Unlocking Electrification with Hourly Emissions Data

Craig Sinnamon, David B. Goldstein, and Anna Kelly

ABSTRACT

International agencies are working to create a sense of urgency toward climate action. Specific actions such as replacing fossil-fuel-fired heating equipment with heat pumps, electrifying transportation, and energy storage are recommended. These broad actions will be evaluated and implemented at individual facilities. The carbon impact of buildings and industrial manufacturing must include the embodied carbon of the steel, wood, glass, and concrete used in construction. But you can't manage what you measure incorrectly. Currently the dominant method for measuring carbon emissions is to multiply energy consumption for each fuel by an emissions factor, using the average contributors to electricity generation. Relying on this method for cost assessments will undercut GHG emission reductions and lead to slower investment in necessary technologies. Recent standards have recommended utilizing long-run marginal contributions to electrical generation ("consequential analysis"). This study addresses the question: How much difference would it make for facility managers to use long-run marginal emissions rather than annual emissions in their feasibility assessments for measures at industrial facilities? We performed a comparative analysis using a sample of approximately 30,000 industrial facilities. We calculated emissions data using two distinct inputs: the eGRID (2021 annual average factors) and the Cambium (8-year average, 2023-2030) hourly long-run marginal emissions factors (as suggested in new draft standards). This comparison tests the hypothesis that using average impacts undercuts global policy goals such as electrification.

INTRODUCTION

The energy efficiency industry aims to contribute to stabilizing the electricity system, ensuring that future power planning aligns with public needs and policy objectives. As has been the case throughout the regulated utility industry's history, key priorities include safety, affordability, reliability, and abundance. However, with increasing investment and policy direction towards decarbonization and electrification, adjustments are needed to incentivize future capacity that aligns with these key priorities and promotes technologies essential for combating climate change and reducing emissions. These adjustments, if done optimally, can greatly reduce the cost of grid modernization by encouraging efficiency and controllability of demand to replace simple increases in kW capacity.

There are some technologies that we know will lead broadly to decreased greenhouse gas (GHG) emissions, such as industrial heat pumps and battery and thermal storage (IEA 2023). However, if a facility is considering such measures, the engineers and facility managers need to calculate the costs, feasibility, and present the technology's effect on the facility's overall GHG emissions over time. Predicting future emissions requires that the assumptions that get used in these models make sense and properly account for what would happen in the future (Gagnon and Cole, 2022). There are three primary ways to predict greenhouse gas emissions to inform these calculations: average annual emissions, short-run marginal emission rates, and long-run marginal emission rates. This article focuses on the difference between average emissions and long-run marginal emissions. Each of these concepts has appropriate use-cases based on their development and intent.

Emissions Rates for Engineers and Facility Managers

Why is this difference important? Because these technologies require significant investment and will be implemented one-by-one after careful consideration by decision makers who rely on the analysis analyses from their engineers and facility managers at each corporation, campus, facility, plant, or building. Facilities will be required to comply with efficiency standards, performance standards, and corporate decarbonization goals, and the engineers and facility managers representing those entities will make the case for which equipment makes sense after they calculate and compare the feasibility, cost savings, and GHG savings of specific measures. As standards improve and data available increases, the costs and paybacks from installing heat pumps to supply heat, industrial dryers, or thermal storage systems will be significantly impacted by operation calculations taking into account the impacts of operating during hours when grid electricity is cleaner and when the grid is dirtiest.

These estimates not only affect whether the manager in charge of the facilities of interest approves the improvement, but also others that may be involved in the go/no-go decision: utilities, state or federal government energy efficiency/decarbonization advisors, accountants who review emissions disclosures, etc. The early years of including carbon estimates in cost analyses will face additional scrutiny to ensure compliance with all applicable standards and requirements.

Recalling back to the concept of average emissions and long-run emissions, we have identified that using one or the other leads to significant differences in the cost and emission outcomes of a feasibility assessment for the aforementioned high-interest technologies such as industrial heat pumps, dryers, and storage. Some (or perhaps most) economically and technically feasible projects will appear to fail to reduce GHG emissions significantly, or even at all, if the analysis uses average emissions. This conclusion is not well documented in the literature because published papers usually focus on successes—such as why a particular project achieved its goals—rather than failures. And it is a failure when viable and necessary projects are not implemented because the preliminary analysis erroneously did show lackluster GHG emissions reductions. This research begins to correct this failing and provide support for upcoming data and standards on GHG emissions analysis for these technologies. Although it may be common within engineering circles and utility industry conference settings to discuss the comparison between nascent and legacy methods, research with the best possible available data is necessary to demonstrate how to implement the newer methods in cost analyses and feasibility assessments.

This article will discuss show the differences in GHG emissions from the legacy and nascent inputs and provide guidance on how to correct the errors that underlie current GHG calculations. It will evaluate the magnitude of the error, demonstrating that it makes a big difference in most grid regions in the U.S., and thus likely in most grids everywhere, and provide a path forward for decision makers, engineers, and technology developers to make recommendations and decisions that lead to a better way to reduce GHG emissions.

SUMMARY OF EMISSION RATES

Average Emission Rates

Average emission rates are a simple metric used to evaluate the environmental impact of energy production and consumption. As such, they are the most commonly used metric in 2024. Unlike marginal emission rates that focus on changes in emissions due to specific shifts in demand or supply—and are thus harder to calculate-- average emission rates provide a broad view of emissions over a given period in the past, typically a year. They can be useful for assigning or attributing responsibility for past actions, being based on historic data, but are not the best choice for evaluating the consequences of future actions.

