



Cambium 2023 Scenario Descriptions and Documentation

Pieter Gagnon, Pedro Andres Sanchez Perez, Kodi Obika, Marty Schwarz, James Morris, Jianli Gu, and Jordan Eisenman

National Renewable Energy Laboratory

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NREL/TP-6A40-88507
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List of Abbreviations and Acronyms

AC	alternating current
AEO	Annual Energy Outlook
ATB	Annual Technology Baseline
BA	balancing area
BECCS	bioenergy with carbon capture and storage
CARB	California Air Resources Board
CCS	carbon capture and storage
CES	clean energy standard(s)
CO _{2e}	carbon dioxide equivalent
CONE	cost of new entry
CSP	concentrating solar power
DAC	direct air capture
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
GEA	generation and emissions assessment
GIS	geographic information system
GWP	global warming potential
IPCC	Intergovernmental Panel on Climate Change
IRA	Inflation Reduction Act
ITC	investment tax credit
LRMER	long-run marginal emission rate
NGCT	natural gas combustion turbine
NREL	National Renewable Energy Laboratory
OGS	oil-gas-steam
PRM	planning reserve margin
PTC	production tax credit
PV	photovoltaics
RAZ	reliability assessment zone(s)
REC	renewable energy credit
RPS	renewable portfolio standard(s)
RTE	round-trip efficiency
SRMC	short-run marginal costs
SRMER	short-run marginal emission rate
USLCI	U.S. Life Cycle Inventory Database

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1 Cambium Overview

The National Renewable Energy Laboratory's (NREL's) Cambium data sets are annually released sets of simulated hourly emission, cost, and operational data for a range of modeled futures of the U.S. electric sector with metrics designed to be useful for long-term decision-making. The 2023 Cambium data set is the fourth annual release. The data sets are a companion product to NREL's Standard Scenarios, which are likewise released annually and are a set of projections of how the U.S. electric sector could evolve across a suite of different potential futures, but covering more scenarios with less temporal granularity (Gagnon et al. 2024). Information about Cambium and related publications can be found at <https://www.nrel.gov/analysis/cambium.html>, and the Cambium data sets can be viewed and downloaded at <https://scenarioviewer.nrel.gov/>.

In this documentation, we describe Cambium 2023's scenarios (Section 3), define the metrics (Section 5), and document the Cambium-specific methods for calculating those metrics (Section 6).

The Cambium data sets draw primarily from the outputs of two models:¹

- The Regional Energy Deployment System (ReEDS) model, which uses a least-cost framework to project structural changes in the U.S. electric sector under different possible futures (Ho et al. 2021)
- PLEXOS, which is a commercial production cost model that we use to simulate the hourly operation of the future electric systems projected by ReEDS (Energy Exemplar 2019).

1.1 ReEDS

The first of two models underlying the Cambium data sets is ReEDS (Ho et al. 2021).² ReEDS is an NREL-developed, publicly available mathematical programming model of the electric power sector. Given a set of input assumptions such as fuel costs, technology costs, and policies, ReEDS models the evolution of generation and transmission assets, solving a linear program to make investment and operational decisions to minimize the overall cost of the electric system. The model has been used to explore how the evolution of the electric sector is impacted by a range of technology and policy scenarios.

¹ We briefly summarize ReEDS and PLEXOS in this section, and we refer readers to the literature cited in each of those subsections for more detailed documentation of how each model functions.

² (Ho et al. 2021) documents the 2020 version of ReEDS. More information about ReEDS, including the most up-to-date documentation, open-source access, and other publications can be found at <https://www.nrel.gov/analysis/reeds/>. See (Gagnon et al. 2024) appendix section A.2 for a list of model changes that apply to both the 2023 Standard Scenarios and 2023 Cambium.

