

Choosing the Best Carbon Factor for the Job: Exploring Available Carbon Emissions Factors and the Impact of Factor Selection

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ABSTRACT

Over 600 local governments in the United States, including nearly half of the largest 100 cities, have enacted climate action plans that include carbon reduction goals and greenhouse gas inventories (Markolf et al. 2020). The magnitude of these goals ranges from modest reduction targets to carbon neutrality. None will be met without significant contributions from the buildings sector. Understanding how energy efficiency and building electrification impact greenhouse gas emissions requires local, time-sensitive, and forward-looking carbon emissions factors for electricity use in buildings. There are a variety of emissions factors currently available from various sources, including average emissions factors and historical short-run marginal emissions factors. Long-run marginal emissions factors and future-year short-run marginal emissions factors are also now available from the National Renewable Energy Laboratory's (NREL's) Cambium data sets. In this paper, we describe the different carbon emissions factors available, including both conventional sources and newly available options. We discuss the types of analyses each emissions factor is best suited to support. Then, using residential energy efficiency and electrification load profiles, we demonstrate how different conclusions result from different choices of carbon emissions factors. For two grid regions, we explore takeaways of using current versus future-year emissions, short-run versus long-run, and levelized versus single-year values. We include a framework for selecting the best carbon emissions factor for the job.

Background and Motivation

As cities, states, and other local governments continue to set carbon reduction targets, the buildings sector is tasked with playing its part in decarbonization efforts. Architects, engineers, planners, and building operators need appropriate tools to understand the impact their choices have on buildings' carbon footprints. One of the key tools in this effort is carbon emissions factors that describe the carbon impact resulting from energy consumed or avoided. There are many such carbon factors available, each appropriate for guiding different types of decisions.

Some work has been done to consider which emissions factors are best suited to a variety of applications (Gagnon and Cole 2022). However, no recent published work has quantitatively evaluated the different results that come from using different emissions factors in buildings sector work, thereby articulating the impact of emissions factor selection.

Currently, many analyses use retrospective annual emissions factors without strong consideration of alternatives. Our goal with this paper is to highlight the strengths and limitations of the various emissions factors available for the quantitative analysis of operational¹ carbon emissions, to support informed factor selection, and to discuss what types of analyses are best supported by the different factors.

Emissions Factors for Electricity

In this paper we focus on three different types of factors that are available to represent the emissions associated with electricity consumption. These emissions factors are of two varieties: average emissions factors, which are *attributional* (i.e., descriptive, describing the state of the grid and allocating responsibility for emissions) or marginal emissions factors, which are *consequential* (i.e., estimating the emissions that are induced or avoided by an action to add, remove, or change electric load) (Brander 2021).

Average Electric Emissions Factors

Average emissions factors or average emissions rates (AER) describe the average emission rate across all electricity on the grid within a specific region and time period, from all sources. They are *attributional*, assigning equal responsibility for electricity sector emissions to each unit of electric load. They generally are created by summing up all emissions from every generator that is running during a specified time period, and then dividing that number by the total electricity generated (or in some cases, consumed). AERs can be calculated retrospectively from empirical data, or forecast for future grid conditions, and can be calculated for any time period (e.g., annual, hourly).

Common sources for average emissions factors include the U.S. Environmental Protection Agency's (EPA's) Emissions & Generation Resource Integrated Database (eGRID), U.S. Energy Information Administration (EIA) data, and NREL's Cambium.

Marginal Electric Emissions Factors

Marginal emissions factors describe the change in emissions that would result from a change in electric load. They are *consequential*, describing the change in emissions on the margin of generation, as a consequence of an action that changes load.

Short-run marginal emissions factors. Short-run marginal emission factors or short-run marginal emissions rates (SRMER) describe changes in emissions that would result from a change in electric load assuming the structure of the grid (i.e., capital assets such as generators and transmission lines) is fixed. SRMERs reflect how an intervention would influence emissions from a given grid in the short-term, generally by assessing which generator or type of generator would be dispatched “on the margin” (i.e., increase or decrease output in response to a change in load) for a given fleet at a given time, and calculating emissions based on the emissions characteristics of that type of generator. They assume that the change in load will not influence the capital asset decision-making of local resource planners. SRMERs are often available in

¹ This paper addresses operational carbon, as opposed to embodied carbon. Elsewhere we discuss operational decision-making, as opposed to capital decision-making, both of which are part of operational carbon accounting.

timeseries (e.g., hourly) format and in some cases are estimated in real-time with the intent to inform operational decision-making.

Common sources for hourly SRMERs include EPA's AVOIDed Emissions and geneRATION Tool (AVERT), WattTime, Resurty, Electricity Map, and NREL's Cambium. The Carnegie Mellon Center for Climate and Energy Decision Making has a Marginal Emissions Factors Repository (Azevedo et al. 2020) that has SRMERs at month-hour resolution. Lastly, EPA eGRID data includes annual "non-baseload" emissions rates, which can be thought of as an annual SRMER.

Long-run marginal emissions factors. Long-run marginal emissions factors or long-run marginal emissions rates (LRMER) describe the change in emissions from a change in electric load taking into consideration how a change in electric load could influence the structure of the grid (e.g., adding load during daylight hours could induce more solar generators to be built) (Hawkes 2014). LRMERs can be calculated with power sector capacity expansion models, which can be used to project how, if at all, the structure of the grid could change in response to a change in electric load.²

A long-run factor can be significantly different than a short-run factor. In the United States, short-run factors are generally dominated by natural gas and coal, whereas the ability of long-run factors to incorporate structural change means that long-run factors can reflect the ongoing deployment of wind and solar generators. Long-run factors are about 50% lower than short-run factors on average for the contiguous United States (Gagnon et al. 2021)

When is it no longer marginal?

Marginal emissions factors are calculated for infinitesimal or incremental changes in load (e.g., the Cambium LRMER is calculated by perturbing total electricity demand by 5%). Therefore, the factors will tend to be less accurate for loads that are significantly greater than what was used to create the factors. The carbon impact of either halving or doubling the electric load in a county, for example, is not going to be well-represented using marginal carbon emissions factors.