The widely used World Resources Institutes Greenhouse Gas Protocol, first issued around 2014, establishes this method. (WRI 2001)

For example, consider a region with a mix of energy sources including coal, natural gas, nuclear, and renewables like wind and solar. The average emission rate for this region would be calculated by considering the emissions associated with each energy source and their respective shares in the overall energy mix. Average emissions assume that the grid and the capacity mix of the area in question are static factors that are not impacted by the energy projects and policies that may be passed over the lifespan of a measure.

Short-Run Marginal Emission Rates

This metric represents the emissions that would arise if new load were added to the system in the short term, usually within minutes or hours. These emissions are evaluated based on the power sources that would come online immediately to meet the additional demand. Often, these power sources include less efficient or higher-emission plants that are only dispatched during periods of high demand or operational constraints. Understanding short-run marginal emissions is important for real-time decision-making and optimizing grid operations.

Long-Run Marginal Emission Rates

The concept of long-run marginal emission rates involves estimating the emissions that would either increase or decrease due to a change in electric demand. This estimation takes into account not just how the change affects current grid operations but also how it influences the overall structure of the grid, including the addition or retirement of capital assets like generators and transmission lines. This distinguishes it from short-run marginal emissions, which assume that grid assets remain fixed.

For a deeper understanding of these metrics, one can refer to "Planning for the evolution of the electric grid with a long-run marginal emission rate" (Gagnon and Cole, 2022).

There will be both short-term and long-term consequences to many interventions. Long-run marginal emissions will provide a more accurate model of today's operational decisions and the long-term impacts of changes in demand on the grid as the grid changes and evolves in response to them. A long-run marginal emission rate is what can be used to identify what the reduced emissions would be of a specific intervention, such as industrial heat pumps.

It can be illustrative to put yourself in the place of a facility planner to decode which metric may be useful to assessing your long-term emissions impact.

EMISSION RATE USE CASE

At a facility level, average emissions are helpful in benchmarking exercises to assess the environmental impact of a utility customer's energy consumption over time and compared to other, similar facilities. By comparing the average emissions of a facility to industry standards or regional averages, or by comparing an industrial facility's specific energy consumption or carbon emissions to its peers, as done by the Energy Star® program, planners can identify opportunities for improvement and set targets for reducing emissions. This metric can help planners track progress towards sustainability goals, such as reducing carbon footprints or achieving energy efficiency certifications. It provides a view of the environmental performance of facilities and guides decision-making on energy efficiency measures and investments.

This metric gave very similar results to marginal emissions when the most-used protocols for evaluating greenhouse gas emissions were developed but has increasingly diverged from the marginal emissions metric as grids throughout the world began relying more heavily on intermittent renewable energy sources such as solar and wind. As this article will show, the divergence has become large when considering the real grids in the U.S. in the 2020s.

When needing to make responsive, day-ahead, plans, the user may want to consider short-run marginal emissions to assist with real-time decision making on energy use within facilities. For example, during periods when short-run marginal emissions are high, the facility can choose to prioritize energy-saving measures like load shedding, shifting non-essential operations to off-peak hours, or temporarily reducing energy-intensive activities. Understanding short-run marginal emissions helps planners optimize energy usage within facilities to minimize environmental impact and potentially reduce energy costs during peak emission periods.

When considering retrofits to electricity-consuming facilities, retro-commissioning projects, or major capital improvements, the facility will want to rely on long-run marginal emissions: Long-run marginal emissions are valuable for creating long-term strategic planning and investment priorities. By considering the broader implications of grid changes and policy shifts on emissions over time, the user can anticipate future emissions trends and plan sustainable strategies accordingly. Long-run marginal emissions allow the user to evaluate the impact of adopting renewable energy systems, implementing energy storage solutions, or investing in energy-efficient technologies. This metric guides strategic decisions that contribute to long-term sustainability goals and resilience against changing energy landscapes.

DATA SOURCES

The Emissions and Generation Resource Integrated Database (eGRID) is a comprehensive database managed by the U.S. Environmental Protection Agency (EPA). It provides detailed information on power plants, their emissions, and their fuel sources across the United States. eGRID is a valuable tool for researchers, policymakers, and the public to understand the environmental impact of electricity generation, including greenhouse gas emissions such as carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NOx).

The Cambium data sets, maintained by the National Renewable Energy Laboratory (NREL) and illustrated in Figure 1, provide simulated emissions, costs, and operational data for a set of modeled scenarios. The Cambium dataset is updated annually and provides scenario modeling of emission, cost and operational metrics for the U.S. electric sector through 2050. The models project the evolution of the grid and how it will meet demand subject to operational and policy constraints and incentives.

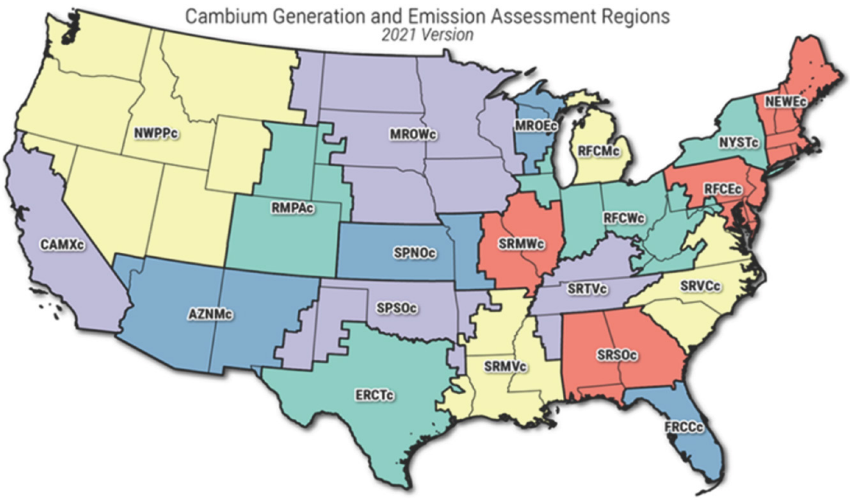

Figure 1. Cambium Generation and Emission Assessment Regions Map (2021 Version)

