

Data Requirements for Decarbonization through Utility Energy Efficiency Programs

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ABSTRACT

The imperative for decarbonization and the rise of variable renewable energy introduce new challenges and opportunities for utility energy efficiency (EE) programs. The emerging climate-forward efficiency framework, which is designed to illuminate transformative strategies to unlock efficiency's full potential as a net-zero resource, prioritizes EE investments as intentional drivers of greenhouse gas (GHG) reductions based on their temporal, seasonal, and geographical impacts. Yet at present, most EE goals are structured as annual energy savings targets that fail to account for efficiency's time-sensitive value. The data requirements to translate energy savings to GHG reductions may include granular end-use load profiles and marginal grid emissions rates. However, it remains unclear how granular these data must be to properly inform design, operation, and evaluation of effective climate-forward efficiency programs. In this paper, we use marginal emissions factors with different granularities (e.g., 15-minute, hourly, daily, annual) in diverse but representative U.S. grid regions to assess the emissions-reduction performance of select EE strategies. We report how the characteristics of a grid region impact the GHG reductions achievable through EE programs. The insights from this research hold relevance for states, utilities, and regulators who must decide on the appropriate levels of investment in data infrastructure needed to realize the full potential for climate-forward efficiency and to optimize efficiency's ability to decarbonize the power sector amid a changing supply-side landscape.

Introduction

Utility Energy Efficiency Programs: Emerging Opportunities for Re-Alignment

Utility energy efficiency (EE) programs, which offer customers incentives to make energy-saving home and business improvements, have traditionally been designed to prioritize the financial benefits that come with reducing energy waste to both the utility and customers. They have been relatively successful in achieving these outcomes. However, the needs of the electricity grid, customers, and society at large are evolving in response to a rapidly changing climate. State policymakers, investors, advocates, and some utilities have committed to decarbonization, recognizing the critical role of the electric sector in aiding emissions reductions. Cost declines for renewable energy have changed grid dynamics, put a premium on demand flexibility, and unlocked building electrification as a core climate solution. Meanwhile, continued inequality, pandemic-induced recession, and historic disinvestment in communities of color reveal the need for equity-focused decarbonization.

EE and greenhouse gas (GHG) emissions reductions are connected in various ways, especially when measures are deployed in places and instances of high grid carbon intensity. For example, seasonal variations in thermal load corresponding with summer air conditioning and winter heating can create bi-annual peaks in energy use and emissions. On a smaller timescale, especially in markets with high penetration of solar and wind energy, hourly differences in emissions intensity of the grid lead to predictable patterns (e.g., the “duck curve”).¹ Peak load reduction has significant implications for GHG emissions broadly, as the marginal emissions rate of the grid during these times is relatively high from the infusion of fossil-heavy “peaker” generation.

As more states and utilities adopt climate targets and opportunities to leverage EE for emissions reduction, grid resilience, and equity outcomes, the case for re-aligning utility EE programs is stronger than ever. Leading practitioners agree that a climate-forward efficiency framework is needed.

The Climate-Forward Efficiency Framework

Climate-forward efficiency efforts, as defined in *The Need for Climate-Forward Efficiency: Early Experiences and Principles for Evolution*, are those that:

- Treat EE as an intentional driver of GHG reductions;
- Scale to meet the magnitude of the decarbonization goals in policy and utility corporate commitments;
- Leverage EE as a tool to mitigate and adapt to the impacts of climate change on customers by advancing equity, enhancing resilience, and improving health outcomes;
- Prioritize EE investments based on their temporal, seasonal, and geographical impacts; and
- Enable prioritization of investments across fuels, systems, and sectors, particularly from electrification.

This framework calls for sweeping changes in the ways that EE is valued by utilities, the role it plays in meeting emissions reduction targets, and how it is deployed in customers’ buildings (Specian and Gold 2021). Optimizing efficiency in alignment with the climate-forward efficiency framework requires cross-sector collaboration, a supportive political landscape for policy and regulatory change, and continued market growth for high-efficiency electric technologies. Accurate, accessible data are needed to inform program design, including where strategic efficiency ought to be deployed. This presents a fundamental challenge for EE portfolio administrators as they determine what data sources and analyses are necessary for climate-forward efficiency decision-making.

The Role of Data

A recent study of Scope 2 emissions accounting finds that using an annual average carbon intensity—as opposed to more granular emissions factors—can bias annual carbon

¹ The duck curve represents the daily net load on the grid (i.e., demand for power minus supply of renewable energy) as a function of time. It is named because the midday trough and quick rise as the sun goes down vaguely resembles the shape of a duck.

inventories by as much as 35%.² This under- or over-estimation of one's carbon footprint was found to be greater when the variability of building consumption, the variability of grid carbon intensity, or the correlation between building energy usage and grid carbon intensity are high (Miller, Novan, and Jenn 2022).

