# Using advanced M&V data to quantify the greenhouse gas impact of energy efficiency projects in commercial buildings

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## ABSTRACT

Commercial buildings' decarbonization goals have increased the importance of understanding the greenhouse gas (GHG) impacts of energy efficiency (EE) projects. Many organizations have set GHG reductions goals, and annual GHG reporting is increasingly required for regulatory or internal reporting purposes. Annual GHG reporting focuses on defining the equivalent emissions of energy consumed (aka 'carbon footprint'), and does not specify emissions reduction calculations for energy efficiency projects.

Scope 2 emissions, indirectly arising from electricity consumption, vary by time and location based on an increasingly diverse generation mix, and the GHG benefits of energy efficiency vary accordingly. There is currently no consensus on methods for determining GHG emission reductions for energy efficiency projects, and there exists a lack of awareness of the different datasets and methods available. The growing adoption of advanced measurement & verification (M&V) using interval data provides a useful data input for such calculations.

This paper describes implications of taking different approaches to calculating scope 2 GHG impacts for a given project, to support informed choices in the approach used. The paper also presents emissions reductions estimates from seven different EE project savings scenarios using different tools. The findings provide insight to building owners, researchers and M&V practitioners on the temporal GHG impacts of savings from EE projects, and how it complements the annual reporting paradigm. This could potentially accelerate the adoption of EE measures to meet decarbonization goals when they are better matched to high-emission periods.


## 1. Introduction

Decarbonization goals have increased the importance of understanding the GHG emissions impacts of energy efficiency projects. Many organizations have set GHG reduction goals (eg. Constellation Energy, The Home Depot, Xcel Energy Inc., Walmart[1]), and annual GHG reporting is increasingly required for regulatory or internal reporting purposes (eg. CDP,[2] RE100,[3] Science based targets[4]). Some jurisdictions are also enacting policies that require reporting GHG emissions or will impose penalties for not meeting GHG targets (eg. CA SB 253,[5] NY Climate act,[6] Boston

[1] https://www.climateaction100.org/whos-involved/companies/page/3/?search_companies&company_region=north-america
[2] https://www.cdp.net/en
[3] https://www.there100.org/
[4] https://sciencebasedtargets.org/
[5] https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=202320240SB253
[6] https://www.nyserda.ny.gov/Impact-Greenhouse-Gas-Emissions-Reduction

BERDO[7]). In addition, Executive Order 14057 outlines an ambitious plan to power federal facilities with 100% carbon free electricity[8].

The GHG protocol,[9] that sets the standards to measure and manage emissions, defines three scopes of emissions. Scope 1 emissions, for example, direct emissions from natural gas usage by a hot water boiler, are relatively straightforward to estimate, since emissions conversion factors for natural gas usage do not change by time or location. Scope 2 emissions, that indirectly arise from electricity consumption, do vary by time and location, due to changes in the resource mix and generation efficiency supplying the electricity. The locational variation may be captured using location-specific emissions conversion factors such as those provided by the EPA's Emissions and Generation Resource (eGrid) online resource.[10] Scope 3 emissions, such as purchased goods and services, business travel or investments, are the result of activities from assets not owned or controlled by the reporting organization, but that the organization indirectly affects in its value chain.

Scope 2 GHG emissions reported from consumed electricity, commonly performed annually, are based on emission conversion factors. Notably, this standard GHG reporting focuses on defining the equivalent emissions of electricity consumed (aka 'carbon footprint'), and does not specify emissions reduction calculations for energy efficiency projects. This distinction may appear trivial, but there is currently no consensus on methods for determining GHG emission reductions for energy efficiency projects. One of the key challenges here is the different ways of calculating emissions, which fall into two main categories:

- Average emissions: Average emissions represent the overall system average for all power generation facilities in a region. These are appropriate for developing a carbon footprint or emissions inventory. They are calculated by dividing the total emissions from all power plants in a given region by the total amount of electricity generated in that region.
- Marginal or non-baseload emissions: Marginal emissions represent the emissions from generation facilities that are dispatched in the energy market in response to an increase or decrease in demand.[11] The calculation methodology varies depending on the specific plants that are used to meet incremental changes in demand.

eGrid recommends average emissions be used when benchmarking building GHG emissions, and non-baseload when quantifying the emissions reductions arising from an energy efficiency project. Non-baseload output emission rates were developed for eGRID to provide an improvement over the fossil fuel output emission rates as an estimate of emission reduction benefits from energy efficiency and clean energy projects. These values are available beginning with data year 2004. Non-baseload values may be less appropriate when attempting to determine the emissions benefits of resources that operate fairly constantly or operate mostly during off peak times, are not very coincident with some intermittent resources, such as CHP or wind power in some locations.

[7] https://www.boston.gov/departments/environment/building-emissions-reduction-and-disclosure
[8] https://www.sustainability.gov/federalsustainabilityplan/carbon.html
[9] https://ghgprotocol.org
[10] https://www.epa.gov/egrid
[11] https://portfoliomanager.energystar.gov/pdf/reference/Emissions.pdf

In isolation, these approaches make sense, though this creates a disconnect whereby the difference in building benchmark GHG emissions before and after the energy efficiency project (based on average emission factors) will not be equivalent to the GHG reduction from energy efficiency (if determined from non-baseload emissions). Figure 1 provides an example of a hypothetical energy efficiency project scenario that highlights the discrepancy between applying the eGrid average emissions factor and the eGrid non-baseload emission factor. Further, given the complexities of generation/grid management, there is uncertainty around which generation resource would be ramped down in the case of overall reduction in demand (i.e., will the “marginal” plant actually be the one that is ramped down if a building reduces its energy use?). Added to this question of average vs. non-baseload emissions is the dimension of time resolution, i.e., whether using an annual emission conversion factor (such as from eGrid) or higher resolution like hourly factors that are available from other sources such as Wattime or Singularity (see Table 1). Using time-varying electricity emission factors, offers an opportunity to better understand the impacts of energy efficiency relative to the regional grid generation mix, to better inform decision making around energy efficiency (Callaway, D. S 2018, Goetsch, Heather, 2022). In summary, three distinct challenges associated with the difference between average and marginal emissions in the context of GHG emissions calculations for EE projects arise:

1. Internally inconsistent applications: The inconsistent application of methodologies and assumptions when evaluating average versus marginal emissions, resulting in potential discrepancies and incompatibility of results.
2. Questioning the significance of marginal emissions: Concerns regarding the validity and relevance of marginal emission calculations, given the complexities and dynamic nature of energy generation.
3. Time-varying aspect: The temporal variability of marginal emissions, which necessitates the consideration of time-dependent factors and their impact on emission profiles.