METHODOLOGY

For the analysis, we used data from the 2022 Cambium dataset. The dataset represents a series of scenarios that contain different mixes of technology, fuel, growth, and policy impacts (Gagnon et al., 2022, 2023). The Cambium scenarios use the ReEDS data which include a variety of policy scenarios, regulations, and technology inputs (Cohen et al., 2019). The 2022 scenarios include a mix of tax credit phase outs, but for brevity's sake, we are not including them here.

The scope of this analysis is looking at manufacturing facilities across six Cambium regions and identifying the extent to which long run marginal emission rates (LRMER) differ from average annual emissions from the eGRID database.

Table 1. Cambium Scenario Descriptions

Scenario	Description
Mid-case	Central estimates for inputs such as technology costs, fuel prices, and demand growth. No nascent technologies. Electric sector policies as they existed in September 2023.
Low Renewable Energy and Battery Costs	Mid-case with lower renewable energy and battery costs.
High Renewable Energy and Battery Costs	Mid-case with high renewable energy and battery costs.
High Demand Growth	Mid-case, with high electrification represented with a 2.8% average growth in demand from 2022 through 2050.
Low Natural Gas Prices	Mid-case with lower natural gas prices.
High Natural Gas Prices	Mid-case with higher natural gas prices.
95% Decarbonization by 2050	Mid-case with inclusion of nascent technologies a linear decrease in emissions to 5% of 2005 emissions by 2050.
100% Decarbonization by 2035	Mid-case with inclusion of nascent technologies a linear decrease in emissions to 0% of 2005 emissions by 2035.

Note: For more details and data on each scenario, refer to NREL Scenario Viewer (https://scenarioviewer.nrel.gov/?project=0f92fe57-3365-428a-8fe8-0afc326b3b43&mode=download&layout=Default).

Methodology

We chose to compare a data source for average annual emissions, eGRID, to a data source with long-run marginal emissions, Cambium, to identify which source would lead to incentivization of electrification for industrial customers in six geographic regions as shown in Table 2.

To ensure that only industrial manufacturing facilities were included in the analysis, NAICS codes were predicted using Power TakeOff's proprietary machine learning algorithm. This algorithm predicts NAICS codes based on properties of the facilities as obtained by their electric

Table 2. Cambium Regions in Analysis

Cambium Region	Geographic Region
RFCEc	Maryland
SRMWc	Southern Illinois
RFCWc	Greater Chicago Area
NWPPc	Washington State
SRSOc	Georgia
NEWEc	Connecticut

or gas utility. The algorithm generated NAICS codes and an associated confidence in the accuracy of that NAICS code. The accuracies are binned into 'High', 'Medium', and 'Low' confidence. To include only industrial manufacturing, we restricted our analysis to those facilities that the NAICS prediction algorithm identified as manufacturing (NAICS codes 31, 32, and 33 with 'High' confidence. This machine learning approach was taken due to missing data and other data quality issues in the data sources used for this analysis. Such an approach is not needed for individual engineers or facility managers conducting project or facility level analyses, or for policy makers who can use high quality data available for their region,, but was a necessary step for an analysis of this scale that relied on the hourly interval data provided via the supplying electric utilities.

For the emissions data, an 8-year average (2023-2030 inclusive) was constructed from the Cambium data to use as our comparison using the low renewable energy and battery cost scenario for this analysis. We chose the scenario bolded in Table 1 to harmonize with the carbon emissions metric used for residential buildings in ANSI/RESNET/ICC Standard 301 and ANSI/ASHRAE/IES Standard 90.2. These standards, in turn, chose this scenario based on the observation that meeting the IPCC's climate goal will require substantial increases in renewable energy, and we want electricity- consuming facilities to optimize for the likely future grid. (Kruis, et. al. 2022). This choice will assure that if the utility sector does its job in meeting the 1.5 C climate change goal, utility customers will project and achieve their goal.

Total annual emissions were calculated for approximately 33,308 facilities using the 2001 eGRID annual factors and the Cambium 8-year average derived from the 2022 Cambium dataset low renewable energy and battery costs scenario. Those facilities were reduced further to a final 3,900 flagged with high confidence of their NAICS code. Although we had industrial sector data for 10 of the regions, only six regions had sufficient data to continue the analysis. We required that each region have at least 50 facilities after all other restrictions were applied.

The Cambium LRMER data is provided in month-hours, 24 data points for each month of the year representing the average LRMER for each hour of the day during each month. The energy consumption data used in this analysis was hourly kWh smart meter data. To combine these two datasets, the 12x24 data points from the Cambium LRMER datasets need to be aligned with the 8760 data points representing one year of hourly data for a facility. To do this, for each facility, and each month of the year, the average 24-hour day consumption profile was calculated resulting in 12x24 data points for each facility representing the month-hour energy consumption patterns at the facility and aligning the consumption data with the Cambium LRMER data.

With this, the ratio of Cambium LRMER to eGRID annual average emissions was calculated for each facility.