The point at which an intervention is too large to apply a marginal factor to depends on many factors, and has not been rigorously studied to our knowledge. As one point of reference, however, AVERT advises to keep load changes under 15% of the fossil generation in any given hour ((U.S. EPA 2021) p. 29).

Other Dimensions

Time resolution. Both average and marginal emissions factors are most commonly available as either a single annual factor, or as a list of 8,760 (or 8,784 if a leap year) hourly factors representing a year. Annual factors are more convenient and easier to use. Hourly factors, however, show carbon emissions' sensitivity to the timing of load changes, both on a daily and seasonal scale, and therefore are particularly important for analysis of demand flexibility, including grid-interactive efficient building technologies. Using hourly factors is less convenient,

² Notably, a LRMER does not *necessarily* include structural change—if a change in load would not induce structural changes in the grid, then a properly calculated LRMER would likewise not include structural change, and the SRMER and LRMER would be equivalent. This is not common in practice, as the grid is constantly evolving, and therefore most demand changes can influence how much and what is built.

as it requires working with timeseries load change estimates or data, and can over-magnify the impact of small errors or limitations.

Other time resolutions are also becoming available. For example, in its 2021 release, Cambium includes month-hour aggregations, which are 24-hour hourly profiles for each month, and year-hour aggregations, which are 24-hour hourly profiles for a year. These options may preserve the daily trend in carbon emissions, and, in the former case, the general seasonal trend as well, allowing for easier application with less concern for mismatched weather data, and with less computational intensity. However, some precision will necessarily be lost if, e.g., a 95°F summer midday hour and an 80°F summer midday hour are averaged together.

Geographic resolution. Emissions factors are available at varying geographic resolutions; some sources make multiple geographic resolutions available. Decisions about geographic resolution balance the desire for precision against the limitations of factor calculation methodologies. Using a fine geographic resolution can capture important nuance: for example, within New York State, the eGRID emissions factor for Upstate New York is around 1/6 of the factor for Long Island, because Upstate includes substantial hydroelectric power. Conversely, the use of finer geographic resolution can raise challenges related to properly attributing induced emissions, particularly when using long-run factors that project structural change. It's common to see emissions factors that break the contiguous United States into approximately 20–30 regions that reflect the administrative entities that plan and operate the electric grid.

Emissions factor weather year. Aligning the weather year of the analysis with the weather data underpinning the carbon emission factors ensures that both the electric generation and building load are responding to the same weather. If the hourly building electric savings shapes reflect weather with a blisteringly hot 1 p.m. on July 1, electric load is going to be very high due to air conditioner usage. If the weather used to create the emissions factors has complete cloud coverage and a thunderstorm that same hour, photovoltaic (PV) generation is going to be very low. In reality, peak summer electric load hours tend to coincide with hours of high PV generation. This correlation, and many other similar correlations between generation and load caused by both experiencing the same weather, will only be represented when both are modeled or otherwise arrived at using the same weather.

Typical meteorological year (TMY) data historically used in building energy modeling uses representative months from past years to build a typical year whose statistical weather metrics match statistical weather metrics over the historical time window of 30 years. The primary issue with using TMY to calculate load shapes is that none of the available carbon emissions factors are constructed using TMY weather. A secondary issue is that if load savings shapes are aggregated across multiple weather stations, the weather at one TMY location may be completely independent of weather in nearby locations. For instance, one city could be experiencing a heat wave and the next city over could be experiencing an unseasonably cold and rainy day.

We did not directly evaluate the significance of weather alignment in this analysis.

Emissions factor grid year(s). In addition to weather, the makeup of electricity generation in a given year has a significant effect on carbon emissions, especially because the generation mix is changing quickly. Tools like AVERT and eGRID represent the grid as it was in the past few years, but it is likely to be very different in the future. NREL uses its Regional Energy Deployment System (ReEDS) and Distributed Generation Market Demand Model (dGen)

capacity expansion models to generate potential future scenarios for the electric grid—the NREL Standard Scenarios—and these underlie the Cambium data. The future of the grid and the rate of change are uncertain. By using factors from a range of scenarios, we can understand the sensitivity of results to this uncertainty.

Energy efficiency and electrification measures have multi-year lifetimes; thus, it is appropriate to use multiple years of future emissions factors that correspond to the expected lifetime of the measure. The multiple years of factors can be simply averaged, or they can be levelized using a discount rate to put greater weight on near-term years than years further out. NREL provides a workbook to assist with the levelization of Cambium long-run marginal emission rates (Gagnon et al. 2022).

Our Approach to Emissions Factor Selection

NREL’s Residential Buildings Research Group has been monitoring the work of various standards-making bodies, as well as working closely with NREL’s Economics and Forecasting Group, which produces the Cambium data sets, to develop best practices around carbon emissions factor selection for various applications. This is an iterative process that we expect will continue for the next several years. Here we share our current collective understanding to provide a jumping-off point for further discussion.

Our Current Approach

We use **AER for inventory-type work**. For example, we would use AER to calculate the percentage of total carbon emissions that can be attributed to the existing residential buildings sector.

We use **LRMER for most other purposes**, including assessing the carbon emissions impact of any change in electric demand from load changes that are long-lived and expected, levelized³ over the lifetime of the intervention. For example, we use LRMER to evaluate the carbon impacts of:

- Weatherization
- New building construction
- Heat pump adoption
- Electric vehicle adoption
- Installation of lighting occupancy controls
- Establishing a new demand response program.

These load changes are typically part of anticipated trends or otherwise incorporated into a utility’s forecasts, and their influence on the structure of the grid can therefore be reasonably assumed to be timed to their appearance.

Other Cases

We plan to use a **time-averaged SRMER-LRMER blend for long-lasting electric load changes that are not in utilities’ forecasts**, though we have not yet had reason to do so in our

³ In this analysis, levelization uses a 3.4% discount rate.

work. We would do this by averaging or levelizing SRMER for the first 3 years⁴ and LRMER for the remainder of the lifetime.⁵ This is because the load change would first influence the grid as it exists initially (i.e., a SRMER is more suitable), but over time the load change would be observed and incorporated into ongoing capital asset decision-making (making a LRMER more suitable in later years).