The remainder of the paper primarily focuses on the third challenge, providing examples and analyses related to the time-varying nature of marginal emissions.

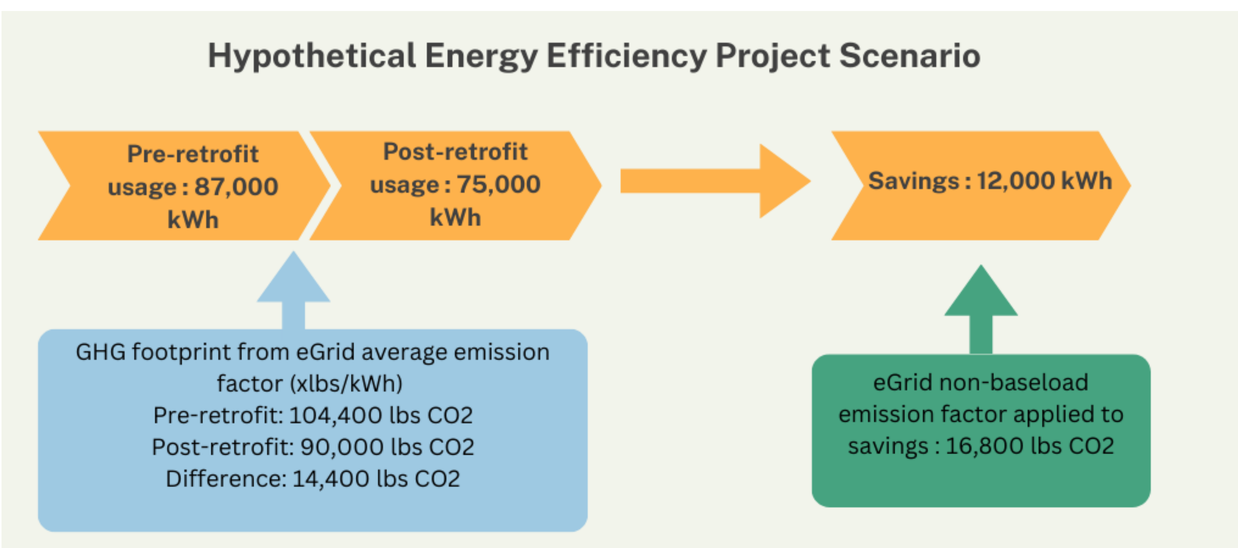


Figure 1: Example GHG emissions before and after an energy efficiency project showing difference between average and marginal emission factors

The growing adoption of advanced M&V using interval data provides a useful data input for such calculations, but many questions remain. Liang, Y et. al 2022 aim to address some of these questions, but many questions still remain such as: How do building owners, researchers and M&V practitioners use this data to calculate the temporal GHG savings from EE projects? What tools are available and what are the implications of using the tools with the interval data? What are the different datasets available? This paper outlines the implications of taking different approaches to calculating GHG impacts for a given energy efficiency project using interval data, to help make informed choices in the datasets/tools used. This paper is organized as follows. Section '2' provides an insight into the annual, seasonal and regional variability in both the average and marginal emission factors from the different datasets/tools. Section '3' presents a sensitivity analysis of different emissions reductions estimates, using 7 different hourly savings shape scenarios. Section '4' highlight results of emissions reductions from an example energy efficiency project and Section '5' projects future emissions reductions using projected emission factors. Finally, Section '6' has a summary of the findings and a conclusion.

## 2. Greenhouse Gas (GHG) impact quantification using advanced M&V data

Three publicly available and one fee-based datasets/tools are used in this study that are described in Table 1. All the tools have a very similar fundamental approach, they start with Continuous Emissions Monitoring System's data reported through the EPA Clean Air Markets Program Data (CAMPD)[12] on hourly electricity generation and emissions at every major fossil fuel fired power plant in the United States.

Table 1: GHG data sources and a description of their data

| Tool / data source | Description |
|---|---|
| AVoided Emissions and geneRation Tool (AVERT)[13] | AVERT data contains approximations of marginal emission rates for 14 AVERT regions and for a national weighted average. AVERT uses a peer-reviewed methodology to analyze electric power sector impacts on an hour-by-hour basis, but it can also produce annual emission rates for each AVERT region and for the nation. The AVERT method uses historical hourly emission rates, with the most recent release being 2022. |

[12] https://campd.epa.gov
[13] https://www.epa.gov/avert

| | |
|---|---|
| Cambium[14] | Cambium data contains long-run marginal emission rate estimates for the contiguous United States. Cambium data contains modeled hourly emission, cost, and operational data for a range of possible futures of the U.S. electricity sector through 2050, with metrics designed to be useful for forward-looking analysis and decision support. The most recent release is 2021. |
| WattTime (fee-based) | WattTime data contains real-time, short-term forecast, and historical marginal emissions data for electric grids around the world. The marginal emissions rate provided is a Marginal Operating Emissions Rate (MOER), in units of pounds of emissions per megawatt-hour (e.g. CO2 lbs/MWh). |
| Singularity | Singularity data contains carbon intensity of consumed electricity within a region, accounting for imports and exports from neighboring regions. (de Chalendar, J., 2019) |

The methodology to explore implications of taking different approaches to calculating GHG impacts for a given energy efficiency project using interval data presented in this paper, comprises four analysis steps.

- First, the average and marginal emissions factors from the different tools described in Table 1 are analyzed. The annual, seasonal and regional variability (for two regions) in emissions from these tools is presented. The two regions selected are CAMX (Western Cooling Council's CAMX subregion that covers California, parts of Nevada and Baja California, Mexico)[15] and FRCC[16] (Florida Regional Coordinating Council's subregion that covers the state of Florida). These regions were selected because they have contrasting climate zones and generation mixes to provide insights for analyzing the impacts of emissions factors.
- Second, a sensitivity analysis using hourly test data that comprises kWh savings or a full year, using 7 different scenarios is presented, each having the same total kWh savings, but different hourly savings.
- Third, an hourly savings from an example energy efficiency project was used to calculate seasonal hourly carbon reduction in two different regions.
- Finally, future savings were calculated using the savings shape from the example energy efficiency project and forecast emissions factors.

