a fully dispatchable generator.

Dispatch decisions **for dispatchable generators** are controlled by $DispatchGen_{g,t}$, which can take any value between zero and the generator's nameplate capacity (controlled by the decision variable

$BuildGen_g$) derated by the gen_forced_outage_rate[g] parameter, which is applied evenly to all timepoints across the year. For example, if the nameplate capacity of a project was 100MW and the forced outage rate was 1%, then the maximum dispatch in any hour would be 99MW. For dispatchable generators, there are no constraints relating to unit commitment or ramp rates.

Dispatch decisions **for baseload generators** are also controlled by $DispatchGen_{g,t}$, but with additional constraints. Users must specify a baseload_capacity_factor[g,t] parameter for each timepoint, which specifies the percent of nameplate capacity at which the baseload generator must be dispatched in each timepoint. Indexing this parameter to each timepoint allows the user to reflect seasonal variations in the generator availability, such as with run-of-river hydro, which may only be available for part of the year. This baseload capacity factor is further derated by both the gen_forced_outage_rate[g] and gen_scheduled_outage_rate[g] parameters (Dispatchable and variable generators do not have scheduled outage rates because it is assumed that scheduled outages could be scheduled when the generator is not operating). Thus, for baseload generators, dispatch is constrained as $DispatchGen_{g,t} = = BuildGen_g \, * \, baseloadcapacityfactor_{g,t} * (1 - genforcedoutagerate_g) * (1 - genscheduledoutagerate_g)$.

For variable generators, dispatch decisions are controlled by two decision variables $DispatchGen_{g,t}$ and $CurtailGen_{g,t}$, and one expression $ExcessGen_{g,t}$,. Users specify a variable_capacity_factor[g,t] parameter, which identifies the percent of nameplate capacity that can be generated in each timepoint, based on expected wind, solar, or other renewable resource availability. Users can either manually define these variable capacity factors, or allow the variable capacity factor to be automatically calculated by NREL's System Advisor Model, given a geographic coordinate, set of generator technical characteristics, and set of historical resource years on which the user wants the expected value to be based. The sum of $DispatchGen_{g,t}$, $ExcessGen_{g,t}$, and $CurtailGen_{g,t}$ must always equal the total available variable generation, derated by the gen_forced_outage_rate[g]. For solar generators, the total available generation is also derated based on the age of the solar plant in the target year, taking into account a 0.5% annual linear degradation factor. The user inputs a COD year for each solar generator, and then a degradation factor is calculated as $\left[1-\left(0.005*\left(modelyear-codyear_g\right)\right)\right]$.

$DispatchGen_{g,t}$ specifies the portion of the generation from each generator that is matched to time-coincident load.

Economic curtailment

$CurtailGen_{g,t}$ specifies the portion of generation from each generator that is economically curtailed in each timepoint. CurtailGen is only allowed for each generator when the nodal price is negative, which is consistent with how economic curtailment would be dispatched in real life. Curtailed generation is still subject to the normal energy PPA cost for a generator, but does pay the negative wholesale cost.

In reality the only time that an operator would choose to economically curtail a generator is when LMP prices are <= 0. Enforcing this constraint also prevents curtailment from being used excessively by the model to satisfy other constraints. For example, when limiting the amount of excess generation allowed, previously the model could just curtail a lot of generation even when LMP prices were positive, even though this would not be realistic behavior.

To limit curtailment, we take an approach similar to how we limit DispatchGen to be <= an upper limit that is defined by its variable_capacity_factor and installed capacity, in order to maintain the linearity of the model. We create a new variable curtailment_capacity_factor which is set equal to variable_capacity_factor when the LMP prices at a generator node are <= 0, and set to zero when prices are positive. This variable is defined in variable_capacity_factors.csv.

To limit curtailment, we set the constraint CurtailGen[g,t] <= GenCapacityInTP * gen_availability * curtailment_capacity_factor for each g, t.