This ratio was constructed using the sum of the product of the month-hour kWh consumption described above and the month-hour marginal lbs CO_2 emissions from the constructed 8-year LRMER average divided by the total annual kWh consumption multiplied by the 2021 eGRID annual emissions factor. The result is a single number for each facility that represents the ratio of these two different approaches to quantifying emissions, the Cambium to eGRID ratio. When this number is larger than 1, the eGRID method gives lower emissions than the Cambium method. When this number is equal to 1, both methods give the same emissions. When this number is less than 1, the eGRID method gives higher emissions than the Cambium method.

The distribution of these ratios as represented by a histogram of all the analyzed facilities in a region gives a large-scale sense for how these different methodologies impact the manufacturing facilities in these regions.

These histograms might be hard to interpret by some readers, so the next section looks at several hypothetical outcomes of the analysis and show what the resulting histogram would look like. This analysis is intended to clarify the significance of the analysis before the results are shown.

POTENTIAL OUTCOMES

There were several possible outcomes of this work. Below some of the possibilities are described along with visualizations of how the data would have looked in these cases. The data is visualized using ridgeline plots which show the distribution of the ratios similar to a histogram.* Note that this analysis is focused on electric data, and cost-benefit analysis outcomes from electrification measures are the vital interpretation of these scenarios.

Potential Outcome 1

There is no difference in using average emissions compared to using the LRMER.

In this case, shown in Figure 2, all the ratios are exactly 1, there is no difference between the average emissions and LRMER for any of the sites in any of the regions. In this case, it doesn't matter if a facility manager was to use one technique or another for measuring the impact of their electrification measures. There would be no difference.

Potential Outcome 2

There is a difference but is it not systematic across facilities. For half of the facilities, GHG emissions are higher when calculated using average emissions, and higher when calculated using LRMER for the other half.

Here in Figure 3, we see that while most facilities have a ratio close to one, indicating that the average emissions and LRMER give quite similar results, there are some examples where emissions calculated

*The data used in this section are simulated data used to describe these potential situations and build familiarity with the visualizations that will be used to describe the real findings in the subsequent section.

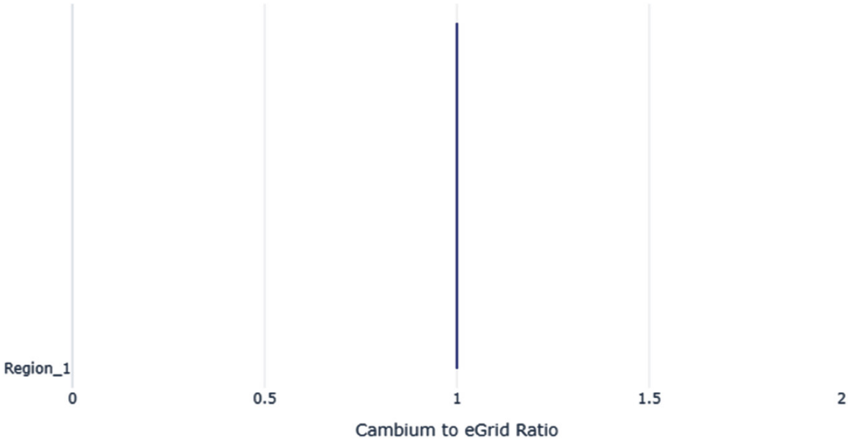

Figure 2. Distribution of Cambium to eGRID Ratios: Simulated Potential Case 1

using LRMER are only 70% of the GHG emissions calculated using annual averages, but others where the GHG emissions are 130% of the emissions calculated using annual averages. In the case where a cost-effectiveness test for a suite of electrification measures at a suite of campuses looked like this, the facility manager could compare between both methods and perhaps be more aggressive about electrification measures at some sites and leave them out at others.

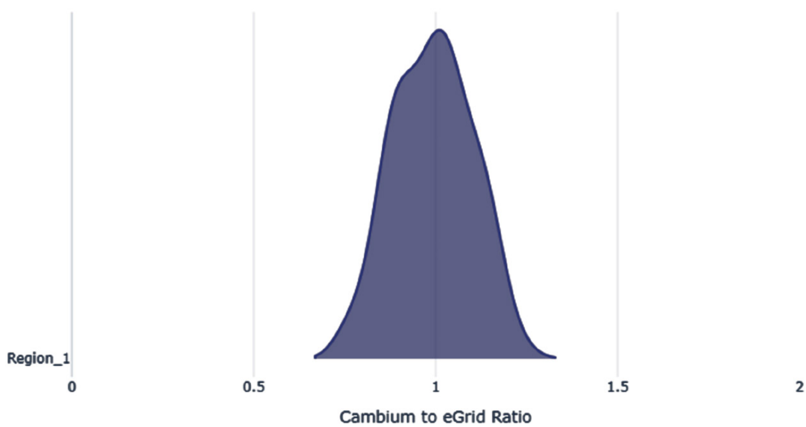

Figure 3. Distribution of Cambium to eGRID Ratios: Simulated Potential Case 2

Potential Outcome 3

Regional GHG emissions trend higher or lower depending on whether they are calculated with LRMER or annual averages, but it is not systemic across regions.

In this case, in region 1, GHG emissions calculated using LRMER are always higher than when calculated using annual averages, but in region 2 the opposite is true, and in region 3 it varies by facility but there is no notable difference between LRMER and annual averages. Also note that the width of the distributions may differ by region, with a larger width indicating more variation between facilities within that region. In this example, it may be useful to envision a national brand with facilities in three geographic regions analyzing pathways that to help them meet their decarbonization goals. If the results looked like they do in figure 4, the decision makers may choose to only conduct those upgrades in region 2, where it is clear that long-term GHG emissions will be best at meeting their decarbonization targets. Potential Outcome 4: GHG emissions are consistently lower when calculated using LRMER than when calculated using annual averages. This outcome is similar among all regions.