The outcomes of the analysis aim to shed light on how M&V practitioners use this data to calculate the temporal GHG savings from EE projects.

[14] https://www.nrel.gov/analysis/cambium.html
[15] https://www.wecc.org/Reliability/CAMX%20Subregional%20Assessment%202022.pdf
[16] https://www.epa.gov/green-power-markets/us-grid-regions

## 3. Results: Annual, seasonal and regional variability in average and marginal emission factors

Figure 2 illustrates the difference between average and marginal emissions, using data from the CAMX region as an example for the year 2020. These examples illustrate the difference in the range of emission conversion factors, and seasonal trends. Taking the average of all values shown in these figures, we see that marginal emission factors trend higher at 0.82 lbs per kWh than average emission factors of 0.51 lbs per kWh. These values compare with an eGrid non-baseload emission factor of 0.91 lbs per kWh and average emission factor of 0.45 lbs per kWh (approximately 10% different from the WattTime and Singularity values, respectively). Figure 2 also shows time periods when marginal emission factors can be close to zero, particularly in the 2000-4500 hour period. This may occur in time periods where load reductions would result in curtailment[18] of grid-level PV generation instead of reducing fossil fuel generation.

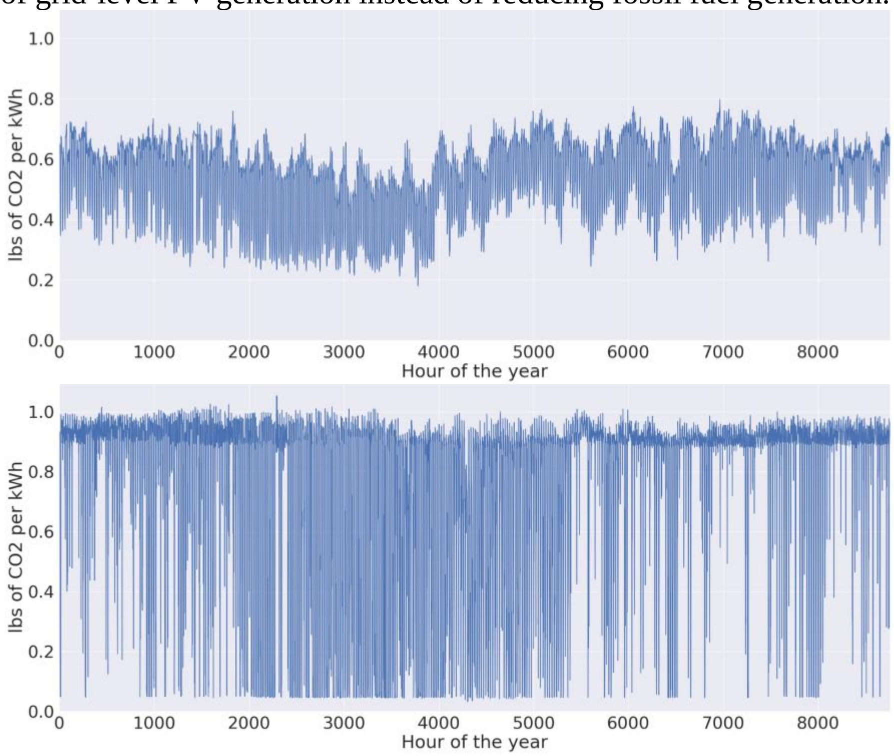



Figure 2: Top: Average emission factors across all hours of the year in 2020, CAMX region (Source: Singularity), Bottom: Marginal emission factors across all hours of the year in 2020, CAMX region (Source: WattTime)

Figure 3 illustrates the seasonal average hourly, average and marginal emission factors for a single region (CAMX) by hour of day and season.[19] We observe a reduction in both average and marginal emission factors during the day in all seasons, with the most reduction seen in the spring season and the middle hours of the day, between 10 am and 2 pm. One of the reasons for this reduction could be due to the high level of solar penetration in the state of California, which this region encompasses, coupled with the fact that cooling load on the grid is lower in the Spring

[18] https://www.caiso.com/documents/curtailmentfastfacts.pdf
[19] Year divided into four seasons of 3 months, where Winter = December to February

compared to Summer (California Energy Commission. (2023).[20] Marginal emissions have a wider range, higher at the high end (0.9 vs 0.65 in the Fall) and lower at the low end (0.2 vs 0.3 in the Spring) ( Holland, S. et al. 2022).

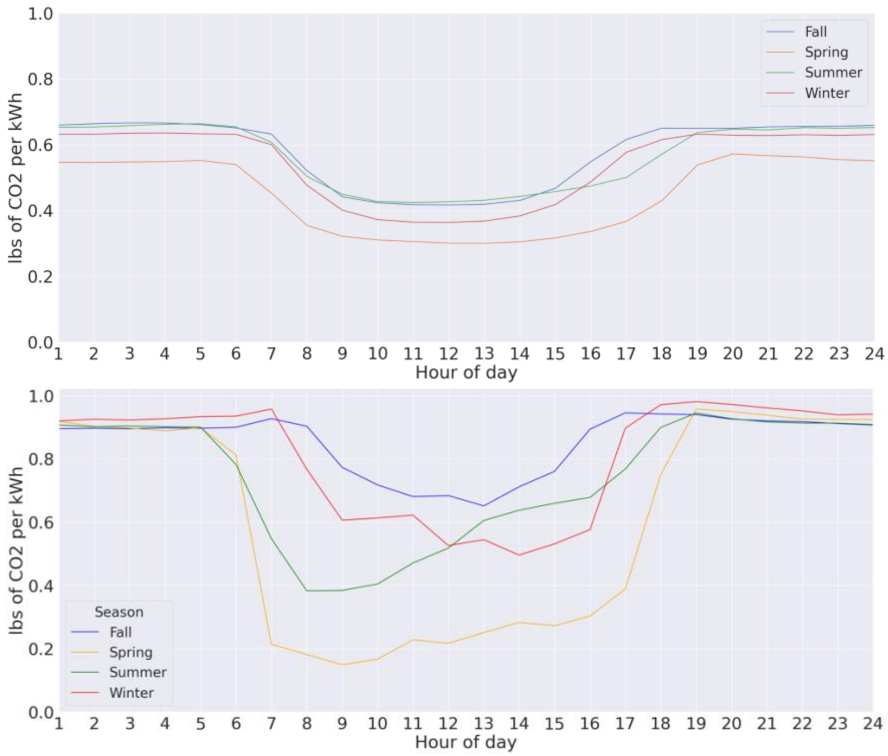



Figure 3: Top:Seasonal average hourly emission factors for CAMX region, Source: Singularity (average), Bottom: Seasonal average hourly emission factors for CAMX region, Source: WattTime (marginal).