It is reasonable to expect that similar factors could bias estimates of GHG avoided through EE. In this context, the data requirements to translate energy savings to emissions reductions may include granular end-use load profiles (EULP) and marginal emissions rates (MER). However, it remains unclear *how* granular these data must be generally to properly inform design, operation, and evaluation of effective climate-forward efficiency programs. It is also unknown how differences in energy conservation measures (ECM) or grid generation mix impact the level of data granularity needed for these purposes.

Most utility EE program goals are presently set in terms of energy conserved (e.g., MWh, therms) annually. However, as the share of electricity generated through variable renewable sources continues to grow, an annual accounting may become too coarse to capture significant variations in the carbon intensity of the grid. Simultaneously, the increasing prevalence of advanced metering infrastructure (AMI) enables utilities to leverage energy consumption data nearly in real-time in hourly (or shorter) increments.³

However, efficiency practitioners have limited capacity, so it is helpful to understand the minimum amount of data needed to properly inform their decarbonization efforts. For example, if energy savings (MWh) and MERs (lbs of CO₂/MWh) were known every minute, calculating the total avoided GHG emissions would simply require multiplying those quantities together, then integrating over the lifetime of the measure for all customers. Specific barriers to this data collection and analysis include obtaining accurate end-use load savings shapes down to a granularity of less than an hour, forecasting MERs at a comparable granularity for the lifetime of the measure, and the computational infrastructure needed to collect, process, and use these data. More broadly, time- and location-dependent variations in the share of the grid powered by renewables—namely solar and wind—result in MERs that vary on small timescales. Accommodating these complexities when it comes to data can be burdensome, so it is critical to find the right resolution to successfully plan for and evaluate efficiency programs on the basis of emissions reductions without over-simplifying to the point of inaccuracy.

It is also important to distinguish between the roles of *short-run* and *long-run* marginal emissions data. Short-run marginal emissions rates represent the change in GHG emissions due to a change in energy demand in a given location when little or no structural changes in the electricity system are being analyzed (Hawkes 2014).⁴ Technology companies and nonprofit organizations like WattTime use these data to create customized tools and models to drive policy change. Short-run MERs are also appropriate for assessing the GHG impacts of real-time demand flexibility.

While the methodology of this paper uses short-run MERs as a result of their prevalence and accessibility, we acknowledge that these MERs account for neither the longer-term load patterns that necessitate the construction of new generation capacity (e.g., increased electrification) nor the changes in electricity fuel mix that occur at constant load. Robust designing of EE portfolios geared toward decarbonization will be better off using long-run

² Scope 2 emissions are those that result from an end user's consumption of electricity.

³ The number of advanced meters in the United States has increased from 6.7 million in 2007 to about 102.9 million in 2020 (FERC 2021; EIA 2021).

⁴ PJM Interconnection is the first wholesale market to report short-run figures on its website (PJM 2021).

MERs, though these data are more difficult to come by (Gagnon and Cole 2022). This highlights one of many areas of uncertainty to which utilities and regulators should respond with the collection and publishing of data.

In this paper, we use MERs with different granularities (e.g., 15-minute, hourly, daily, annual) in diverse but representative U.S. grid regions to assess the emissions-reduction performance of select EE strategies, which are then used to report how the characteristics of a grid region impact the GHG emissions reductions achievable through EE programs. The insights from this research hold relevance for states, utilities, and regulators who must decide on the appropriate levels of investment in data infrastructure needed to realize the full potential for climate-forward efficiency and to optimize efficiency's ability to decarbonize the power sector amid a changing supply-side landscape.

Methodology

In this paper, we evaluate how the granularity of energy savings and marginal emissions data affect estimates of GHG emissions avoided as a result of those energy savings. We investigate two ECMs (residential heating and commercial lighting) in three grid regions (CAISO – San Bernardino, California; MISO – Indianapolis, Indiana; and SPP – Kansas).

Energy Conservation Measures

We model the GHG reduction potential of two distinct ECMs: conversion of inefficient residential electric heating equipment to electric air-source heat pumps and commercial lighting upgrades. We used the following considerations for selecting our measures:

- Look to measures that have large savings potential over the next couple of decades, either because they save significant amounts of energy or because they are concentrated at times that dirty power plants operate.
- Use measures that are sufficiently “spikey” to enable us to assess how downscaling and smoothing away details affect carbon reductions.
- Use energy savings load shapes that we do not anticipate will change significantly in the future.
- Assess measures from the residential and commercial sectors.