We are **still developing our approach for transient, short-lived decisions, including operational decisions that are not part of a longer-term operational pattern**. Using a SRMER reflects the near-term emissions impact and may be appropriate to use alone in some instances—for example, in evaluating utility-controlled energy storage, when grid planners are aware of the controllable nature of the load and know not to factor it into later capital-asset decision-making. Transient building-load dispatch decisions, however, will result in loads that grid planners presume the grid must meet in the future; their timing and magnitude may therefore influence the future of the grid, making a component that represents that future structural change warranted in the analysis of their carbon emissions. We are not aware of an appropriate emissions factor for this purpose at the present time, and so our plan is to use LRMER or SRMER, or potentially a time-averaged blend, based on the specific circumstances of the work.

Additional Limitations of This Approach

There are additional limitations to this current emissions factor selection framework. Many electric-sector reporting frameworks, such as scope 2 emissions accounting, call for AER, an attributional approach. This creates a potential disconnect: if we prioritize measures using LRMER (i.e., consequentialist analytical framework) to estimate their impacts, the results of the prioritized measures are not necessarily allocated to those measures under an attributional reporting framework.

Emissions Factor Comparison Methodology

This discussion of appropriate emissions factor selection leads to the question of how important emissions factor selection is. We used a variety of emission factors to calculate carbon emissions impacts from 10 energy measures in two states to foster a quantitative understanding of the impact of selecting an inappropriate emissions factor for the task.

Load Changes

We created measure impact load profiles using the DOE/NREL ResStock™ tool (Wilson et al. 2017). ResStock models the residential building stock of the United States, with approximately one model run for every 200 homes in the country to portray the diversity in the U.S. housing stock. The development team recently completed extensive refinement of the building characteristics used in the tool through the End-Use Load Profiles (EULP) project (NREL 2021), (Wilson et al. 2022), which included calibration against a wide range of data sets, such as the EIA's Residential Energy Consumption Survey (RECS) and utility advanced

⁴ We use “3 years” in this section to represent the time for load changes to start having an impact on the grid through the actions of local resource planners. This depends on local conditions but is generally in the 3- to 5-year range.

⁵ We would use a social discount rate to weight near-term emissions more heavily than emissions in later years. For example, a 20-year intervention would place a weight of 0.19 on the SRMER with a 3% social discount rate, or a 0.15 weight using a simple average.

metering infrastructure (AMI) data. The modeling for this paper used the ResStock tool with all EULP refinements. All single-family detached homes with year-round occupancy were included.

We selected 10 varied upgrade measures to show a range of load changes including positive and negative load changes, different impacts in times of day (“shapes”), and different magnitudes. In general, they are aggressive measures in terms of the efficiency levels targeted coupled with the number of homes eligible for the upgrade, in order to accentuate differences between savings shapes. Table 1 shows information about these 10 measures.

Table 1: Energy Measure Descriptions⁶

1. All LEDs	Assumed Lifetime: 30 yrs	Modeled Homes Eligible: 65%
<i>Description:</i> 100% LED lighting		
<i>Applies to:</i> Homes with any less-efficient lighting		
2. Storm Windows (low-E)	Assumed Lifetime: 30 yrs	Modeled Homes Eligible: 79%
<i>Description:</i> Low-e exterior storm windows and resulting improved air sealing		
- 15% ACH50 reduction for adding low-E storm windows where they weren't before		
- 10% ACH50 reduction for low-E storm windows replacing clear storms		
<i>Applies to:</i> Homes with the following window types:		
- Single, Clear, Metal - Single, Clear, Metal, Exterior Clear Storm		
- Single, Clear, Non-Metal - Single, Clear, Non-Metal, Exterior Clear Storm		
- Double, Clear, Metal, Air		
3. Exterior Wall Insulation	Assumed Lifetime: 30 yrs	Modeled Homes Eligible: 91%
<i>Description:</i> 1" polyiso continuous insulation, R-6.5, 19% whole home reduction in ACH50		
<i>Applies to:</i> All homes with <R-19 wall insulation		
4. High Efficiency Appliances	Assumed Lifetime: 8 yrs	Modeled Homes Eligible: 99.96%
<i>Description:</i> Refrigerators EF 21.9; Dishwashers 144 kWh; Clothes Washers ENERGY STAR® Most Efficient; Clothes Dryers Electric Heat Pump, Ventless		
<i>Applies to:</i> Homes with lower-efficiency appliances ⁷		
5. Good Air Source Heat Pump (ASHP)	Assumed Lifetime: 15 yrs	Modeled Homes Eligible: 79%
<i>Description:</i> SEER 16, 9.0 HSPF, 0°F min. compressor temperature		
<i>Applies to:</i> Homes with centrally ducted heating or cooling (includes homes with no AC and any space heating fuel)		
6. Better ASHP	Assumed Lifetime: 15 yrs	Modeled Homes Eligible: 79%
<i>Description:</i> SEER 22, 10 HSPF, 0°F min. compressor temperature		
<i>Applies to:</i> Homes with centrally ducted heating or cooling (includes homes with no AC and any space heating fuel)		
7. Best ASHP	Assumed Lifetime: 15 yrs	Modeled Homes Eligible: 79%
<i>Description:</i> SEER 29.3, 14 HSPF, 50% capacity retention at -15°F		
<i>Applies to:</i> Homes with centrally ducted heating or cooling (includes homes with no AC and any space heating fuel)		
8. Better ASHP with Additional Usage of Supplemental Heat	Assumed Lifetime: 15 yrs	Modeled Homes Eligible: 79%
<i>Description:</i> SEER 22, 10 HSPF, 20°F min. compressor temperature ⁸		
<i>Applies to:</i> Homes with centrally ducted heating or cooling (includes homes with no AC and any space heating fuel)		
9. Heat Pump Water Heater (HPWH)	Assumed Lifetime: 12 yrs	Modeled Homes Eligible: 99.96%
<i>Description:</i> 80 gal, 3.45 UEF water heater		
<i>Applies to:</i> Homes with any other water heater		
10. Temperature Setbacks	Assumed Lifetime: 12 yrs	Modeled Homes Eligible: 98.74%
<i>Description:</i> Setpoint offsets increases for heating/cooling. Heating: 0–3°F, 3–6°F, 6–12°F; Cooling: 0–2°F, 2–5°F, 5–9°F		
<i>Applies to:</i> Homes configured for heating and/or cooling setpoint offsets		

⁶ For full modeling details, refer to the following files in the branch of the ResStock repository for this analysis:

https://github.com/NREL/resstock/blob/run/grid-impacts-aceee/aceee_project_file_550k_testing.yml

https://raw.githubusercontent.com/NREL/resstock/run/grid-impacts-aceee/resources/options_lookup.tsv

⁷ e.g., a home with no dishwasher in baseline had no dishwasher in the upgrade either

⁸ With a higher compressor shutoff temperature, this heat pump will use additional supplemental heating (e.g., when ambient temperatures go below 20°F, as opposed to 0°F for the Good and Better ASHP measures).