Certain renewable contracts also specify a buyer curtailment allowance, which is a number of MW*hours per year that a generator can be economically curtailed by an offtaker without paying the PPA cost. The user may specify a `buyer_curtailment_allowance` in hours for each project. So for example, if the allowance is entered as 10 hours, and the model builds 50MW of that resource, up to 500MWh of generation from that project may be economically curtailed in a year without paying the PPA energy cost for those curtailed MWh. However, adding this as a separate decision variable would potentially slow the model, so instead we implemented this as a post-processing calculation in the summary report that credits back this allowance if used. For each generator that has a buyer curtailment allowance, the available credit is calculated as buyer_curtailment_allowance * GenCapacity * ppa_energy_cost. We then take the minimum of this total allowance and the total cost of curtailed energy for each generator to make sure that we are crediting back only the part of the allowance that was actually used.

To reduce the number of decision variables, CurtailGen is only indexed to those generators for which a non-zero curtailment limit is specified. $ExcessGen_{g,t}$ represents the portion of generation that is neither matched to load by $DispatchGen_{g,t}$ nor economically curtailed by $CurtailGen_{g,t}$, and thus represents the portion of generation that is in excess of load in each timepoint. $ExcessGen_{g,t}$ is like a slack variable that allows for total contracted generation to exceed load in each timepoint, even though the load balance constraint requires a strict equality between supply and demand. However, to reduce the number of decision variables in the model, ExcessGen is calculated as an expression as $DispatchUpperLimit_{g,t} - DispatchGen_{g,t} - CurtailGen_{g,t}$. The user still pays the PPA energy cost and earns Pnode revenue from $ExcessGen_{g,t}$.. The full set of constraints governing dispatch decisions for variable generators includes:

- Maximum annual curtailment: $\sum_t CurtailGen_{g,t} \leq BuildGen_g * gencurtailmentlimit_g$, where gen_curtailment_limit[g] is the number of hours specified in a PPA contract that can be economically curtailed.
- Dispatch upper limit: $DispatchGen_{g,t} + CurtailGen_{g,t} + ExcessGen_{g,t} == BuildGen_g * variablecapacityfactor_{g,t} * \left(1 - forcedoutagerate_g\right)$
    - For solar generators, the right hand side of this constraint is also multiplied by the solar_age_degredation[g] factor for each generator.

Limiting excess generation: Because excess generation is allowed in the model, the cost-optimal solution may result in the selected portfolio generating more energy in a year than the user consumes in load. If the user wants to limit the amount of excess generation that is allowed in the portfolio (for risk mitigation reasons, for example), the user may optionally specify a constraint on the total amount of excess generation. The limit can be either “annual” or “hourly”, and is expressed as a percentage of load. For example, if the user did not want total generation to exceed 110% of load, they would specify the limit as 10%. If the user selects an annual limit, then the total annual volume of excess generation could not exceed the threshold based on the total annual volume of load. Mathematically, this annual limit is constrained as $\sum_t(ZoneTotalGeneration_{z,t} - ZoneTotalStorageLosses_{z,t}) \leq \sum_t zonedemandmw_{z,t} * (1 + excessgenerationlimit)$. If the user selects an hourly limit, the volume of excess generation in each hour could not exceed the threshold based on load in the same hour. Mathematically, this hourly limit is constrained as $ZoneTotalExcessGen_{z,t} \leq ZoneDemandMW_{z,t} * excessgenerationlimit$. An annual constraint allows for greater flexibility in matching load and generation shapes, as it allows seasonal mismatches in generation and load. For example, in the summer when solar is generating at higher output, large amounts of excess generation may be allowed, as long as the total annual volume of excess generation is below the limit. An hourly limit is more useful if the user wants to make sure that the supply and demand shapes match closely throughout the year, while allowing for some flexibility for generation to not exactly equal demand in all hours. If a user seeks to exactly match generation and demand in every hour (in which all excess generation would have to be stored by a battery, and batteries could only discharge when needed to fill an open position), then they could set an hourly limit equal to zero.