We included space heating because adoption of heat pumps is likely to play one of the largest roles in reducing building sector emissions over the next couple of decades. Not only can a heat pump operate at 2–3 times the efficiency of a natural gas furnace or electric resistance heater, but it has the potential to be fully decarbonized if it is powered by clean electricity. Higher-performance units also have a crucial role to play in mitigating future winter peaks, which are likely to result primarily from electrification of space heating in multiple regions of the country by 2050 (Specian, Cohn, and York 2021). Heating demand is also driven by weather. A drop in outdoor temperature is correlated with increased heating demand and electricity usage, allowing us to probe the correlations between demand on the grid and the carbon emissions resulting from meeting that demand.

We chose to look at a lighting conservation measure for several reasons. First, conversion of inefficient lighting systems to LEDs remains one of the most cost-effective ECMs employed by utilities. However, much potential savings in the commercial sector remain. Lighting load is largely independent of weather, which offers a test of a measure that is much less correlated with carbon emissions than heating.

We generated energy savings load shapes from the National Renewable Energy Laboratory's (NREL) EULP database, which was released in late 2021 (NREL 2021). This groundbreaking three-year effort was supported by Lawrence Berkeley National Laboratory, Argonne National Laboratory, and several industry partners. The EULP database uses ResStock and ComStock, which statistically represent the properties of the U.S. building stock, and physics-based building energy modeling with EnergyPlus and OpenStudio. These models were subsequently calibrated using load data from 2.3 million meters from 11 utilities and 15 end-use metering datasets. Comparisons between the models and empirical data informed more than 70 improvements to the models during the calibration process. The result is one of, if not the, largest and most comprehensive end-use load profile datasets in the world.

The EULP database reports energy consumption during 2018 or during a typical meteorological year. Our methodology combines the database's energy use load profiles with WattTime's calculated marginal emissions rates. To preserve insights that are a function of the correlation between load and marginal emissions, we chose to work with energy consumption and marginal emissions from 2018.

At this time, the EULP database reports only end-use load shapes, not end-use *savings* load shapes. Therefore, we needed to generate our own savings load shapes from the database for each geographic region we studied. We defined our heating ECM as the conversion of residential buildings with inefficient electric heating (i.e., baseboard, boiler, furnace, or wall furnace) to electric air-source heat pumps.⁵ We divided the aggregated load for those two categories by the number of buildings in each category to derive the per-building load shapes. We then subtracted those results to derive expected demand reduction (in kW) per building every 15 minutes for the entirety of 2018. During some of the coldest time periods, the demand savings ran negative as the heat pumps switched to backup electric resistant heating mode.

Our lighting ECM involves a conversion of interior and exterior commercial lighting to LEDs. We assume that the shapes of both lighting measures remain the same, but that their profiles are reduced in magnitude. We assume a 50% reduction in demand for interior lighting and a 40% reduction in demand for exterior lighting.⁶ In California, where there is above-average LED saturation already, we lower the reductions to 40% for both interior and exterior lighting.

Marginal Emissions Rates

WattTime calculates marginal emissions factors using a proprietary model that extends the basic methodology used by both Siler-Evans et al. and Callaway et al. (Siler-Evans et al.

⁵ EULP database users can filter buildings by a wide range of modifiers. In this case, these modifiers belong to the "HVAC Heating Type and Fuel" category in the EULP database.

⁶ Advanced lighting controls could yield an additional 10–15% savings for interior lighting and an additional 20% savings for exterior lighting. However, those additional measures could alter the savings load shapes in addition to the magnitude and are therefore not explored further here.

2013; Callaway, Fowle, and McCormick 2018). WattTime adapts this methodology by calculating the marginal operating emissions rates in real time with 5-minute increments using a combination of grid data from the respective ISOs and 5 years of historical Continuous Emissions Monitoring System data (Shrader et al. 2019).

For this analysis, we selected three regions to represent different levels and types of renewable energy penetration and generation. CAISO San Bernardino represents a balancing authority with high solar penetration (approximately 45% gas, 19% solar, 10% nuclear, 9% hydro, and 8% wind). SPP Kansas City represents a balancing authority with high wind penetration (approximately 30% coal, 30% wind, 28% gas, and 7% nuclear). MISO Indianapolis represents a balancing authority with low renewable penetration and dominated by fossil fuels (approximately 34% gas, 33% coal, 15% nuclear, and 12% wind). All marginal emissions data are from 2018 to ensure consistency with the end-use load savings shapes derived from the EULP database.

Determining Emissions Rates at Different Granularities

Utilities typically calculate GHG emissions avoided by EE using an annual conversion factor. However, emissions rates can be calculated at much higher resolutions (e.g., 15-minute granularity). In this paper we answer the question: What is the minimum temporal granularity of MERs needed to accurately quantify the GHG reduction benefit of EE programs?