We ran these upgrade measures for the building stock in two states: Texas and Michigan, and downselected the results to include only homes in the Electric Reliability Council of Texas (Cambium) (ERCTc) and Reliability First Corporation – Michigan (Cambium) (RFCMc) Generation and Emission Assessment (GEA) regions (Gagnon et al. 2021). We then extracted hourly aggregate savings shapes for each fuel (electricity, natural gas, propane, and fuel oil), state, and upgrade. Each aggregate savings shape is computed as the average difference between site fuel consumption in that hour post-upgrade and pre-upgrade for each home that received any portion of the upgrade. We ran these measures using 2012 actual meteorological year (AMY) weather, to align with Cambium’s weather year.

Annual energy savings results are shown in Figure 1 by location, upgrade, and fuel. Figure 2 shows the hourly savings shapes for July 1.

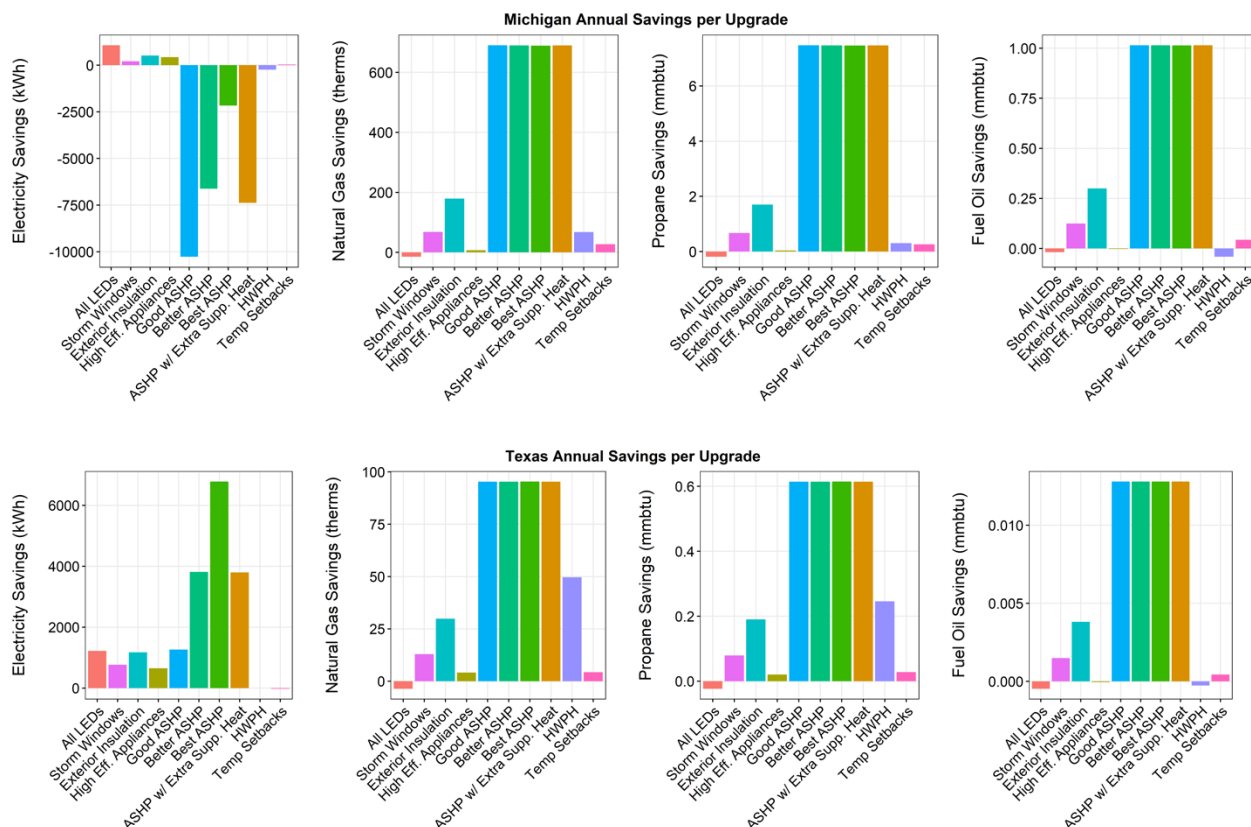


Figure 1. This figure shows the annual savings values for each fuel per location (TX and MI) and upgrade. Note that a negative value corresponds to an increase in usage from the base case. ASHP options include the addition of central AC in homes that don’t currently have AC. ASHP electricity savings in Texas are positive because they include about 50% of homes where ASHPs replaced electric resistance heating.