Because the total cost of a generator is the sum of PPA contract cost and wholesale market (Pnode) revenues, there is a chance that a generator may have a net negative cost if the wholesale revenue is greater than the PPA contract cost. In that case, because this is a cost minimization optimization, the model would try to build as much of that resource as possible, even if its shape doesn't match the timing of load and it leads to a large amount of excess generation. For annual renewable targets, this is not an issue, because the time-coincidence of the generation is not a desired outcome, but for hourly renewable goals, this can lead to undesirable portfolio choices. To prevent this, the user can specify an **excessgen_penalty**, which is a flat $/MWh penalty applied to all excess generation. This provides a disincentive for negative-cost generators to build more than is needed to meet load, and to displace dispatched generation from another higher priced generator to excessgen. This penalty must be set high enough to cause negative-cost generators to have a net positive cost, so it may take some experimentation to find the right penalty value. Optimization outcomes may also be sensitive to this parameter, so if using, it is recommended to run several sensitivity parameters with the excessgen_penalty set to different values.

Note on variable capacity factors for variable generators

As noted above, a variable capacity factor (VCF) for each variable resource must be specified, which defines how many MWh will be generated in each timepoint for each MW of capacity built. The user can manually input these VCFs, or allow them to be simulated by PySAM (v3.0.1), which is a python wrapper for NREL's System Advisor Model. Currently, MATCH is set up to be able to simulate wind or solar PV generation. The wind simulation utilizes data from the Wind Toolkit, and the solar simulation uses PVWatts v8 and data from the NSRDB. The model downloads wind or solar resource data corresponding to the project's geographic coordinates, and uses parameters specified by the user to simulate generation and calculate a VCF.

For solar, these parameters include the project's layout (azimuth, ground coverage ratio), array type (efficiency, bifaciality factor), inverter information (efficiency, DC to AC ratio), tracking information (tilt, tracking axes, rotation limits), losses, and optionally information about wind stow. All build capacities in the model are in MWac, while PvWatts simulates based on a DC capacity, so care must be taken to adjust the SAM inputs for this: the solar capacity should be entered as the MWac value, the DC-to-AC ratio should be set to 1, the inverter efficiency should be set as close to 100% as possible (which is limited to 99.5% in SAM), and any system losses on the DC side of the system should be removed from the losses. Wind inputs include details about the turbine height, power curve, losses, and layout.

Resource data for wind and solar is currently available for 2007-2014. The user can choose to specify a single resource year for modeling, or multiple resource years, which will be averaged together to calculate an expected value of generation. Averaging too many years, especially for wind, eliminates much of the variability, and can make wind look more like a baseload resource, so care should be taken. After the model run is complete, the model will perform a sensitivity analysis to calculate the portfolio time-coincident performance using each single resource year from which the expected value was derived.

System Power

Because this model assumes that the user's load is part of a larger power system or balancing authority, any power that is not met by contracted generation in each hour can be met by "system power," which represents electricity delivered from the grid. The amount of system power that is used in each hour is controlled by the decision variable SystemPower[z,t].

For a load serving entity, system power represents the total amount of electricity procured from wholesale power markets that is un-hedged by a PPA contract. To minimize risk, an LSE would typically procure hedge contracts to match 100% of their load, so the model allows the user to specify a parameter hedge_premium_cost[z], which represents the cost premium that an entity would pay to hedge each MWh of system power. In reality, a hedge contract has a specific shape which may not match the open system power position exactly, meaning that in reality, an entity is often under- or over-hedged. For simplicity, this model assumes perfect hedging of all MWh of system power.

In reality, a hedge contract works similarly to a PPA, where there is a contract cost paid per MWh, and a revenue earned from settling the hedge contract at a specific node. However, instead of optimizing separate hedge contract and wholesale market revenue costs, which may lead to unintended incentives for the use of system power, the premium cost is meant to represent a premium above the cost of system power. Thus, the user specifies the hedge premium cost as a percent of a specific pricing node, which would typically be the node at which the user's load is located. For each load zone, the user specifies a `hedge_premium_percent` and `hedge_node`. Because nodal prices may be negative, the hedge premium cost includes a floor of $0.01.

$$HedgePremium_{z,t} = \max(0.01, nodalprice_{hedgenode,t} * hedgepremiumpercent)$$

Storage Charge/Discharge Decisions

Storage charging and discharging decisions are controlled by two separate decision variables $ChargeStorage_{g,t}$ and $DischargeStorage_{g,t}$. Additionally, the state of charge of each storage asset is tracked using a decision variable $StateOfCharge_{g,t}$.