Figure 4 below gives an example of the variation in hourly emission factors between two different regions, CAMX and FRCC (example uses Singularity average emission factors). These regions were arbitrarily selected to highlight regional and temporal differences in emission factors. The largely reduced emission factors during the day in all seasons observed in the CAMX region are not seen in the FRCC region. For instance, electricity consumed between 11 am and 1 pm in the CAMX region has half the impact on GHG reported emissions than the electricity consumed in the FRCC region during the same time period. If an energy efficiency project in the FRCC region achieved different savings at different times of the day/year, hourly GHG calculations would not end up much different from using a single eGrid annual average emission factor. On the other hand, in the CAMX region, there might be a significant difference in the GHG reduction estimates when using hourly data.

[20] https://www.eia.gov/state/analysis.php?sid=CA#50

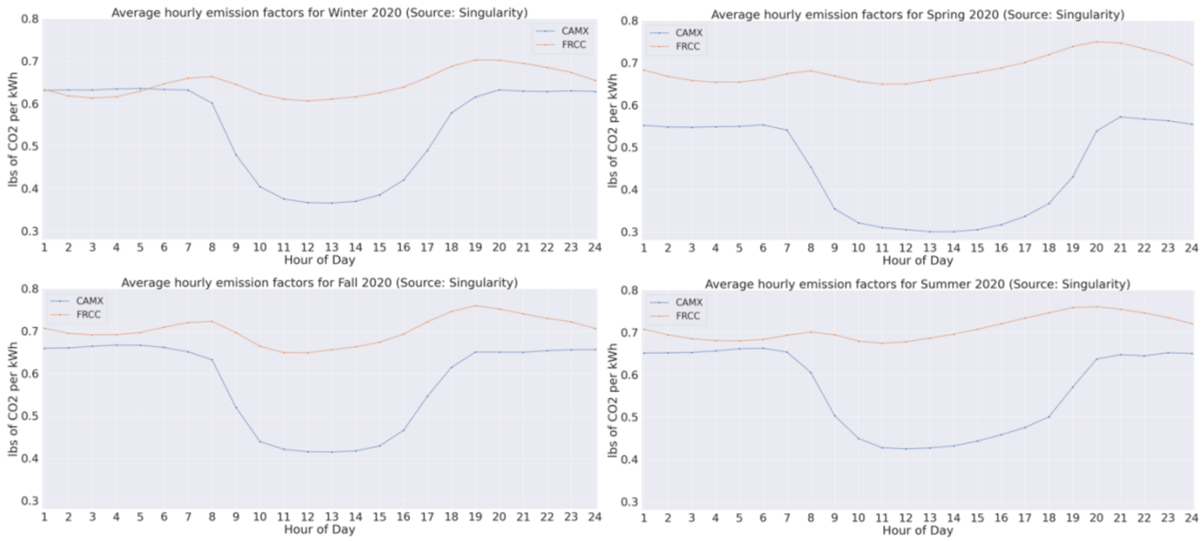
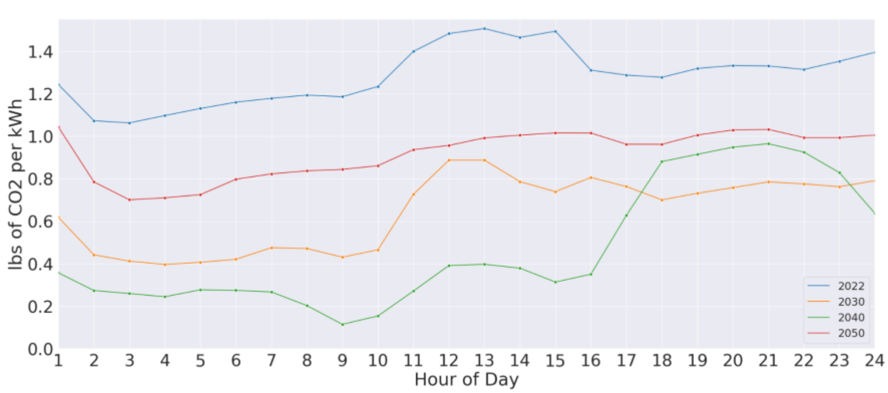



Figure 4: Seasonal variation in average hourly emission factors for CAMX and FRCC region, Source: Singularity. Top left: Winter, Top right: Spring, Bottom Left:Fall, Bottom right:Summer

While all the figures above leveraged historical grid emissions data, the Cambium dataset represents simulations of future grid emissions, projected through to 2050 (with historical data being referenced in developing inputs to those simulations). The current available version of Cambium, released in 2021,[22] provides long run marginal emissions projections for all U.S. regions, at two-year intervals, from 2022 through 2050. Cambium includes projections for 70 different scenarios, and the mid-case, which has central or median values is modeled here. Figure 5 illustrates the projected changes in hourly emission factors across the full Cambium time period, i.e. up to 2050, for two different regions, CAMX and FRCC. In general, we observe lower projected emission factors for the CAMX region when compared to FRCC. We also observe that projected emission factors are higher in 2050 than 2040. This could be due to the assumptions included in the model such as the phase out of the federal investment and production tax credits in 2030 that causes a slight reversal in electricity sector decarbonization (Gagnon, P. et. al 2023). Such forecasts of emission factors are useful to understand future impacts of energy efficiency projects on GHG emissions.