In addition to exploring emissions rates every 15 minutes (i.e., the same frequency as our ECM data), we further processed the emissions data to lower granularities with two dimensions: an hourly dimension and either a monthly, seasonal, or annual dimension. For example, to calculate the *month_hour*, we averaged together the emissions for every hour (such as 1:00am–2:00am) for every day in every month, creating a total of $24 \times 12 = 288$ unique values; for *season_hour*, we averaged together the emissions for every hour for every day in a season (Feb/March/Apr, May/Jun/Jul, Aug/Sept/Oct, Nov/Dec/Jan), creating $24 \times 4 = 96$ unique values; and for *annual_hour*, we averaged together the emissions for every hour for every day in the year, creating only 24 unique values. We used the same process for each hour of the day for each of those categories.

We followed the same method for every 3 hours (e.g., 12am–3am, 3am–6am), averaging the 3-hour blocks for every day in the month, season, and year; and obtained a single value by averaging every value for each month, season, and year. Table 1 describes the different granularities of data used and how many unique values are associated with each as a measure of complexity.

Figures 1–3 show the variation in emissions factors for different grid regions. The left-most bar shows the distribution in emissions for the actual 15-minute data, while the right-most bar shows the average annual marginal emissions value.⁷ In CAISO (Figure 1), the marginal emissions rates range from close to zero to nearly 1,200 lbs CO₂/MWh when using the most-granular data. As the granularity of the data decreases in each of the cases, much of this

⁷ The whisker plots show the distribution of values in the different temporal granularities of data. The “x” shows the mean value. The median value is shown in the middle of the box. The ends of the boxes show the 25th and 75th percentile values. The ends of the whiskers show the 5th and 95th percentile values. The dots show outliers.

variability is lost. For example, in the *annual_hour* data, the maximum MER never exceeds 1,000 lbs CO₂/MWh and barely dips below 600 lbs of CO₂. A similar effect can be seen in SPP (Figure 2) as well. Only in MISO (Figure 3), where the distribution of emissions factors is limited even in the most granular data, do the reduced granularity emissions factors fail to show a significant change in distribution.

Table 1. Description of different granularities of emissions factors

	Daily data granularity		
	Hour	3-Hour	Day
Month	A value for each hour in each month (288 unique values)	A value for each 3-hour block in each month (96 unique values)	A value for each month (12 unique values)
Season	A value for each hour in each season (96 unique values)	A value for each 3-hour block in each season (24 unique values)	A value for each season (4 unique values)
Annual	A value for each hour in the year (24 unique values)	A value for each 3-hour block in the year (8 unique values)	A single annual value (1 unique value)

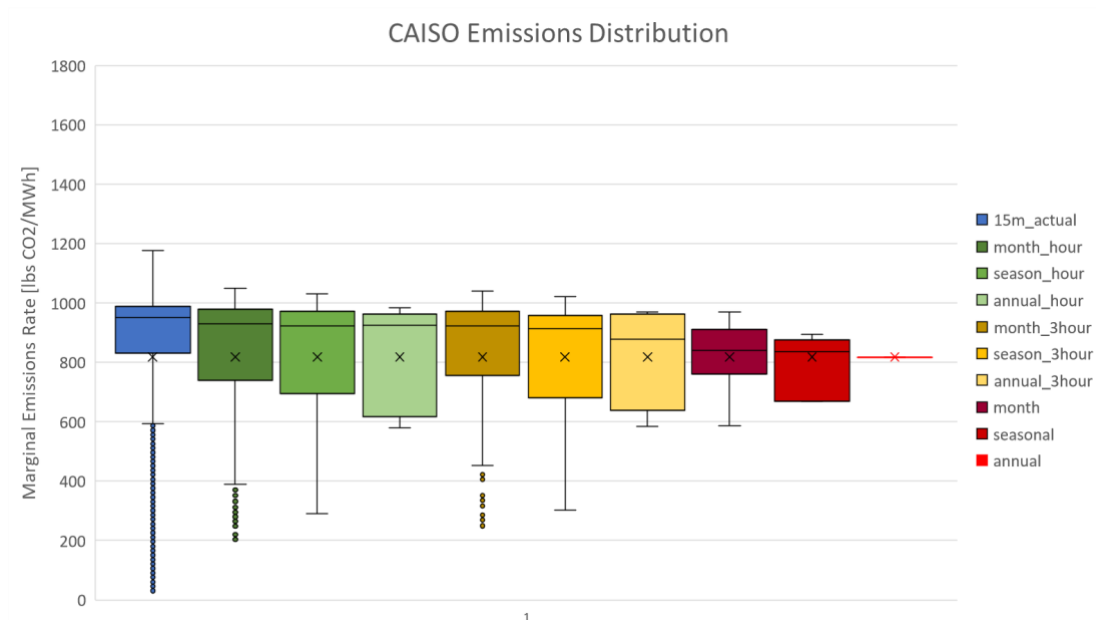


Figure 1. Emissions distribution in different data granularity scenarios in CAISO