Because charging and discharging decisions are represented by two separate decision variables, there is the possibility of a storage asset simultaneously charging and discharging in each timepoint. Because each timepoint in this model represents one hour, it is physically possible for a storage asset to both charge and discharge in the same hour (for example, if it charged for 30 min and discharged for 30 min). Preventing simultaneous charging and discharging altogether would require the use of a binary decision variable which would significantly increase the complexity of the model. Thus, as a compromise, we implement a constraint that doesn't prevent simultaneous charging and discharging, but is still physically realistic. This constraint takes the form $ChargeStorage_{g,t} + DischargeStorage_{g,t} \leq BuildGen_g$. However, the user may optionally specify if they want the model to use the strict storage binary discharge constraint.

Storage discharging in each timepoint can be any value between 0 and the nameplate power capacity of the storage asset, as defined by $BuildGen_g$. Additionally, for hybrid projects, the combined discharge and generation from the paired generator cannot exceed the project's interconnection limit, which is assumed to be the nameplate capacity of the generator portion of the project. This is constrained as: $DischargeStorage_{g,t} - ChargeStorage_{g,t} + DispatchGen_{storagehybridgenerationproject[g],t} + ExcessGen_{storagehybridgenerationproject[g],t} \leq BuildGen_{storagehybridgenerationproject[g]}$

Storage Charging: For some storage assets, the charging power capacity and discharging power capacity can be different values. Thus the user can specify a storage_charge_to_discharge_ratio[g] parameter, which is used to constrain the upper limit of charging as $ChargeStorage_{g,t} \leq BuildGen_g *$

$storagechargetodischargeratio_g$. Additionally, hybrid storage assets are required to only charge from dispatched generation from their paired hybrid generator, which is enforced using $ChargeStorage_{g,t} \leq DispatchGen_{storagehybridgenerationproject[g],t}$. Finally, we constrain that all storage must charge from dispatched generation (rather than from system power, if available) using the constraint $\sum_g ChargeStorage_{g,t} \leq \sum_g DispatchGen_{g,t}$ for all generators in each load zone. We do this to simplify accounting of the eligible renewable/carbon-free energy content of discharged energy.

This combination of constraints means that storage can discharge both to fill open positions when there is not enough generation capacity to match load in a timepoint, or can discharge when economically optimal even if there is already excess generation. In this latter case, because of the equality constraint in the load balance constraint, DischargeStorage will displace DispatchGen in the timepoint, leading to more ExcessGen.

Storage charging and discharging decisions are also constrained by limits on each storage asset's **state of charge**, which is tracked using a decision variable $StateOfCharge_{g,t}$. In this model, we account for both roundtrip efficiency losses and storage leakage (self-discharge) losses. We split the roundtrip efficiency into an AC-DC conversion loss when charging and a DC-AC conversion loss when discharging, using the simplifying assumption that $ACDC\ loss = DCAC\ loss = \sqrt{Roundtrip\ Efficiency}$. The state of charge (represented in the following equation as $SOC_{g,t}$ for brevity) is calculated using the constraint: $SOC_{g,t} == SOC_{g,t-1} - SOC_{g,t-1} * storageleakageloss_g + ChargeStorage_{g,t} * \sqrt{RTE_g} - \frac{DischargeStorage_{g,t}}{\sqrt{RTE_g}}$. The state of charge is further constrained as $0 \leq SOC_{g,t} \leq BuildStorageEnergy_g$.

Finally, the user can also specify a **limit on the total number of cycles** that are allowed in a year, using the parameter storage_max_annual_cycles[g]. We define a cycle as discharging the full energy capacity of a battery once. This constraint is enforced using $\sum_t \frac{DischargeStorage_{g,t}}{\sqrt{RTE_g}} \leq BuildStorageEnergy_g * storagemaxannualcycles_g$.