[22] Even though 2022 data is now in the past, the source data year used for the 2022 Cambium mid-case projection was prior to 2022.

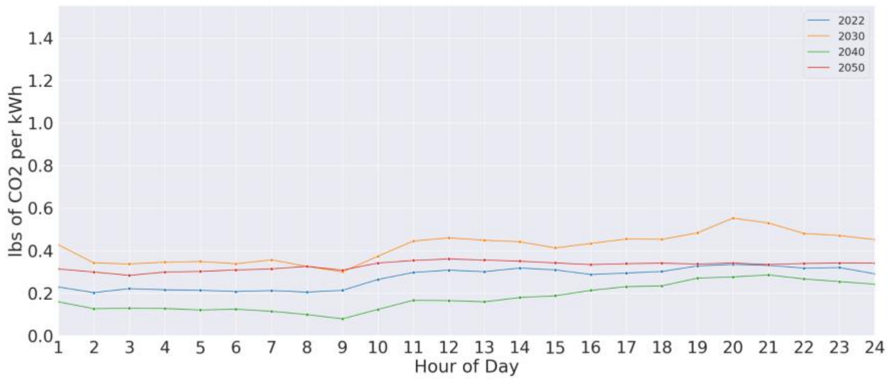



Figure 5: Top: Average hourly emission factors (lbs per CO2) for FRCC region, Source: Cambium, Bottom: Average hourly emission factors (lbs per CO2) for CAMX region, Source: Cambium.

Unlike WattTime, Singularity, and Cambium, the AVERT tool does not report hourly emission factors; AVERT can analyze hourly data across a full-year period and estimate emissions, but the output summarizes total emissions rather than hourly. As such, it may be used to estimate energy efficiency project emission reductions but there is reduced transparency in how its emissions estimates are calculated. AVERT is designed for analysts who wish to improve their understanding of emission benefits statewide or multi-state energy policies and programs and not specifically for project level M&V.

## 4. Emissions reduction estimates: sensitivity analysis

The opportunity to use advanced M&V hourly savings estimates as an input to GHG reduction estimates allows for accounting of the time-varying emissions of a complex grid generation mix. Given that using hourly data entails more effort & complexity, it is helpful to understand how significantly different the outputs could be. In this section we show the variation in estimated GHG emissions using different datasets/tools in combination with a set of hourly test data. The hourly test data comprises kWh savings for a full year (8760 values) with 7 different scenarios, each scenario having the same total kWh savings (87,600kWh) for the full period. One scenario reports a flat 10kWh savings for every hour of the year; two scenarios see savings only reported at nighttime or daytime respectively and four scenarios see savings only reported in one season. The description of the scenarios is given in Table 2.

Table 2: Different savings scenarios

| Scenario | Description |
|---|---|
| S1 | 10kWh flat hourly savings |
| S2 | 20kWh night savings |
| S3 | 20kWh day savings |
| S4 | Savings only in summer |
| S5 | Savings only in winter |
| S6 | Savings only in spring |
| S7 | Savings only in fall |

Figure 6 below shows illustrative examples of two savings shapes from these test datasets, one where the kWh savings are only in the summer hours and the other with kWh savings only during day time hours. The test dataset of different savings scenarios represent upper bound extreme cases of savings and are only meant to illustrate how sensitive the GHG estimates are to changes in input hourly data.

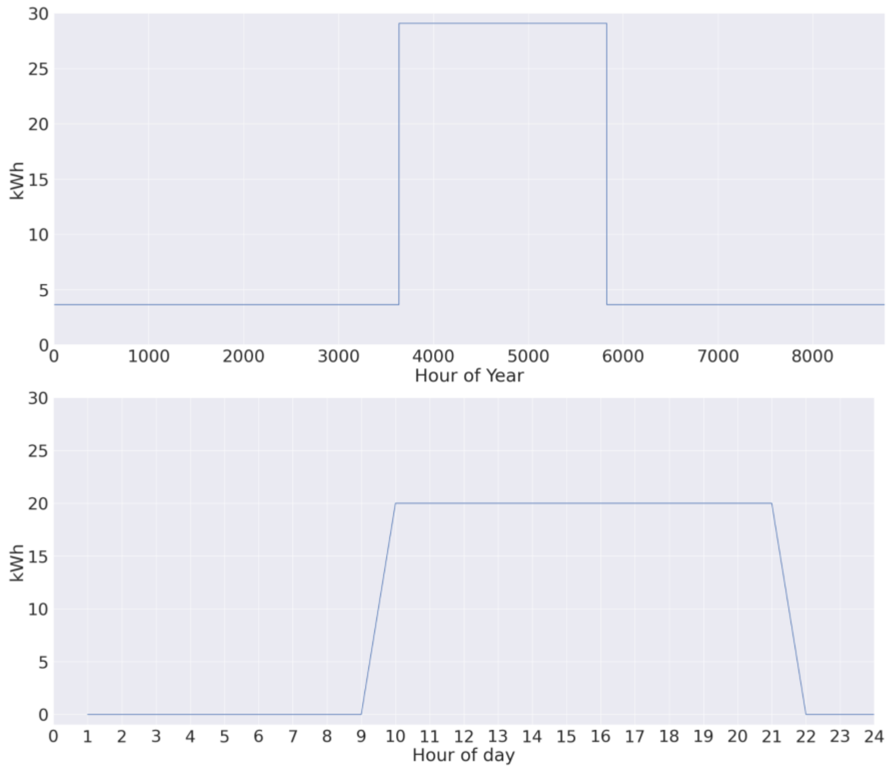



Figure 6: Top: Scenario 4 (S4) Full year kWh savings occur only during summer hours.
Bottom: Scenario 3 (S3) Single day kWh savings occurs only during day time hours.

Table 3 and Table 4 below report the GHG estimates for the different scenarios across the different GHG emissions factor data sources/tools for two different regions. The estimates in these tables are calculated by multiplying the hourly kWh savings with the emission factors and then summing the total lbs CO2 for each scenario.