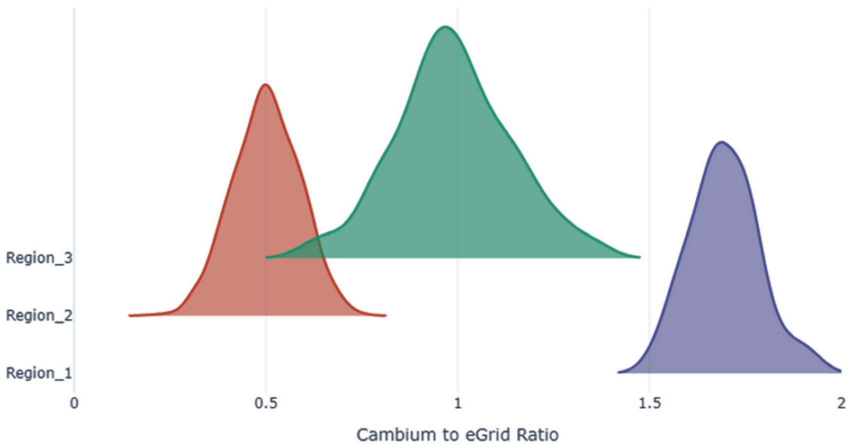

Figure 4. Distribution of Cambium to eGRID Ratios: Simulated Potential Case 3

Here, while there is some variation by facility, GHG emissions calculated using LRMER are always lower than emissions calculated using annual averages.

This outcome implies that substituting electricity for fossil fuels (whose impacts are nearly identical using all three evaluations methods) will be analyzed as emissions-reducing in more cases than average emission factors would predict, and that conducting those upgrades would be beneficial to the grid and the brand's decarbonization targets across the board.

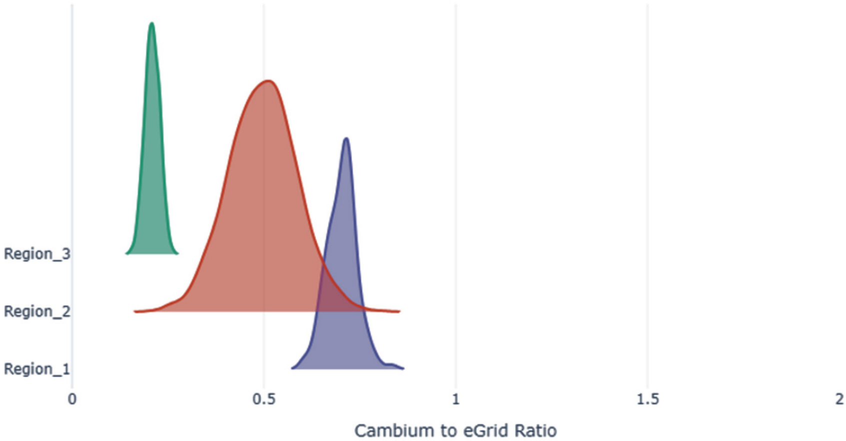

Figure 5. Distribution of Cambium to eGRID Ratios: Simulated Potential Case 4

Potential Outcome 5

GHG emissions calculated using LRMER are consistently higher than when calculated using annual averages, and that difference is systematic between regions.

In this final example, GHG emissions using LRMER are higher than when calculated using annual averages, In this case, substituting electricity for fossil fuels (whose impacts are nearly identical using all three evaluations methods) will be less attractive to facilities with decarbonization targets because the increased electric load will be interpreted as increasing emissions, rather than showing emissions reductions that are the result of a cleaner grid operating under real-world investment conditions.

FINDINGS

Figure 7 demonstrates the range of LRMER to annual average emissions distributions for the 3,900 facilities included in the final analysis