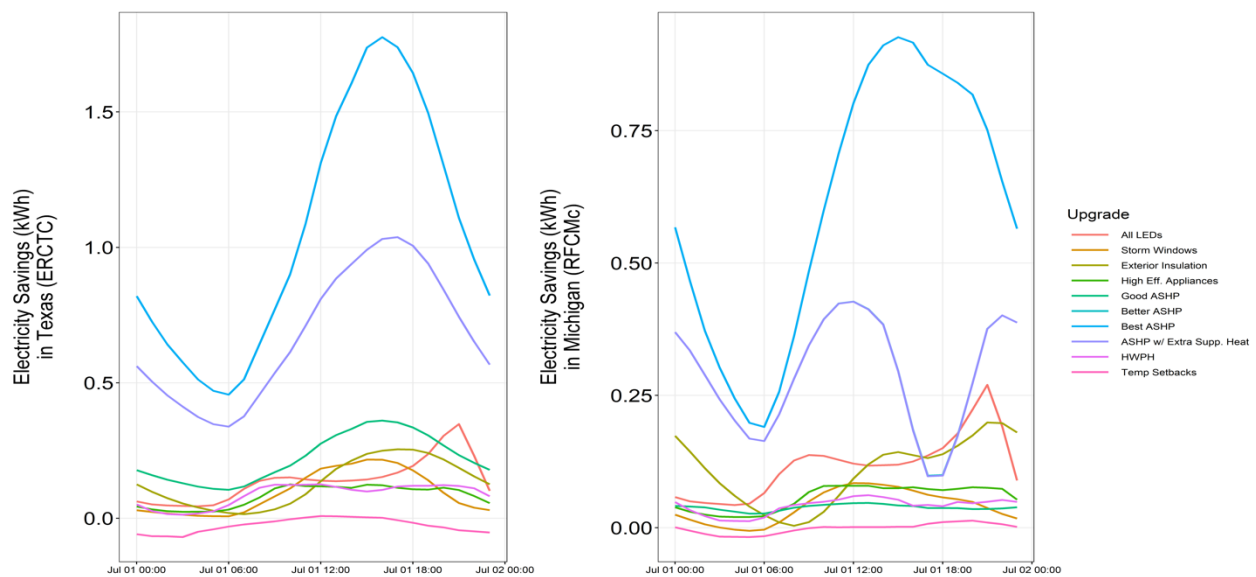


Figure 2. This figure shows hourly savings values for electricity for each upgrade in each analyzed state for July 1. The ASHP measures save electricity in Michigan on July 1 because they cool more efficiently.

Emissions Factors

For this analysis we used emissions factors from AVERT, Cambium, and eGRID, and then compared the results.

AVERT. AVERT, developed by the EPA, is an Excel-based tool that allows users to evaluate emissions impacts from energy efficiency and renewable energy changes using a variety of input options (U.S. EPA 2020a). It allows for hourly savings shapes inputs. The target audience is state-level planners. It is a SRMER tool because it does not attempt to incorporate the grid-infrastructure changes caused by an electric grid load change.

At time of analysis, 2019 and 2020 AVERT versions were available, and we used both.⁹ Because AVERT is based on real data, 2020 includes effects of COVID-19 and 2019 does not. We used only the CO₂ results, not results from other pollutants such as SO_x and NO_x.

The 2020 AVERT uses 8,784 hours of hourly data. Our outputs also had 8,784 hours of data due to the use of 2012 weather, so we were able to use them directly. For 2019 AVERT, we had to remove one day of ResStock results data. We used the Texas support files for the ERCTc (Texas) emissions analysis and the Midwest (roughly consistent with MISO) support files for the RFCMc (Michigan) emissions analysis. Our use of 2012 weather in the creation of the load change values created a mismatch between the AVERT weather year and the weather year of the energy savings data. Without the option to use the same weather year for all hourly emissions factors (i.e., Cambium and AVERT), we prioritized using the same load changes for all

⁹ An average load change per home, which is what our averaged savings shapes effectively represent, is too small for AVERT to successfully compute emissions savings. To reconcile this limitation, we used 1,000x the per-home average and then divided the annual result by 1,000 to receive a per household emission saving number. The AVERT support team approved this approach, though they were not themselves sure of its limitations. Even multiplied by 1,000, many upgrades' hourly average load changes were much smaller than 1 MW and it is not clear what sensitivities the AVERT tool has to small changes in loads.

emissions factor calculations and matching the weather year to Cambium, because it allowed for direct comparison between AER, SRMER, and LRMER, accepting the resulting limitation with regards to AVERT.

AVERT is not meant to be used for analyses more than 5 years from the data year without using the statistical model and future year scenario template, which allow the user to input custom changes to the grid that AVERT will incorporate into the analysis. AVERT does not provide preset future scenarios for use.

Cambium. Cambium, developed by NREL, is a database of hourly emissions, cost, and operational data for modeled futures of the U.S. electric sector, designed for long-term decision-making. It builds upon NREL's Standard Scenarios, which are an annually produced set of potential futures for the U.S. electric grid. The Cambium data are available at multiple time resolutions, geographic resolutions, future grid scenarios, and for even years from 2022–2050.

For this analysis we used 18 Cambium emissions factor options for each location, all from the Low RE Cost scenario from the 2021 Cambium release. These were the AER, LRMER, and SRMER, each for 2022 (single-year), 2030 (single-year), and 2030 levelized over the lifetime of the upgrade (denoted as “2030-end of life” or “2030-EOL”), for the hourly and annual time aggregations. Note that many of these combinations are *not* recommended for analysis (e.g., a single-year of LRMER; use of SRMER for efficiency measures), but are included to understand the impact of using non-recommended factors. We used the “combined” values which include both pre-combustion and combustion emissions.

Cambium uses 2012 weather data for all data years. However, it has only 8,760 values in the hourly data (omitting December 31). Accordingly, we removed December 31 data from our ResStock results. The impact of the missing day is small relative to other factors and does not change the conclusions. We used a discount rate of 3.4% in the levelization. Because 2050 is the last year of Cambium data, levelization that starts at 2030 and goes more than 20 years uses repeated 2050 values to complete the time series.

eGRID. eGRID, also developed by the EPA, is a database of environmental characteristics of nearly all electric power generated in the United States. It includes both average and “non-baseload” emissions factors with annual resolution (U.S. EPA 2020b). The “non-baseload” emissions factors are designed to represent annual SRMER.

We used annual eGRID CO₂ output emissions rates (average and non-baseload) for the RFCM and ERCT eGRID regions (similar to Cambium GEAs) along with an annual total of the 8,760 hour savings used with Cambium. The missing 24 hours relative to AVERT results is small relative to other factors and does not change the conclusions.