Table 3: GHG estimates for different savings scenarios and tools for CAMX region (lbs CO2)

| Source /Scenario | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Singularity | 44,953 | 48,525 | 41,382 | 42,397 | 47,400 | 39,450 | 50,696 |
| % change from S1 | - | +7.9% | -7.9% | -5.6% | +5.4% | -12.2% | +12.7% |
| WattTime | 72,122 | 78,642 | 65,603 | 68,606 | 80,086 | 63,429 | 76,551 |
| % change from S1 | - | +9% | -9% | -4.8% | +11% | -12% | +6.1% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| AVERT | 42,440 | 42,090 | 42,770 | 43,150 | 42,240 | 41,170 | 43,330 |
| % change from S1 | - | -1% | +0.7% | +1.6% | -0.5% | -3% | +2% |

Table 4: GHG estimates for different savings scenarios and tools for FRCC region (lbs CO2)

| Source /Scenario | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Singularity | 67,510 | 65,261 | 69,759 | 73,149 | 67,630 | 62,816 | 66,672 |
| % change from S1 | - | -3.3% | +3.3% | +8.3% | -0.1% | -6.9% | -1.2% |
| WattTime | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
| AVERT | 42,360 | 40,280 | 44,450 | 43,790 | 41,340 | 41,940 | 42,530 |
| % change from S1 | - | -4.9% | +4.9% | +3.3% | +2.4% | +1% | +0.5% |

We assess the sensitivity of the timing of hourly savings on the GHG estimates against a baseline scenario of S1 in which there is a flat 10 kWh savings for every hour of the year. In the CAMX region, for both average (Singularity) and marginal (WattTime) emission factors, scenarios S2, S5 and S7 produce higher GHG estimates than the baseline, while scenarios S3, S4 and S6 produce lower than the baseline. For the FRCC region, and scenarios S3 and S4 produce higher average GHG estimates than the baseline, while all other scenarios produce lower than the baseline. Marginal emission factors were not available for the FRCC. In general, we observe that the Singularity and WattTime tools have large sensitivities to change in the timing of savings with Singularity approximately +/-12% in the CAMX region and +8/-7 % in the FRCC region and WattTime approximately +12/-11% in the CAMX region. We observe outputs from AVERT do not follow the patterns of the either of the other tools are not very sensitive to the various scenarios.

## 5. Emissions reduction estimates: example project

As illustrated in the section 4, the temporal variation in energy efficiency project kWh savings (the 'savings shape') has an impact on the magnitude of GHG emission reductions. Having illustrated this using hypothetical, simplified savings shape examples, here we demonstrate an analysis approach using a more representative example. Data for this sample were drawn from M&V of a sample energy efficiency project in a commercial building, with some data cleaning and interpolation for missing data periods. The advanced M&V approach employed for this project followed IPMVP Option C (avoided energy use approach) (Energy, D. (2001), using hourly consumption data from before and after an energy efficiency project. As shown in Figure 7 (top), the hourly savings for this project vary by time of year, and Figure 7 (bottom) indicates variation in savings by time of day (Figure shows an excerpt of the year, for illustrative purposes). The somewhat jagged nature of the data and occasional anomalies are commonly observed in hourly data from commercial buildings.

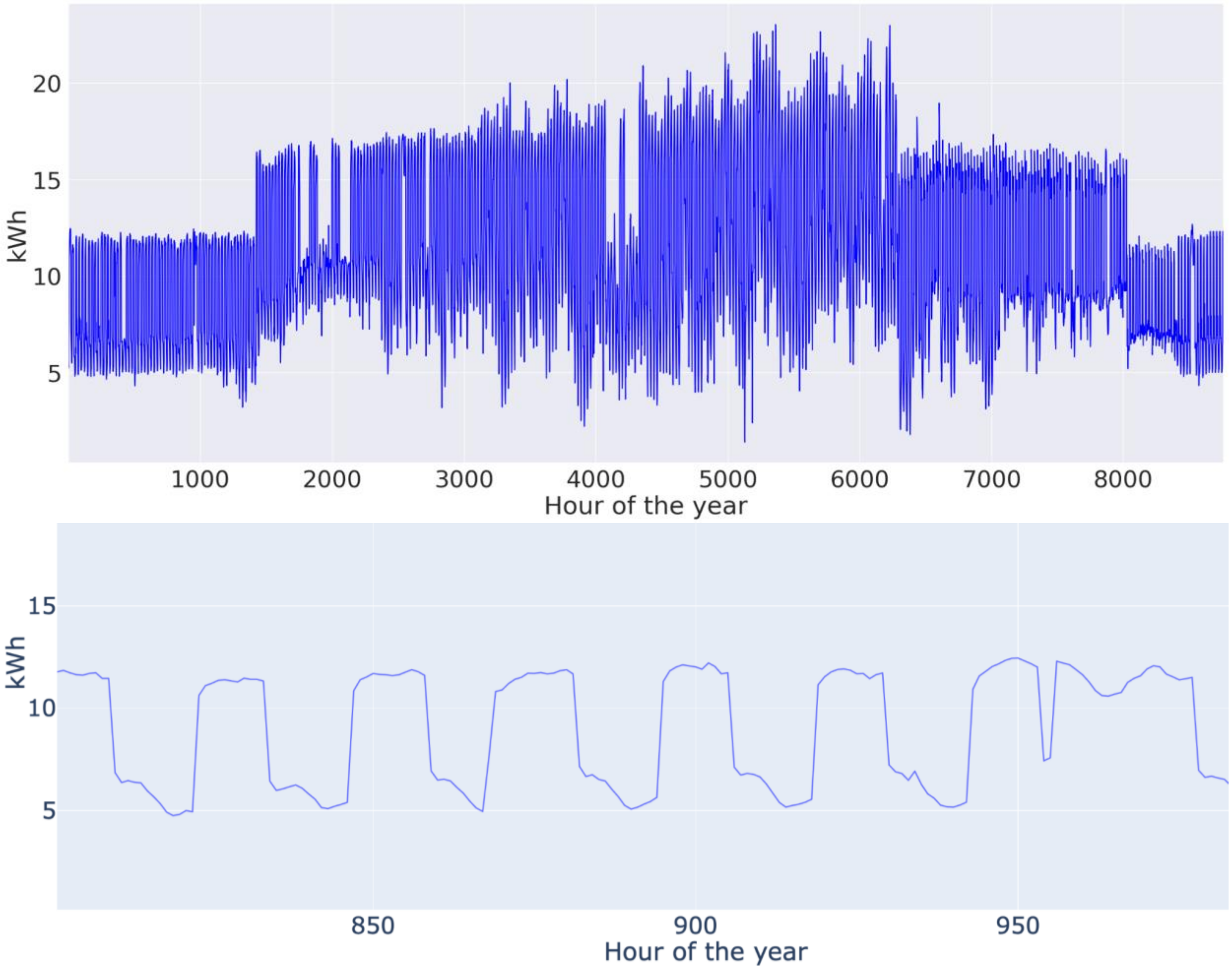



Figure 7: Top: Example project hourly savings across the whole year.
Bottom: Example project hourly savings across a single week