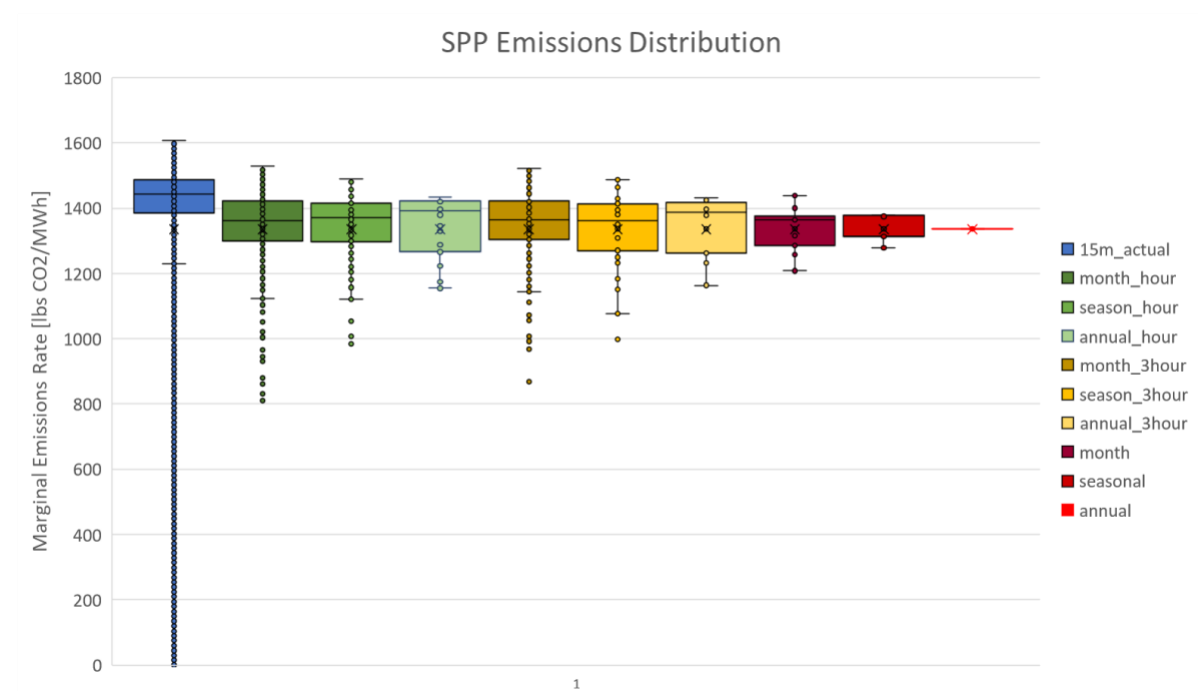


Figure 2. Emissions distribution in different data granularity scenarios in SPP

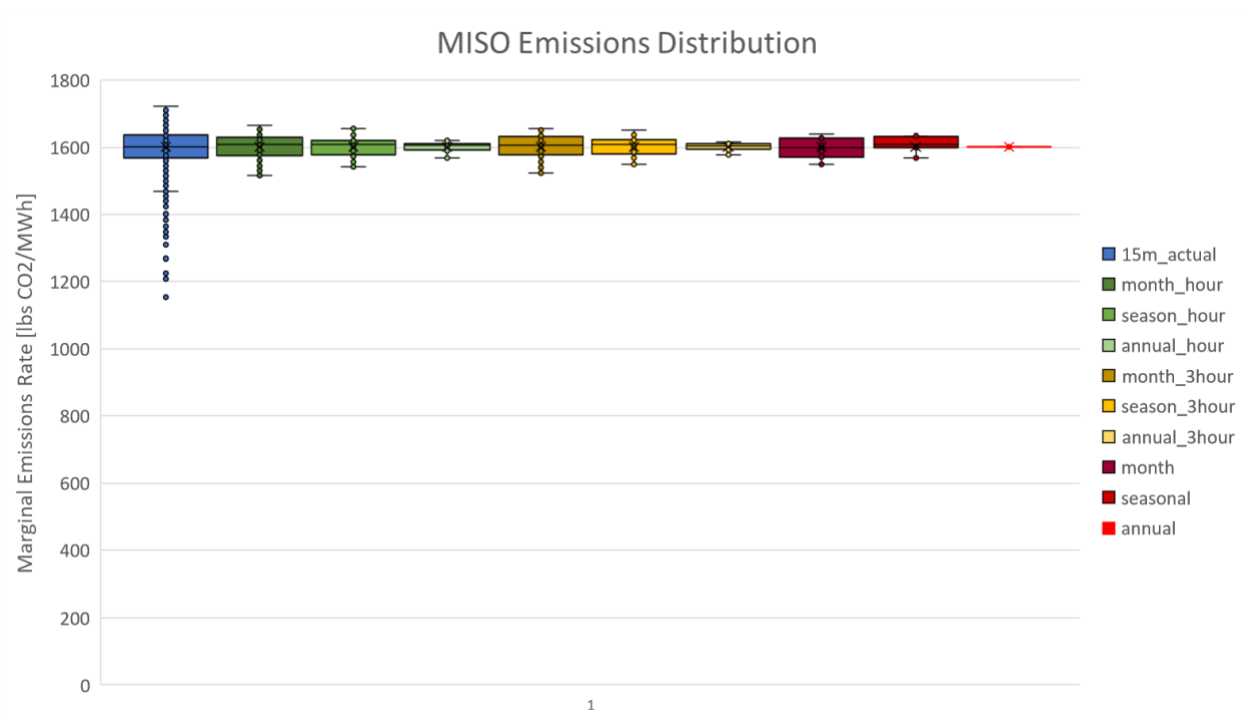


Figure 3. Emissions distribution in different data granularity scenarios in MISO

Calculating Emissions Effects of Efficiency Measures

To determine the calculated emissions-reduction impact of each ECM, we multiplied each end-use savings profile by both the 15-minute MERs and each of the nine downscaled MERs described in Table 1. This enables nine comparisons with the “ground truth,” and helps us quantify how less-granular marginal emissions rates affect the accuracy of our calculated emissions reductions for two EE measures in three grid regions.

Results