Demand Response

There is not currently a functioning demand response module in the model, but we plan to add this functionality in the future. The demand response module would be able to model load curtailment, load shifting, energy efficiency, and electrification programs. Each of these demand-side programs would have an associated capacity cost and load modifying shape (positive and/or negative in each timepoint). Resources like load shifting and curtailment could be dispatched based on the available capacity and load modifying shape of the resource.

Resource Adequacy

The resource adequacy module is based on the current rules (which change frequently) that apply to Community Choice Aggregators in California.

Each CCA is required by the CPUC to contribute a certain amount of both system RA and flexible RA each month of the year. This monthly requirement can be met based on resources in the CCA's portfolio, or by buying RA capacity on the market. Each generator contributes qualifying capacity to this requirement based on the effective load carrying capacity (ELCC) value that is assigned to each type of generator in each month. Additionally, each CCA has been assigned a "midterm reliability requirement" which specifies that a certain capacity of firm (baseload) resources and a certain capacity of long-duration energy storage (defined as storage with an energy to power ratio >= 8 hours) must be procured.

Based on the RA requirement and the qualifying capacity contributed by each generator in the selected portfolio, the model calculates an open position for each month using the decision variables $RAOpenPosition_{mo}$ and $FlexRAOpenPosition_{mo}$. This open position must be closed by procuring capacity from the market based on the parameter ra_cost[mo] and flex_ra_cost[mo]. This open position cost is included in the objective function.

Optionally, the user may also choose to include the value of selling excess RA capacity into the market in the objective function, based on the parameters ra_resell_value[mo] and flexible_ra_resell_value[mo]. Because flexible RA must be sold paired with system RA, we include a decision variable $SellableExcessFlexRA_{mo}$, which is constrained as $SellableExcessFlexRA_{mo} \leq \min(RAExcess_{mo}, FlexRAExcess_{mo})$. The excess values for both system and flexible RA are calculated as $TotalQualifyingCapacity_{mo} - rarequirement_{mo} + RAOpenPosition_{mo}$.

The midterm reliability requirement is enforced using $\sum_g BuildGen_g \geq midtermfirmrequirement$ for all g in BASELOAD_GENS. For the LDES requirement, the model defines a new set LONG_DURATION_STORAGE, which is the subset of all STORAGE_GENS with a storage_energy_to_power_ratio >= 8. This requirement is enforced using the constraint $\sum_g BuildGen_g \geq midtermldesrequirement$ for all g in LONG_DURATION_STORAGE. All generators must be eligible for RA to contribute to either of the midterm requirements.

Objective Function

The objective function seeks to minimize the total cost of the portfolio, considering the following costs. Certain types of costs may be optionally added to the objective function to test certain scenarios

Required costs

- Contract costs
    - **Dispatched Generation PPA Cost**: Contract cost of generated energy that matches load in each hour
        - $\sum_{g,t} DispatchGen_{g,t} * PPAEnergyCost_g$ for all g in GENERATION_PROJECTS

- **Excess Generation PPA Cost**: Contract cost of generated energy that exceeds load in each hour
  - $\sum_{g,t} ExcessGen_{g,t} * PPAEnergyCost_g$ for all g in NON_STORAGE_GENS
- **Storage Capacity PPA Cost**: Contract cost of storage energy capacity built
  - $\sum_{g} BuildGen_g * PPACapacityCost_g$ for all g in STORAGE_GENS
- **Hedge Premium Cost**: Premium cost of procuring hedge contracts to match grid energy that isn't matched by PPA contracted energy
  - $\sum_{z,t} SystemPower_{z,t} * HedgePremiumCost_z$