Emissions factors for on-site fuel use. To represent the carbon impacts of each measure, we accounted for carbon impacts of both changes in electricity consumption and changes in the consumption of other fuels: natural gas, propane, and fuel oil. We used the same values from EIA (U.S. EIA 2021) for every location and scenario. These are 53.07 kg CO₂/MMBtu for natural gas, 63.07 kg CO₂/MMBtu for propane, and 73.16 kg CO₂/MMBtu for distillate fuel oil.

CO₂ vs CO₂ Equivalent

AVERT offers CO₂ while eGRID and Cambium offer both CO₂ and CO₂e, so we used CO₂ values from all three emissions factor sources. The non-electric emissions factors we used

are also in CO₂. However, the difference between CO₂ and CO_{2e} for electricity is insignificant for this analysis. For Cambium, the difference between CO₂ and CO_{2e} is around half a percent. For eGRID it is as high as 1%. This analysis does not include the effects of fugitive methane emissions for on-site fuel use, which can make the CO_{2e} rate for on-site fuel use 20%–50% higher than the CO₂ rate (Pistochini et al. 2022).

Results of Emissions Factor Comparison

Total Avoided Carbon

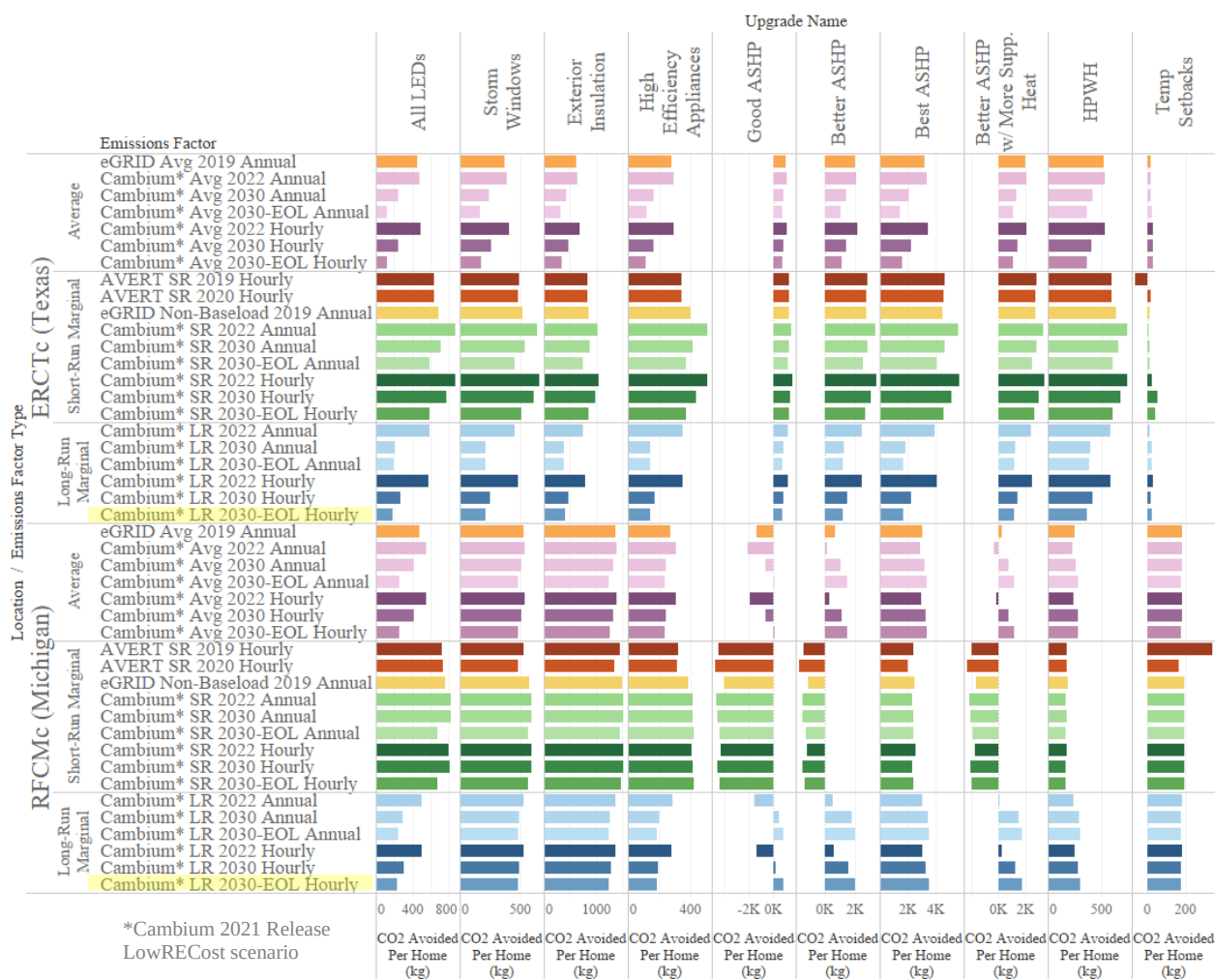


Figure 3. Comparison of average per-home carbon emissions reductions (accounting for all fuels) using different electric grid emissions factors for 10 energy measures modeled using 2012 weather. The choice of emissions factor has a significant impact on the results, and for Michigan in particular, can determine whether a heat pump causes an apparent increase or decrease in carbon emissions. The most appropriate factor for energy efficiency measures is highlighted, based on the framework described above and assuming a 2030 implementation date (LRMER 2030–EOL Hourly). (Note: x-axis scales are independent for each upgrade.)

Avoided Carbon per Unit of Energy Reduction

Figure 4 shows the 10 measures' carbon savings normalized by their energy savings. This type of calculation can inform carbon-focused prioritization of efforts that have the same energy impact.