Figures 4 and 5 compare the total emissions savings from the heating and lighting ECMs, respectively, using 15-minute and annual emissions factors, showing the total difference in calculated avoided emissions. Note that the 15-minute bars (in blue) represent as close to the ground truth in emissions reductions as is possible with the data used in our model. The red bars represent the estimated emissions reductions if we had used one annual energy savings reduction with one annual averaged marginal emissions rate, as opposed to the 8760*4 value pairs that went into the 15-minute modeling.

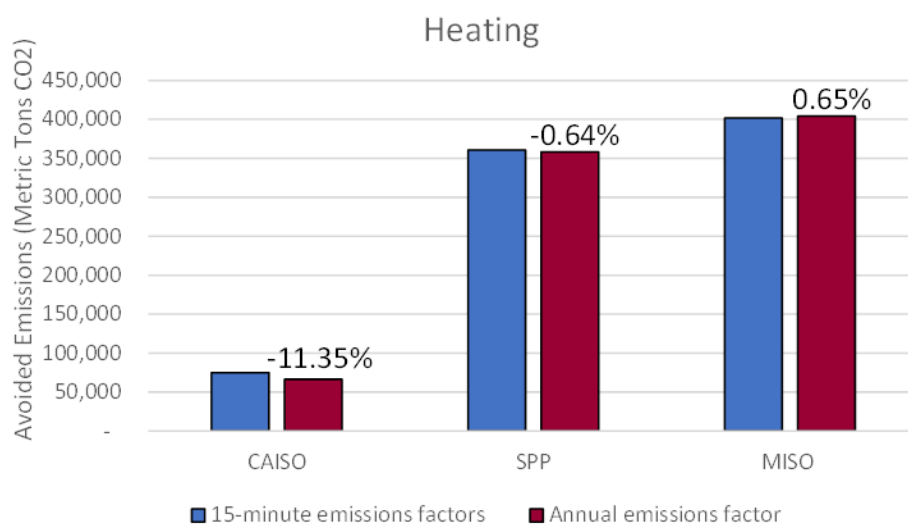


Figure 4. Comparison of the total calculated emissions savings from the adoption of heat pumps using 15-minute and annual emissions factors.