- Resource Adequacy Costs
  - **RA Open Position Cost**: the cost of procuring RA on the market to close an open position left by our generation portfolio.
    - $\sum_{req,mo} RAOpenPosition_{req,mo} * RACost_{req,mo}$
- Wholesale market costs
  - **DLAP Load Cost**: Cost of procuring energy from the wholesale market at the Default Load Aggregation Point
    - $\sum_{z,t} ZoneDemand_{z,t} * NodalCost_{nodeforzone[z],t}$
  - **Storage Wholesale Price Arbitrage**: Net revenue from storage arbitraging wholesale energy prices at different times of day
    - $\sum_{g,t} StorageDischarge_{g,t} * NodalCost_{nodeforgen[g],t} - StorageCharge_{g,t} * NodalCost_{nodeforgen\{g],t}$ for all g in STORAGE_GENS
  - **Dispatched Generation Pnode Revenue**: Pnode revenue from contracted generators selling load-matched generation into the wholesale market
    - $\sum_{g,t} -1 * DispatchGen_{g,t} * NodalCost_{nodeforgen[g],t}$ for all g in NON_STORAGE_GENS

- **Excess Generation Pnode Revenue**: Pnode revenue from contracted generators selling excess generation into the wholesale market.
  - $\sum_{g,t} -1 * ExcessGen_{g,t} * NodalCost_{nodeforgen[g],t}$ for all g in NON_STORAGE_GENS

- Penalties (optimized, but not included in the total cost of energy)
  - **Excess Generation Penalty**: A flat $/MWh penalty value applied to all MWh of excess generation, only if the renewable goal type is an hourly (time-coincident) goal
    - $\sum_{z} ZoneTotalExcessGen_{z,t} * excessgenpenalty$

Optional costs (can be added to the objective function by the user using an option flag)

- **Resale value of Excess RA**: the market resale value of any excess RA capacity in our portfolio
- **Resale value of excess RECs**: the market resale value of any excess RECs (counted on a time-coincident basis). Calculated as $\sum_{g,t} ExcessGen_{g,t} * recresalevalue$

Costs not included in the objective function but used to calculate total cost of energy

- **Fixed Costs**: Any fixed costs paid per year (admin costs, CAISO costs, etc.).

All input costs are rounded to the nearest whole cent ($0.01) before being loaded into the model.

During post-processing, the REC costs or resale revenues are calculated differently based on whether there is an open position or long position. If there is a REC open position, only procure enough RECs to meet base load plus storage losses (rather than loss-adjusted load). However, if long on RECs, only sell RECs in excess of loss-adjusted load.

Load Balance Constraint

The main constraint that governs the dispatch of resources in the model requires supply to equal demand in all hours in each zone. A zone generally represents a balancing authority within which both the load and generators are located. A model will typically have a single zone, unless you are modeling a time-coincident goal for an entity that has load in multiple grid regions.

Specifically, the following decision variables must be adjusted such that

$ZoneTotalGeneratorDispatch_{z,t} + ZoneTotalStorageDischarge_{z,t} + SystemPower_{z,t} == ZoneDemand_{z,t} + ZoneTotalStorageCharge_{z,t}$

Where

- $ZoneTotalGeneratorDispatch_{z,t} = \sum_g DispatchGen_{g,t}$ for g in GENS_IN_ZONE[z]
- $ZoneTotalStorageDischarge_{z,t} = \sum_g StorageDischarge_{g,t}$ for g in STORAGE_GENS_IN_ZONE[z]
- $SystemPower_{z,t}$ is a decision variable describing the amount of non-contracted grid power is being consumed
- $ZoneTotalStorageCharge_{z,t} = \sum_g StorageCharge_{g,t}$ for g in STORAGE_GENS_IN_ZONE[z]

Renewable Energy Targets

Resources are built and dispatched in the model in order to satisfy a renewable energy target, which describes the minimum amount of load that must be matched by generation from contracted generation. A fundamental assumption of this model is that all generators inputted into the model count toward achieving this target, and that any load that is not met by dispatched generation from these projects will be served by system (grid) power. Although throughout the document and model these targets refer to “renewable” energy, the model can be used to analyze any type of clean/carbon-free/renewable energy target, as long as all of the generators inputted into the model are eligible to meet the user’s defined target.

The user can specify two different types of renewable energy targets: a volumetric target or a time-coincident (24/7) target.