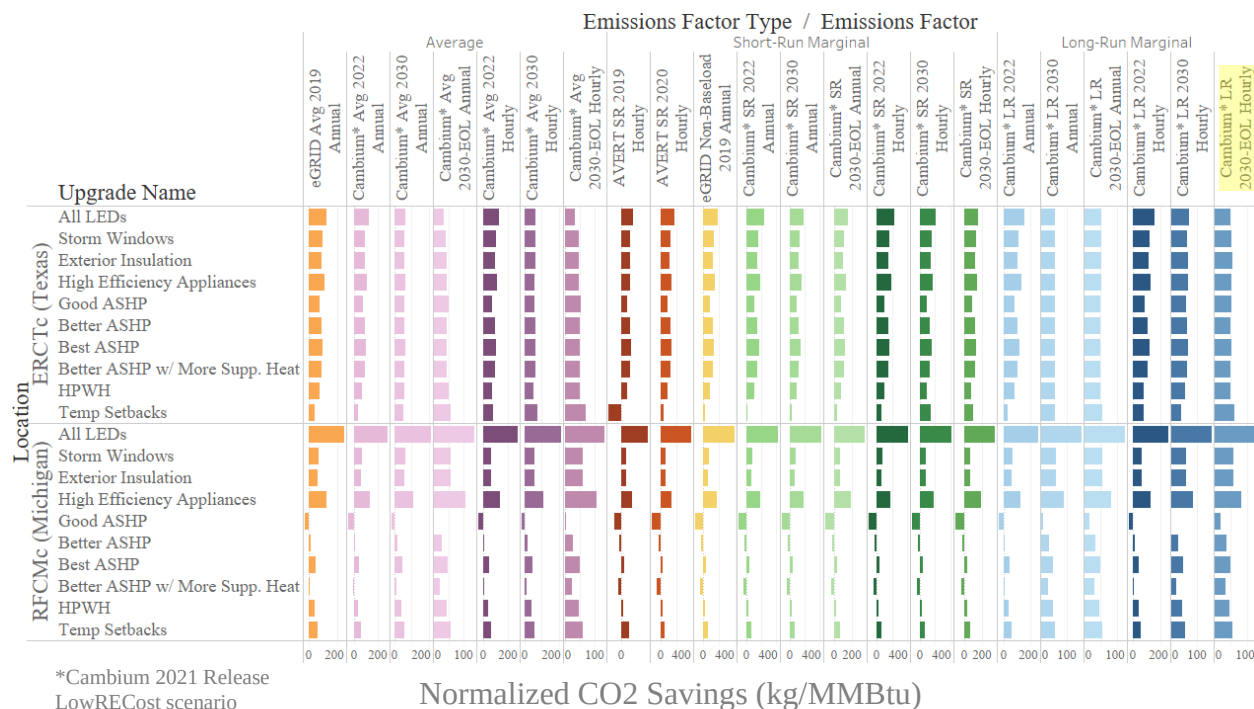


Figure 4. Comparison of carbon emissions reductions **normalized per unit of site energy saved** (accounting for all fuels) for 10 measures, using different electric grid emissions factors. In Michigan, measures that impact predominantly electricity (e.g., All LEDs, High Efficiency Appliances) have higher normalized reductions than measures that save a mix of electricity and other fuels (e.g., Storm Windows). This effect is not seen in Texas because (1) Texas has a higher fraction of homes that heat with electricity as compared to Michigan; and (2) electricity in Texas generally has lower carbon intensity than in Michigan. (Note: x-axis scales are independent for each emissions factor.)

Figure 5 shows total carbon savings from electric load changes only, normalized by the change in electric load, for the hourly carbon emissions factors. The corresponding annual emissions factor is shown as a beige line (e.g., Cambium SR 2022 annual for Cambium SR 2022 hourly, with eGRID non-baseload used for the AVERT values). For “2030-EOL” factors, the beige line can differ between measures because the lifetimes, and thus levelization periods, are different. This figure shows how well the timing of the electricity savings is aligned with the timing of the fluctuations in the emissions factor, creating an effective annual carbon emissions factor.