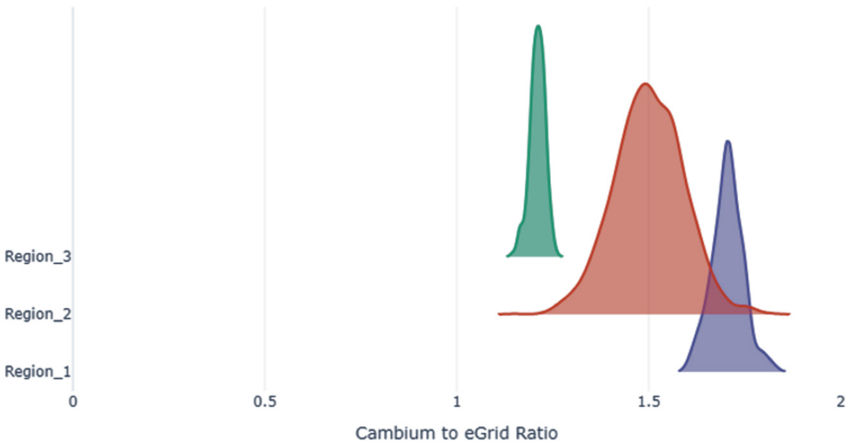

Figure 6. Distribution of Cambium to eGRID Ratios: Simulated Potential Case 5

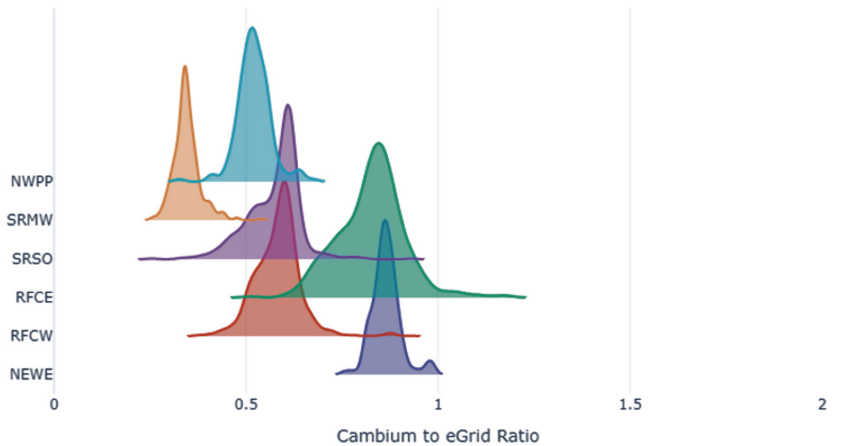

Figure7. Distribution of Cambium to eGRID Ratios Across Cambium Regions

dataset, by region. Recall these this data are using the scenario where renewable energy and battery costs are lower compared to other scenarios. (Past projections have consistently underestimated the renewables build-out.) In this scenario, in regions where the overall ratio is <1, the GHG emissions calculated using LRMER are lower than that of the emissions calculated using annual averages. Using LRMER emissions data to make the calculation allows for the individual facilities to meet decarbonization targets and claim GHG intensity for grid-beneficial measures than if the analysts were using annual averages to make their assessment. In short, using the LRMER for their measurement and reporting leads to decreased overall emissions compared to if they had used annual average.

Note what this does to projects that replace fossil fuels with electricity, such as heat pumps in buildings and industry, and charging of electric motor vehicles that replace fossil-fired car and truck engines.

The emissions of the electric alternative are lower than they would appear using the annual average emissions rates. But the avoided emissions from fossil fuels are the same.

Thus, heat pumps are (more correctly) evaluated as saving emissions in many circumstances when they might otherwise be evaluated (using annual average metrics) as not accomplishing much or even increasing emissions.

A similar outcome applies to batteries and thermal storage. For both technologies, there are losses in the storage process, which increases energy consumption. If we use annual average emissions rates, storage appears to increase emissions. Yet in the real world it can reduce emissions. The LRMER methods correctly account for this fact, while the annual average methods do not give storage the appropriate emissions reduction credit.

It is important to note that the variability of the ratios shown in Figure 7 is not due to random error, but rather due to plant-to-plant variations in the timing of electricity consumption. Detailed results show region by region descriptions of the ratio of GHG emissions calculated using LRMER compared to annual averages and provides in-depth analyses of two Maryland industrial facilities to provide further clarity.

Detailed Results

Southern Illinois (SRMWc) LRMER emissions range from 30 to 38% of annual average emissions for the majority of facilities, highlighting the impact of marginal emissions calculation. In the Greater Chicago area (RFCWc), LRMER with the low renewable energy and battery cost scenario falls within 45 to 65% of annual average emissions.

In Washington State (NWPPc) the majority of facilities exhibit LRMER between 46 and 55% of annual average emissions. In Georgia (SRSOc), LRMER emissions range from 40 to 65% of annual average emissions in this region. And last, in Connecticut (NEWEc), the LRMER rates fell between 72% and 103% of the average annual emissions.

In Maryland (RFCEc), most facilities exhibit LRMER emissions within 75 to 90% of annual average emissions, but outliers demonstrate significant differences depending on the facility.

We created some examples from Maryland, since Maryland is a state with planned changes to the grid to decrease carbon emissions over the next few years. While the state currently is powered by 12% coal, the state plans to eliminate coal generation by the end of 2025. Additionally, the state is powered by the Calvert Cliffs nuclear reactor which accounts for 39% of the state's generation.

Looking at facility level examples can illustrate the disconnect between emissions and consumption. See Figures 8 and 9 to see the consumption and emissions for a winery with annual consumption of about 500 MWh in Maryland (RFCEc region).

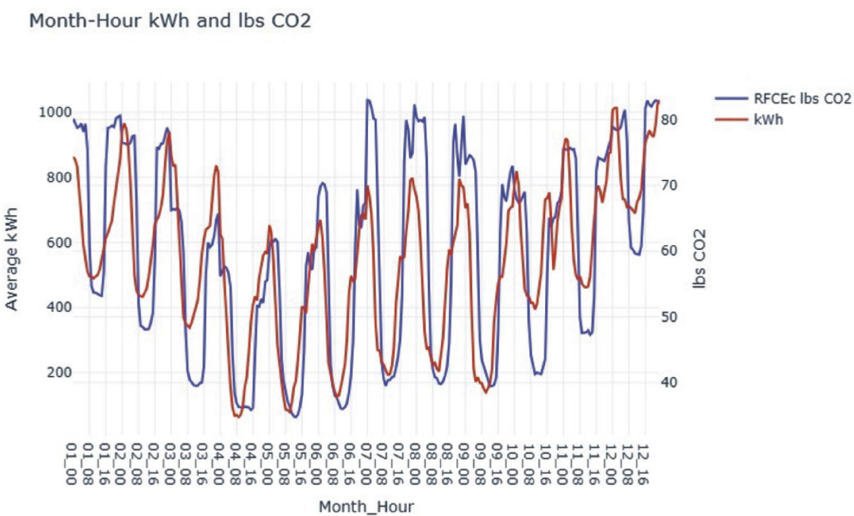

Figure 8. Consumption and GHG emissions for a Winery in Maryland

Looking at Figure 8 the winery shown has clear seasonal energy consumption patterns, with a winter peak. The emissions shown in blue are the state-level emissions for each month-hour. In this example, the facility's electricity consumption and GHG emissions peak during mid-summer. In the heatmap, the GHG emissions are most extreme overnight in the summer when the grid is taxed and lowest during the day when the