We assume this energy efficiency project was implemented in two different grid regions and we calculate the average hourly carbon reduction for each season. Figure 8 shows the average hourly carbon reduction for two grid regions, based on average emission factors (Singularity). In this instance, both regions have the highest carbon reductions (savings) in the summer. In the CAMX region, there are higher carbon reductions in the earlier hours of the morning (5 am-9 am) in all seasons, and then they drop during the day (9 am- 4 pm) with an exception in the fall, in which we observe a minor increase in the later evening. For the FRCC region, carbon reductions in the spring and summer seasons are higher during the day, with those in the summer almost twice those in fall.

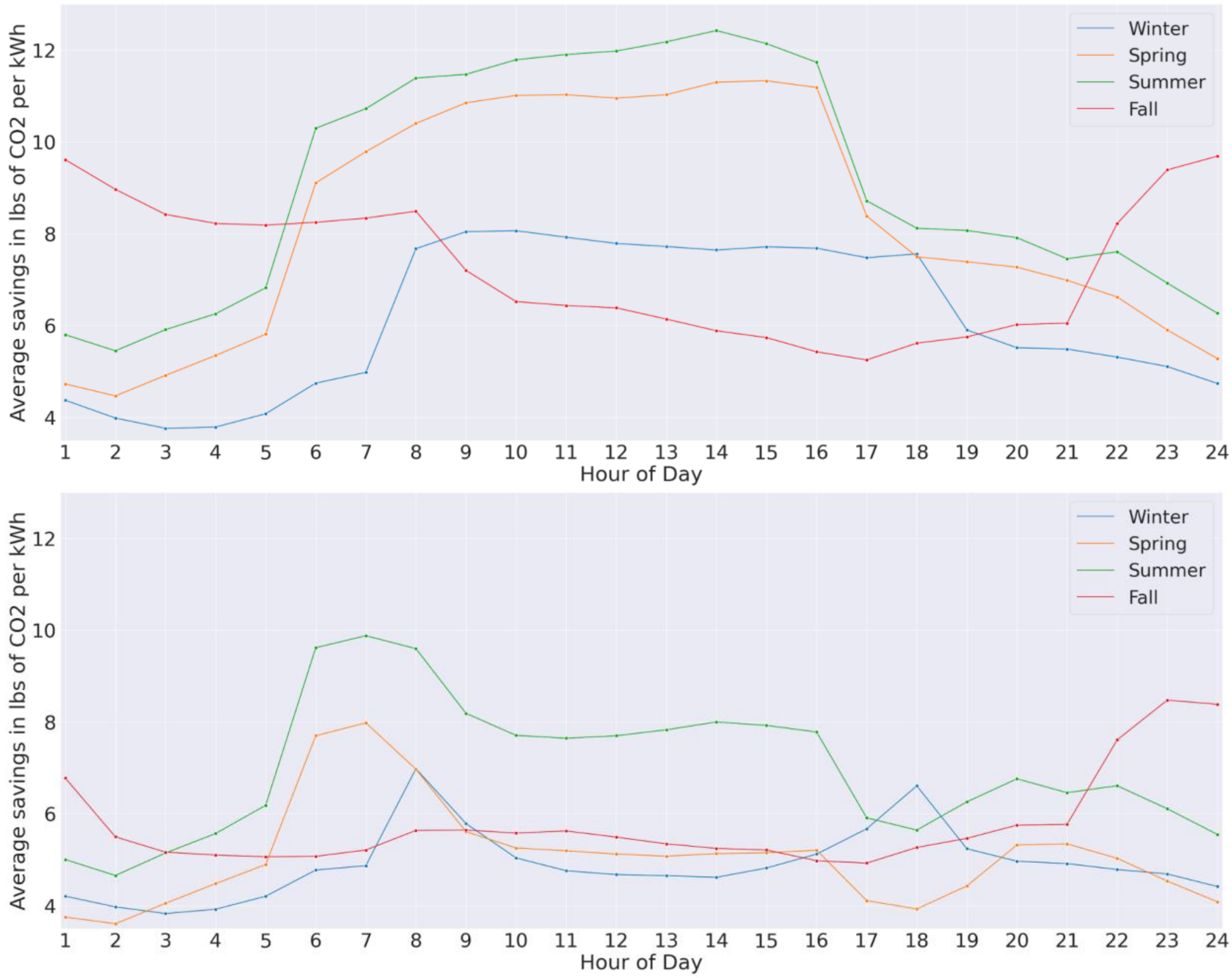



Figure 8: Top: Average hourly carbon reduction in lbs CO2 per kWh for FRCC region, Souce: Singularity. Bottom: Average hourly carbon reduction in lbs CO2 per kWh for CAMX region, Source: Singularity.

Table 5 summarizes the total estimated annual GHG reduction for the example project, using different datasets/tools and the variation in total emissions reduction compared to a single eGrid total average emissions factor. It is crucial to acknowledge that, as demonstrated in the table, marginal emissions factors are likely to be generally higher than their average counterparts.

Table 5: Total estimated annual GHG reduction for the example project using different datasets/tools

| | **CAMX Region** | | **FRCC Region** | |
|---|---|---|---|---|
| | GHG Reduction | Compared to eGrid (average) | GHG Reduction | Compared to eGrid (average) |
| eGrid (average) | 52,271 | 100% | 81,901 | 100% |

| | | | | |
|---|---|---|---|---|
| eGrid (non-baseload) | 103,164 | 197% | 100,113 | 122% |
| Average hourly (Singularity) | 49,653 | 95% | 68,081 | 84% |
| Marginal hourly (WattTime) | 75,269 | 143% | n/a | n/a |
| AVERT | 52,280 | 99% | 105,576 | 128% |
| Cambium (2022 Mid-Case) | 92,795 | 177% | 121,043 | 147% |

We observe in both regions, the Singularity average emission factor is closest (-5%/-16%) to the eGrid average while the estimates from Cambium (+77%/+47%) and eGrid non-baseload (+97%/+22%) are the farthest away.