A volumetric renewable target (also known as an “annual target,” which is the status quo type of renewable energy accounting) is based on matching the total volume of load within the modeling period to the total volume of generation from contracted resources. This means that net generation (the sum of dispatched and excess generation less any storage losses) must be greater than or equal to the total demand times the target percentage (e.g. 50%, 100%)

$$\sum_t \left[ZoneTotalGeneratorDispatch_{z,t} + ZoneTotalExcessGen_{z,t} - \left(ZoneTotalStorageCharge_{z,t} - ZoneTotalStorageDischarge_{z,t} \right) \right] \geq \sum_t RenewableTarget * ZoneDemand_{z,t}$$

A time-coincident target is based on matching dispatched generation to load in each hour, and ensuring that the total volume of time-coincident generation meets or exceeds some percentage of the total volume of load in the year. In each timepoint, any generation in excess of the time-coincident load does not roll-over or count toward meeting the goal. Likewise, in each timepoint, any load that is not matched by generation or storage discharge must be met by system power. Because system power is used to fill in any gaps when time-coincident generation is not available, we can conveniently define this target based on the inverse percentage of system power consumed:

$$\sum_t SystemPower_{z,t} \leq (1 - RenewableTarget) * \sum_t ZoneDemand_{z,t}$$

Grid-mix/standard delivery resources

The MATCH model does not currently include the functionality to automatically include grid-mix or standard delivery renewable or clean energy based on Cambium. However, a user may manually model this using the following steps:

- Create a new GENERATION_PROJECT called something like "grid mix renewables" and specify it as a variable resource by setting `gen_is_variable` to 1
- Set the `ppa_energy_cost` and `ppa_contract_cost` to zero and assign it to a `gen_pricing_node` that is all zero for every hour
- Set `gen_capacity_limit_mw` and `gen_predetermined_cap` equal to the annual average hourly MW of load that you are trying to match.
- Create a manual capacity timeseries that represents the percent of renewable/clean energy being delivered in each hour
- Set `gen_is_additional` to zero

Emissions Optimization Target

In addition to renewable/clean energy procurement targets, some entities are interested in procuring energy from sources that will displace the greatest amount of marginal emissions from the grid. Emissions optimization goals are coordinated using the `match_model.optional.emissions_optimization` module. This module calculates the direct and indirect avoided emissions impact of all generator and storage dispatch, and converts these emissions impacts into a dollar figure using an internal carbon price so that these emissions impacts can be optimized in the objective function alongside all other financial parameters.

Direct emissions and CCS

For each generator in NON_STORAGE_GENS, the user specifies a `gen_emissions_factor` per MWh of generation. Total direct emissions are calculated as the sum of `TotalGen[g, t] * gen_emissions_factor[g]` for each generator.

Users can also specify a `gen_ccs_capture_efficiency` which represents what percentage of carbon emissions are captured if a plant as a carbon capture and sequestration system equipped. In this case, total direct emissions are calculated for such generators as `TotalGen[g, t] * gen_emissions_factor[g] * (1 – gen_ccs_capture_efficiency[g])`.

Because CCS equipment generally consumes electricity, a user can also specify a `gen_ccs_energy_load` for each generator, which specifies what percent of dispatched generation the ccs equipment consumes. For each CCS-equipped generator, this additional load is calculated as `-1 * DispatchGen[g,t] * gen_ccs_energy_load[g]`, and appended to Zone_Power_Injections.

Indirect Avoided emissions

Avoided emissions reflect the amount of carbon emissions from other generators on the grid that a generator indirectly displaces. Avoided emissions are calculated based on the region-specific long-run marginal emission rate for each generator. For each GENERATION_PROJECT, a user must specify the binary parameter `gen_is_additional` to indicate whether each generator is a new/additional generator that does not already exist on the grid. Only generators where `gen_is_additional` is set to 1 can have an indirect avoided emissions impact. For each GENERATION_PROJECT the user also specifies `gen_cambium_region`, which indicates the name of grid region defined by NREL's Cambium model where the generator is located (and thus where it would displace emissions). Because Cambium includes five different future scenarios, the user must also specify which `cambium_scenario` to use when defining the scenarios that will be run. During the creation of model input files, the script automatically downloads and creates input files with the relevant LRMERs for each region used in the model.