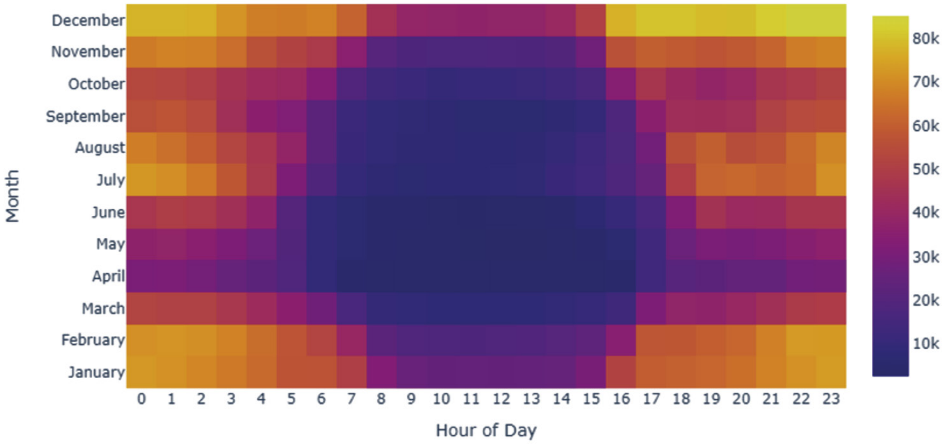

Figure 9. Month Hour Emissions Heatmap for Winery in Maryland

sun is shining, and renewable sources can carry the load. In this case, since the grid emissions and the electricity consumption are highly correlated, measures that reduce consumption throughout the year during the highest consumption times of the day will have the most significant emissions reduction impact as measured by LRMERs.

A second example, shown in Figures 10 and 11, is a pharmaceutical manufacturing facility with annual consumption of about 19 GWh, also in Maryland.

This facility also has weather or seasonally dependent energy consumption, but with a summer peak. In this example, GHG emissions are not as highly correlated with the facility-level energy consumption through the year. Because of how this facility operates, the strategies that this facility would employ to reduce emissions would be very different from that of the winery. Here the greatest potential for emissions reduction as measured using LRMERs will be realized overnight during the summer when both consumption and grid emissions are high.

LESSONS LEARNED AND CONCLUSIONS

The lower GHG emissions when calculated using LRMER compared to annual averages in each territory present an opportunity to

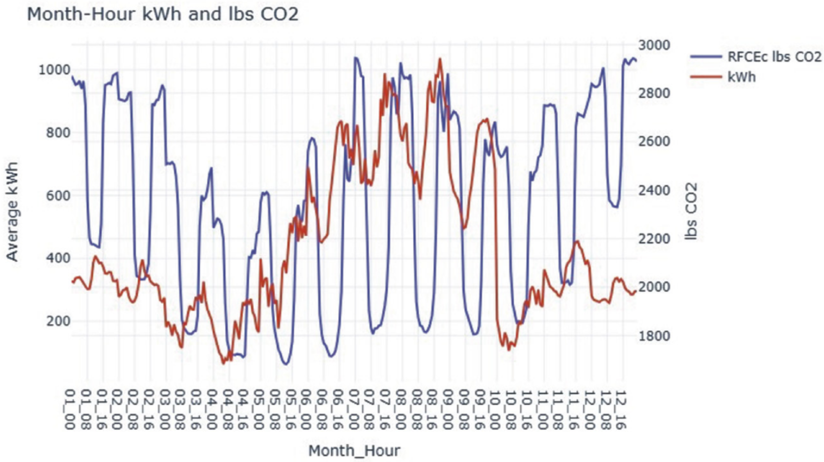

Figure 10. Consumption and Emissions for Pharmaceutical Manufacturing in Maryland

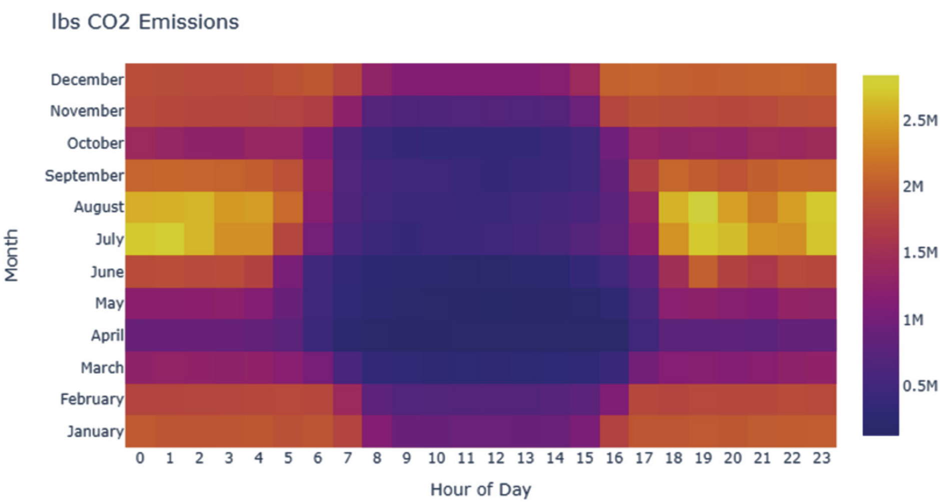

Figure 11. Month Hour Emissions Heatmap for Pharmaceutical Manufacturing in Maryland

accelerate electrification efforts. This acceleration results from more accurate estimates of the savings from fuel switching and demand flexibility that show greater savings than traditional methods. By prioritizing the use of LRMER over static annual average emissions, we can leverage this dynamic data to drive and optimize the transition towards greater electrification. We found a significant divergence between the two datasets that requires urgent action to ensure that the measure prioritization and measurement and verification (M&V) choices we make aren't jeopardizing investment in decarbonization projects that actually combat climate change. The conclusion found is that all studied regions show that we will encourage electrification more if we use hourly emissions data rather than annual averages.