## 6. Projecting future scenarios

As shown in Table 5 above, Cambium's 2022 mid-case scenario produced an estimate of 92,795 lbs $CO_2$ reduction annually for the example project data in the CAMX region. Figure 9 below illustrates changes in emission reductions for future years in the Cambium dataset for two different regions, using savings profiles from the example project in Section 5. We observe a relatively constant carbon reduction in the CAMX region in the future. For the FRCC region, we observe a large reduction in the amount of carbon reduced between 2022 and 2028, and then it is relatively stable until 2046. These kinds of projections are useful to illustrate how energy efficiency project impacts can vary in the future in different regions based on different grid decarbonization strategies.

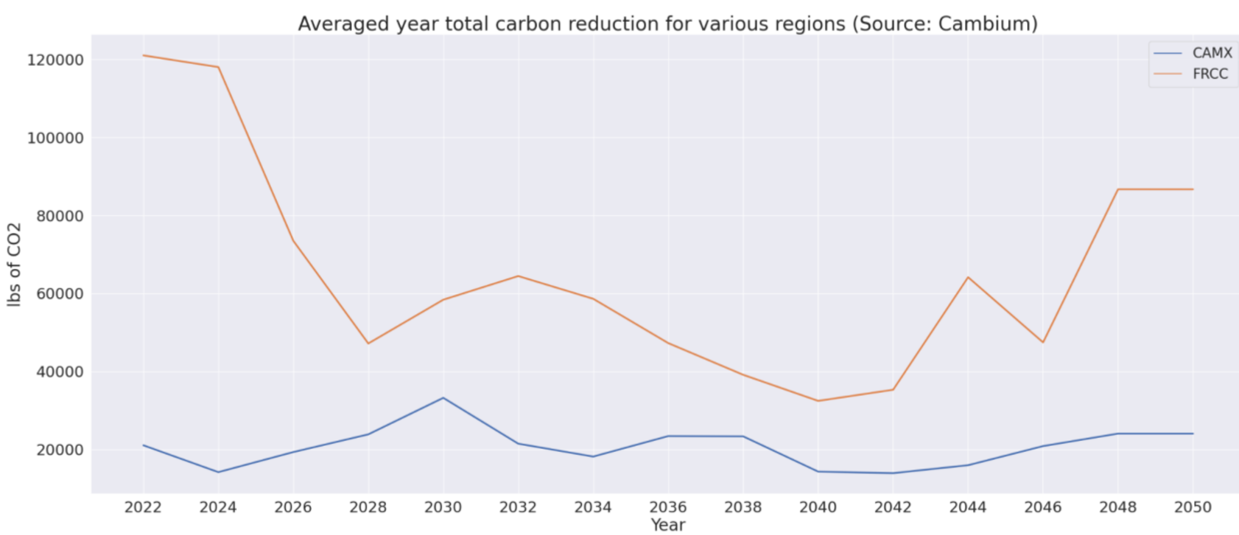



Figure 9: Projected carbon reduction for CAMX and FRCC regions for a hypothetical energy efficiency project

## 7. Discussion and Conclusion

There is a growing interest in quantifying GHG emissions impacts of EE projects. However, the commercial buildings market industry is still getting to grips with GHG emissions accounting norms using annual electricity consumption data and eGrid average emission factors. Moving to the broad scale use of hourly emission factors is a long way off business-as-usual, but goals for achieving 24/7 carbon-free electricity should drive more interest in this area.

The growing adoption of advanced M&V using interval data along with newer datasets/tools provides a useful data input to calculate the GHG emissions impact from EE projects. This paper sheds light on some of the advantages and challenges in hourly reporting of emissions concerned with an M&V use case. While all the tools have a similar fundamental data source (CAMPD data), their methodologies on estimating emission factors from that data are different, resulting in different carbon reduction estimates. Hourly emission factors can help understand temporal decarbonization impacts of EE projects, for instance an EE project in one region can have a different carbon reduction during the same hours in another region. This time-varying electricity emission factor, offers an opportunity to better understand the impacts of energy efficiency relative to the regional grid generation mix, and to better inform decision making around energy efficiency. As the observed marginal emission factors are generally higher, they can increase CO2 reduction estimates when compared with average emission factors. This increase creates a disconnect with CO2 footprint calculations using average emission factors.

The use of average emission factors from Singularity, that is freely available, tracks the grid emissions more closely to real time as compared to an eGrid annual emission factor. In addition, the Singularity estimates show the closest alignment (-5%/-16%) to the eGrid average and may therefore be the most appropriate for use in hourly emission reduction estimates. The Cambium projections of emission factors are useful to illustrate how energy efficiency project impacts can vary in the future and do factor in various grid decarbonization scenarios through the different scenarios. AVERT was not seen to perform well in a sensitivity analysis and is not specifically suited for project level M&V.

The findings provide insight to building owners, researchers and M&V practitioners on the temporal GHG impacts of savings from EE projects, and how it complements the annual reporting paradigm. Key insights include:

- Temporal Variability: Emissions factors vary by time and location; thus, using time-varying factors provides a more accurate reflection of the GHG benefits of EE projects.
- Tools and Methods: The analysis highlights the differences between tools and their suitability for various types of assessments, emphasizing the importance of selecting the right tool for the assessment.
- Regional Differences: Understanding regional and seasonal differences is crucial for accurate GHG calculations, as evidenced by the variations in emission factors across different regions.
- Sensitivity and Projections: Sensitivity analysis and future projections help in understanding the potential impact of EE projects over time, guiding more informed decision-making.

By following these recommendations, organizations can enhance the accuracy and reliability of their GHG impact assessments for EE projects. This could potentially accelerate the adoption of EE measures to meet decarbonization goals when they are better matched to high-emission periods.

## References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