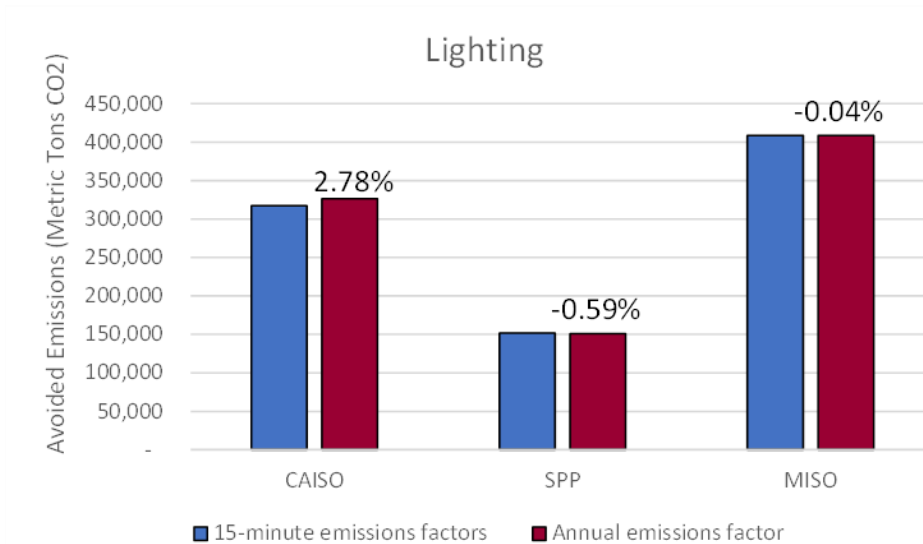


Figure 5. Comparison of the total calculated emissions savings from lighting conservation measures using 15-minute and annual emissions factors.

Table 2 shows the error in calculated emissions reductions that results from using energy savings and MERs averaged over different time scales. Negative differences (in red) indicate that the averaging has underestimated the true emissions reduction, while positive differences (in blue) indicate that the averaging has overestimated the true emissions reduction. Lighter shades of red and blue indicate greater agreement between the true emissions reduction and the emissions reduction calculated through averaging.

For example, using the same set of 24 hourly MERs for the entire year (i.e., *annual_hour*) in CAISO leads to a 7.7% underestimation of avoided GHG resulting from the heating ECM. Conversely, using the same set of 8 MERs for the entire year (i.e., *annual_3hour*) in MISO leads to a 0.6% overestimation of avoided GHG emissions resulting from the heating ECM.

Table 2. Differences in calculated savings compared to ground truth savings (i.e., 15-minute emissions data).

CAISO Heating ECM				CAISO Lighting ECM			
	Hour	3-Hour	Day		Hour	3-Hour	Day
Monthly	-0.8%	-1.3%	-6.4%	Monthly	-0.7%	-0.5%	3.0%
Seasonal	-3.3%	-3.7%	-8.7%	Seasonal	-0.8%	-0.5%	2.9%
Annual	-7.7%	-7.9%	-11.3%	Annual	-0.9%	-0.7%	2.8%

SPP Heating ECM

	Hour	3-Hour	Day
Monthly	0.4%	0.4%	0.7%
Seasonal	-0.7%	-0.7%	-0.3%
Annual	-1.2%	-1.2%	-0.6%

SPP Lighting ECM

	Hour	3-Hour	Day
Monthly	-0.1%	-0.2%	-0.6%
Seasonal	-0.1%	-0.2%	-0.6%
Annual	-0.1%	-0.1%	-0.6%

MISO Heating ECM

	Hour	3-Hour	Day
Monthly	-0.1%	-0.1%	0.0%
Seasonal	0.1%	0.1%	0.2%
Annual	0.6%	0.6%	0.6%

MISO Lighting ECM

	Hour	3-Hour	Day
Monthly	-0.1%	-0.1%	-0.1%
Seasonal	-0.1%	-0.1%	-0.1%
Annual	0.0%	0.0%	0.0%

Discussion

This analysis shows that the accuracy of calculated GHG reductions can vary based on both the ECM's savings shape and the grid region in which it is deployed. It is encouraging that, given the grid mix of 2018, the difference in calculated GHG reductions between using highly granular 15-minute data and a single annual average MER is less than 1% in the regions of SPP and MISO that we studied. Only in CAISO did the downscaling of our data have an appreciable impact on the accuracy of calculated GHG reductions.

Comparing Annual Emissions Factors to 15-Minute Emissions Factors

In CAISO (the solar-dominated region in this study), the 11% difference between highly granular data and annual averages for the heating ECM is due to the significant and predictable variations in emissions achieved from aligning electricity usage with the times of the day that have the lowest marginal emissions rates. Solar generation is concentrated to a few, predictable hours on most days, which provides a structural pattern of which efficiency measures can take advantage. The variability in solar production also affected the accuracy of the lighting ECM compared to SPP and MISO. However, the lighting ECM, which delivered an equal percentage of energy savings every hour of the year, was less susceptible to GHG calculation errors than the heating ECM.

In SPP (the wind-dominated region in this study), there is high variation in emissions rates due to the variability of wind generation, but little divergence in the calculated annual emissions between the annual mean marginal factor and the 15-minute marginal factor. This difference is limited due to low correlation between emissions and efficiency profiles. In general, wind generation does not follow a regular pattern of which efficiency measures can take advantage.

In MISO (the fossil-dominated region in this study), emissions variability is low, leading to little difference between the annual average MER and the more granular marginal factors. Here, the effectiveness of the ECMs for emissions reductions is not dependent on the shape of

the generation profiles. However, this will likely change as more renewable energy enters the generation mix.