There are some limitations to this work. We used the 2022 Cambium dataset rather than the 2023 dataset, as the 2023 dataset had not yet been released at the time that this analysis was initiated. Additionally, this dataset was limited to six geographic areas, rather than a full geographic spread due to the data that was available. Energy consumption patterns may vary between regions, and grid emissions whether average annual emissions or LRMER will differ as well. While this study provides valuable insights into the factors driving energy costs in certain regions, we recognize that the findings may not be directly applicable to other regions. Future research efforts to extend the geographic breadth of this work would be valuable.

We also used the LRMER Cambium projections exclusively. It would be useful to add to the body of knowledge on this topic for alternate research to ignore the 2025 Cambium projection and conduct short-run marginal emissions calculations using interpolations between recent observed data and the 2030 projections (Gagnon et al., 2023). In spite of these limitations, the results shown in this article demonstrate the value of LRMER.

As smart meters that collect and record hourly data and tools that make that data accessible become more common, using LRMER becomes easier to carry out. While data quality, data access, and regulatory compliance must always be considered, smart meter data is becoming increasingly accessible to individual energy managers. Many utilities provide portals that allow users to download spreadsheets with historical energy consumption data, and tools such as Green Button Connect My Data can provide programmatic interfaces to access the data as well.

Policy makers and other stakeholders will want to check their location specific climate action plans, GHG reduction laws, and other regulatory documents to identify if average annual emissions are being used in future planning, rather than LRMER, and adjust accordingly.

References

1. Cohen, S., Becker, J., Bielen, D., Brown, M., Cole, W., Eurek, K., Frazier, W., Frew, B., Gagnon, P., Ho, J., Jadun, P., Mai, T., Mowers, M., Murphy, C., Reimers, A., Richards, J., Ryan, N., Spyrou, E., Steinberg, D., Sun, Y. Vincent, N. and Zwerling, M. (2019). Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018. National Renewable Energy Laboratory (NREL). Technical Report NREL/TP-6A20-72023. Available at https://www.nrel.gov/docs/fy19osti/72023.pdf.
2. Gagnon, P., Andres Sanchez Perez, P., Obika, K., Schwarz, M., Morris, J., Gu, J., and Eisenman, J. (2023). Cambium 2023 Scenario Descriptions and Documentation. NREL. Technical Report NREL/TP-6A40-88507. Available at https://www.nrel.gov/docs/fy24osti/88507.pdf.
3. Gagnon, P., and Cole, W. (2022). Planning for the evolution of the electric grid with a long-run marginal emission rate. IScience, 25(3). Available at https://www.nrel.gov/docs/fy22osti/80472.pdf.
4. Gagnon, P., Cowiestoll, B., and Schwarz, M. (2022). Cambium 2022 Scenario Descriptions and Documentation. NREL. Technical Report NREL/TP-6A40-84916. Available at https://www.nrel.gov/docs/fy23osti/84916.pdf.
5. World Resources Institute (WRI). (2001). The Greenhouse Gas Protocol. A Corporate Accounting and Reporting Standard (Revised Edition). First published 2001 and subsequently revised in the 2011 and 2013 timeframe. Current edition available at https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf.
6. IEA. (2023). Net Zero Roadmap: A Global Pathway to Keep the 1.5°C Goal in Reach, 2023 Update. Available at https://www.iea.org/reports/net-zero-roadmap-a-global-pathway-to-keep-the-15-0c-goal-in-reach.
7. Kruis, N. (2022). "RESNET Load Flexibility Task Group: Developing Ratings that Incentivize Demand Responsive Buildings and a Cleaner Grid." Proceedings of the 2022 ACEEE Summer Study on Energy Efficiency in Buildings. American Council for an Energy-Efficient Economy (ACEEE), Washington D.C.

AUTHORS BIOGRAPHY

Craig Sinnamon is the director of analytics and data management at Power TakeOff, a utility implementation contractor. Craig has a background in mathematics and has worked to advance methodology and basic assumptions around weather data and how to model the impacts of energy efficiency programs using machine learning and big data analysis. His primary research focuses on adapting for grid level impacts including non-routine events, improving modeling methodologies to utilize high granularity advanced metering infrastructure data, updating weather sources used for savings claims and grid planning, and decarbonization data sources. Craig Sinnamon may be reached at craig.sinnamon@powertakeoff.com.

David B. Goldstein, PhD, works for his consulting firm David B. Goldstein and Associates, Inc. Prior, David spent 43 years with the Natu-

ral resources Defense Council. David Goldstein has been a global leader in energy efficiency and energy policy advocacy since the early 1970s. He has developed policies on energy efficiency standards and incentives that have been adopted by states and cities, as well as nations, around the world. He graduated from the University of California, Berkeley, with a Ph.D. in physics in 1978, and was awarded a MacArthur Fellowship in 2002. David may be reached at david.b.goldstein.ee@gmail.com.

Anna Kelly specializes in policy development and energy efficiency program design and evaluation methodologies for innovative approaches to energy efficiency. Anna Kelly was awarded the young energy professional of the year award by the Association of Energy Engineers in 2023. She has been designing, administering, implementing, and evaluating energy efficiency programs since 2014. Anna Kelly may be reached at akelly@sbwconsulting.com.