For additional generators, the avoided emissions are calculated as `-1 * TotalGen[g,t] * lrmer[gen_cambium_region[g], t]`, and for storage they are calculated as `ChargeStorage[g,t] – DischargeStorage[g,t] * lrmer[gen_cambium_region[g], t]` (positive generation thus has a negative emissions impact).

The total emissions impact is the sum of all direct and indirect emissions impacts.

Optimizing emissions in the objective function

In order to optimize emissions impacts in the objective functions, all emissions totals must be converted to dollars. To do this, the user specifies an `internal_carbon_price` in dollars per emissions unit when configuring each scenario.

Overview of configuring and running models

The model is configured as a "model run," each of which can have multiple scenarios. Each of these model scenarios can be solved in series or parallel, depending on the capabilities of your computer.

Each model run is configured by entering input data into a single Excel workbook with multiple tabs for different types of inputs. A user can specify which inputs (for example, specific generators, loads, prices, etc.) correspond to different named scenarios within the model run. The main element that must remain constant across all scenarios in a model run is the target year that is being modeled.

Once all inputs and scenarios have been configured, a python script loads all of the data from the Excel workbook, simulates generation profiles for variable generators using a package called PySAM (a python version of NREL's system advisor model), and repackages it into separate CSV files, formatted for input into the model, in separate input directories for each scenario.

The user then runs the models using a Jupyter notebook. Scenarios can be solved in series and parallel. Each solver instance will be opened in a command prompt window, which will display solve progress and/or identify any errors that may occur. After each scenario finishes solving, it will export results as csv files into output folders for each scenario, and then also run a Jupyter notebook that creates an interactive HTML summary report for each scenario. After each scenario finishes solving, the model will automatically move on to start solving the next scenario in the queue that has not yet been started.

After all scenarios have finished solving, a scenario comparison csv file will be generated, which allows the user to compare key metrics/results from each scenario side by side.

Output Metrics

Each scenario will have an HTML summary report, which includes key results and metrics, as well as interactive plots of certain outputs. This section provides an overview of the metrics included in each summary report:

- Percent of load met by renewable energy, both in terms of time-coincident accounting and annual volumetric accounting
- Results of the sensitivity analysis for how well the portfolio would perform (in terms of time-coincident renewable percentage) based on renewable generation in individual weather years. This is calculated using a simplified model that uses a greedy algorithm for storage charging and discharging.
- Carbon footprint of the portfolio, including both total absolute emissions and the average emission factor for delivered energy (based on hourly accounting of emissions).
- A heatmap showing the carbon intensity of delivered energy in each hour of the year
- A sunburst plot showing the composition of the selected portfolio, by contract status, generation technology, and project name.
- A stacked bar chart of average cost per MWh generated for each generator, including the individual cost components.

- Interpretations of the reduced costs for each generator
- A pie chart showing the source of total delivered energy by generation technology
- A table that breaks down all cost components and the total cost, expressed both in terms of annual real cost and cost per delivered MWh.
- A stacked bar plot showing the quarter-hour average cost of power, including all cost components
- A table showing the resell value of any excess RA or RECs
- A table showing the monthly RA position for both system and flexible RA
- An area plot showing load, generator dispatch by technology, and battery charge/discharge for all 8760 hours of the year
- A version of the above plot averaged by month-hour
- A line plot of wholesale electricity prices at each node for all hours of the year
- A line plot showing the month-hour average shadow price of energy efficiency (or curtailment)
- An area plot showing the month-hour average shape of the net position, calculated both with and without storage dispatch.
- A line plot showing the aggregated hourly state of charge for both hybrid storage and standalone storage
- A table with stats about storage cycles and average state of charge
- A calculation of avoided emissions from additional generators in the portfolio, based on levelized long-run marginal emission rates from NREL's Cambium model.
- Tables showing input assumptions for both generators and storage assets.