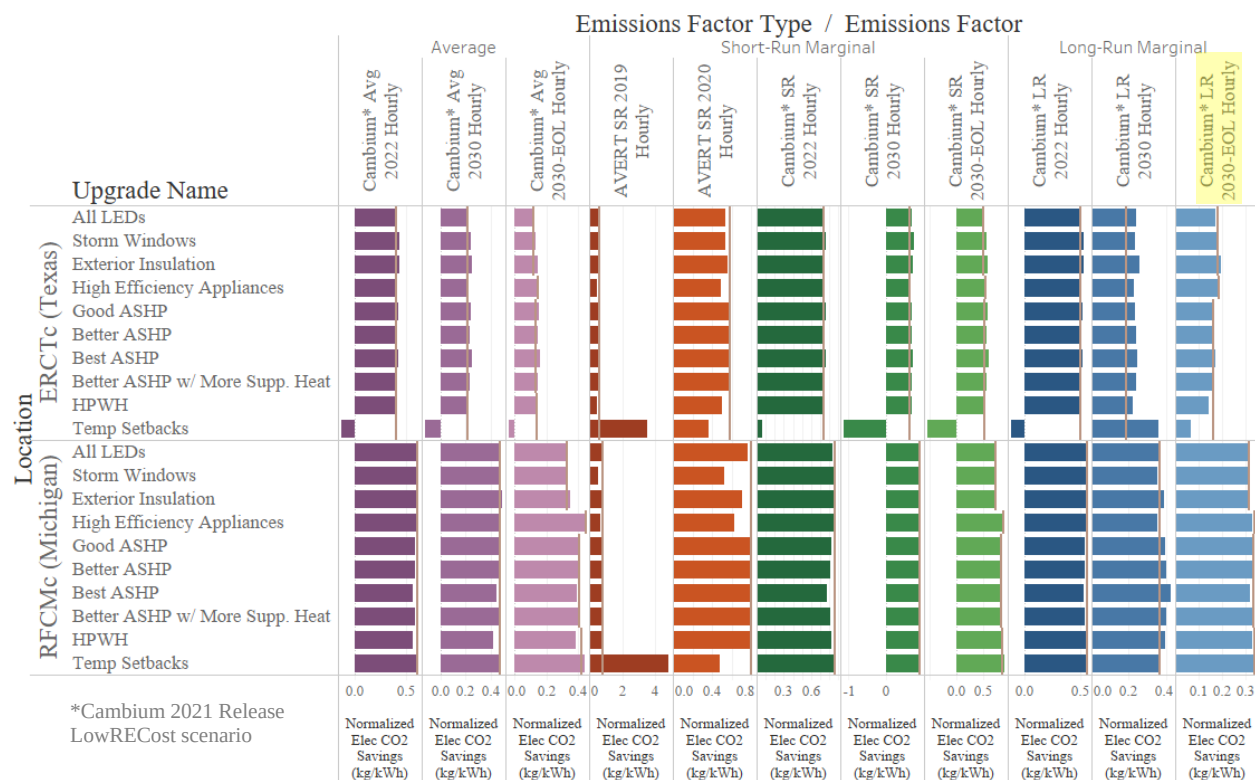


Figure 5. Comparison of carbon emissions reductions **from changes in electric load normalized per unit of electricity saved** for 10 measures, using different hourly electric grid emissions factors. The corresponding annual grid emissions factor is shown as a beige line (e.g., Cambium SR 2022 Annual is shown on the same axis as Cambium SR 2022 Hourly; note: eGRID non-baseload is used for AVERT). The lifetime aggregations vary with the lifetime of the upgrade per Table 1. This figure shows the impact of the **timing of each measure’s electricity load profile** on carbon emissions reductions. In general, the choice of emissions factor is more significant than the difference between measures. This suggests that using full-year hourly (8,760) emissions factors may be less necessary than previously thought, at least for energy efficiency and electrification measures where use of long-run marginal factors is suggested. The exception is our temperature setbacks measure, which has times of increased energy consumption (i.e., recovery periods) as well as times of energy savings, resulting in much greater differences between the results when using annual versus hourly factors than with any of the other measures. (Note: x-axis scales are independent for each emissions factor.)

Discussion

One major finding of this analysis is that there are very different conclusions depending on which set of carbon emissions factors is used. For example, we see over a factor of 7 difference in emissions reductions for the “All LEDs” measure depending on the emissions factor used. We also see changes in whether a measure increases or decreases carbon emissions. The “Better ASHP” measure provides all homes with ducted heating or cooling with a SEER 22, 10 HSPF ASHP and electric resistance backup heat, removing any on-site fuel usage for heating and the accompanying carbon emissions but increasing the electricity usage for heating and in some cases adding a new electric cooling load if the home did not already have air conditioning. In Michigan, the increase in carbon emissions due to this increased electricity consumption is greater than the carbon emissions avoided by the removal of on-site fuel use for heating when using any of the LRMERs or AERs in our analysis – but using any of the SRMERs, the measure

is shown to increase carbon emissions. Choosing a present-day versus a future LRMER has the same impact for “Good ASHP” in Michigan —emissions decrease using any metric for “Best ASHP.”

Table 2**Error! Reference source not found.** shows the maximum avoided emissions of the different emissions factor approaches as a percentage of the minimum avoided emissions by location and upgrade. This quantifies the range of emissions savings that can be predicted depending on which factors are chosen. The choice of emissions factors therefore has a very large impact on emissions savings—up to 735% in the case of All LEDs. Each one represents different metrics (average, LRMER, SRMER) and methodologies. Even using the same methodology and different target years can yield widely varying results. For instance, when comparing Cambium’s LR 2030 vs LR 2022 for High Efficiency Appliances in ERCT, the average carbon emissions reduction varies by a factor of 100% (346 vs 173 kg/home/year). Therefore, it is important to be intentional when choosing an appropriate carbon emissions metric and methodology because the magnitude of the impact of that choice can be as large or larger than the predicted energy savings.

Table 2. Maximum Avoided Emissions as a Percentage of Minimum Avoided Emissions by Location and Upgrade

Location	Upgrade Name									Temp Setbacks
	All LEDs	Storm Windows	Exterior Insulation	High Efficiency Appliances	Good ASHP	Better ASHP	Best ASHP	Better ASHP w/ More Supp. Heat	HPWH	
ERCTc (Texas)	735%	398%	337%	432%	210%	320%	389%	319%	205%	-75%
RFCMc (Michigan)	347%	124%	123%	230%	-18%	-121%	176%	-78%	178%	209%

For some measures the energy savings and its interaction with emissions is so pronounced that decisions are clear regardless of what emissions factor is chosen. For instance, if a manufacturer or technology accelerator wanted to see whether HPWHs would have greater avoided carbon emissions in Texas or Michigan, the answer is independent of which metric is selected—HPWHs have greater impact in Texas, where they are largely replacing less efficient electric water heating, than in Michigan, where they are largely replacing water heaters using fuels other than electricity. Likewise, temperature setbacks and insulation, as modeled, have a much larger carbon emissions reduction in Michigan, where heating loads are much higher than in Texas.

Another useful way to utilize these results is to look at the normalized avoided carbon emissions—the amount of carbon emissions avoided per unit of energy saved. These can be used for prioritization of energy efforts through a carbon lens. When prioritizing which of several measures to focus on sooner, for the same expected energy (or electricity) savings, decision makers may wish to prioritize those that will lead to higher carbon impact. The grid is expected to undergo substantial transition in the next 20 years, and these sorts of prioritization efforts allow buildings to play a more impactful role in that transition.

One insight from Figure 5 is that for most measures, when using a lifetime-levelized LRMER as is suggested for all efficiency and electrification measures, it appears that using an *annual* LRMER value is a reasonable approximation—the differences in results between annual and hourly factors is very small. However, this may not be the case in other regions, or for short-lived, operational interventions.

Conclusions

In this paper, we describe several of the available sources for carbon emissions factors, describe our approach to selecting the right emissions factor for the job, and demonstrate the significance of choice of factor by evaluating the emission reductions of 10 energy efficiency and electrification measures in two grid regions using a subset of the available emissions factors. We find that the conclusions drawn from an analysis can vary substantially based on the emissions factors used, and that it is therefore critical that emissions factors are intentionally chosen to be representative of the conditions being studied. For the two grid regions, we find that the emissions factor type (AER, SRMER, or LRMER) and year have more overall impact on the results than the source of the emissions factor or the time aggregation (hourly vs annual). For the buildings sector, our team uses average emissions factors for inventories, long-run marginal emissions factors for capital decisions such as efficiency and electrification measures, and, depending on the specifics, short-run marginal emissions factors, long-run marginal emissions factors, or a blend, for operational decisions such as real-time dispatch of demand response.

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