Identifying the Appropriate Granularity of Emissions Factors

While there is a large difference in CAISO between the 15-minute granularity and the annual averages, there is close agreement between the 15-minute granularity and the *hourly_monthly* averages (i.e., 12 sets of 24 MERs, one set each month). This shows that the annual average factors are too broad of a simplification of the data and important information about the performance of the efficiency measures is lost. While the *hourly_monthly* emissions factors are also a simplification, the results are close enough to the actual 15-minute data to capture the results of the performance of the efficiency measures. The smaller number of values used in the annual assessment is clearly insufficient to capture dynamic grid conditions of a solar-dominated region. However, using the 288 values in the *hourly_monthly* factors, which is less than 1% of the values in the 15-minute data, achieves nearly the full accuracy of the 15-minute data. The loss in effectiveness using different granularities of data can be seen in Figure 6.

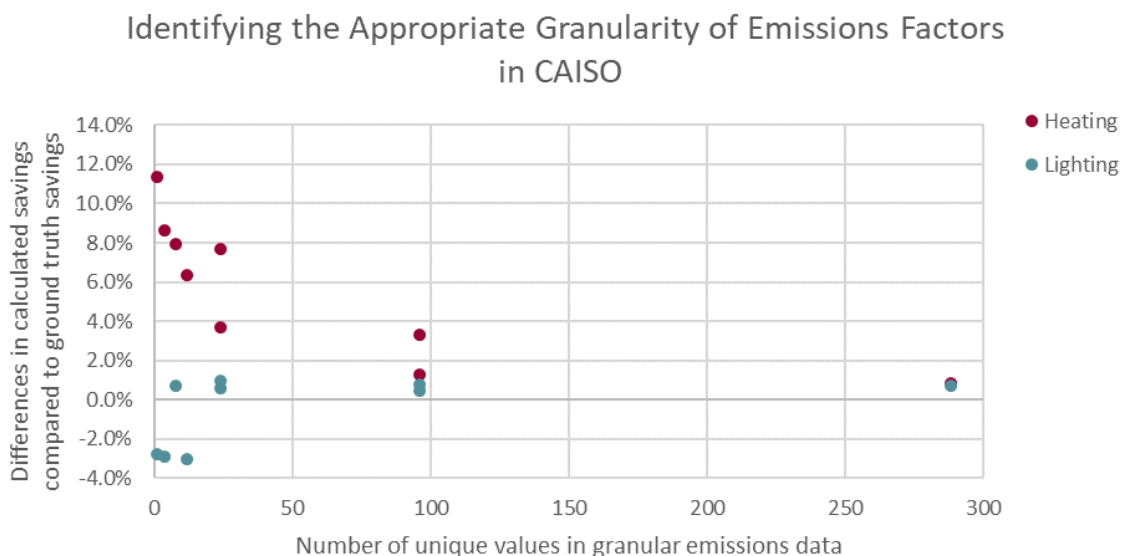


Figure 6. Emissions data granularity compared to loss of accuracy in emissions savings calculation

Conclusion

Based on these limited results, this study suggests that using granular emissions data can provide value in solar-dominated grid regions that show predictable variation in marginal emissions factors. These granular data can help EE program administrators accurately assess and properly value the emissions-reduction potential of their programs. However, with the current mix of generation in most grid regions, highly granular data does not provide a substantially

improved analysis of the emissions benefits of efficiency programs above that provided by an annual average marginal emissions factor.

Our CAISO results suggest, though, that as renewable energy generation continues to proliferate (especially with the projected rapid scaling of solar power generation), granular emissions factors will be needed to determine the effectiveness of efficiency programs due to increased variability in emissions profiles (US DOE 2021). In present solar-dominated regions, our results show that hourly-by-month emissions factors capture sufficient detail to accurately assess the GHG benefits of efficiency measures, and therefore 15-minute level data is not strictly required. This reduces the complexity of assessing the emissions efficacy of efficiency programs.

In wind-dominated regions, greater active demand controls are needed to take advantage of high variability in emissions due to the unpredictability of wind overgeneration.

There are several areas where future research could be useful. First, instead of looking at short-run MERs, we should consider long-run MERs that reflect the grid of the future. Moreover, rather than looking at just one year (as we have here), we should look at the emissions reductions achieved during every year of an ECM's lifetime. Second, we should expand the number of regions investigated to verify whether our early conclusion about the importance of solar variability (and seeming lack of importance in wind variability) in estimated GHG reductions continues to hold. Third, we could consider additional ECMs, including envelope weatherization, controls, water heating, and air conditioning, to see if new conclusions emerge.

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