The conterminous United States (i.e., the lower 48 states and the District of Columbia) is represented in ReEDS as 134 model balancing areas (BAs), which are connected by a representation of the transmission network. The network starts with existing transmission capacity and can be expanded as part of ReEDS' decision-space. Likewise, the model starts with representations of all existing generation capacity and announced future builds for each BA, and it can choose to build new capacity or retire old capacity to meet demand at the lowest cost. Historical patterns are used as a starting point for assumptions about end-use electricity demands, and assumptions about the evolution of that demand vary by scenario.

The linear program for balancing supply and demand within ReEDS includes a representative set of 246 time periods that are meant to capture seasonal and diurnal trends. A submodule, Augur, is used to calculate key parameters from hourly data, where the native ReEDS representation is too coarse. The ability of variable generators (e.g., wind and solar) and storage to contribute firm capacity, curtailment of variable generators, and the energy arbitrage value of storage generators are examples of parameters derived in Augur.

The linear program that forms the core of ReEDS makes investment and retirement decisions for bulk power system assets. For behind-the-meter solar photovoltaics (PV), the model imports projections from NREL's Distributed Generation Market Demand Model (dGen, [Sigrin et al. 2016]).³

1.2 PLEXOS

The ReEDS reduced-form dispatch, aided by Augur's parameterization, aims to capture enough operational detail for realistic bulk power system investment and retirement decisions, but it does not have the temporal resolution that is desired for Cambium databases. To obtain more-detailed simulations of the electric systems projected by ReEDS, NREL developed utilities to represent a ReEDS capacity expansion solution in the second of the two models that Cambium draws from: PLEXOS (Energy Exemplar 2019).⁴

PLEXOS is a commercial production cost model that can simulate least-cost hourly dispatch of a set of generators with a network of nodes and transmission lines. It incorporates representations of unit-commitment decisions, detailed operating constraints (e.g., maximum ramp rates and minimum generation levels), and operating reserves; and it can be run with nested receding horizon planning periods (e.g., day-ahead and real-time) to simulate realistic electric system operations.⁵

For representing a ReEDS solution as a PLEXOS model, the spatial resolution from ReEDS is retained: the 134 BAs in ReEDS are represented as transmission nodes in PLEXOS, and the connections between them are modeled using the line capacities and loss rates in the ReEDS

³ (Sigrin et al. 2016a) is the most recent documentation of the dGen model. More information about dGen, such as the most up-to-date documentation, open-source access, and other publications can be found at <https://www.nrel.gov/analysis/dgen>.

⁴ The ability to represent a ReEDS-modeled solution in PLEXOS has also been used to study ReEDS-built systems for other NREL analyses (Frew et al. 2019; Cole et al. 2020; Cole et al. 2019).

⁵ Separately from ReEDS, PLEXOS has been used extensively by NREL for analyses of the electric sector, such as the Western Wind and Solar Integration Study (Lew et al. 2013) and the Eastern Renewable Grid Integration Study (Bloom et al. 2016).

aggregated transmission representation. Generation capacity at each node is, however, converted from aggregate ReEDS capacity to individual generators using a characteristic unit size for each technology. For consistency, ReEDS cost and performance parameters are used when possible and reasonable, but values derived from previous NREL studies (e.g., Lew et al. [2013]) are used when parameters are unavailable from ReEDS or are available but unreasonable because of structural differences between the models.

Once the ReEDS solution is converted to a PLEXOS database, the hourly dispatch of the grid can be simulated for a full year. For Cambium databases, we run PLEXOS as a mixed integer program, with day-ahead unit commitment and dispatch (without any real-time adjustments for subhourly dispatch or forecast error). For each modeled year, generators have constant heat rates, short-run marginal costs (SRMC), and maximum generator outputs. Supply and demand are balanced at the busbar level, and distribution losses are captured in data pre- and post-processing, as described in Section 6.7. Inter-BA transmission is represented as pipe flow with constant loss rates, with no intra-BA transmission losses. Generator outages are represented by derating installed capacity to an effective capacity based on annual average outage rates that vary by technology. Three operating reserves are represented—regulation, flexibility, and spinning reserves.

We draw from these simulated results—from both ReEDS and PLEXOS—to calculate the metrics reported within Cambium databases, with varying degrees of post-processing, as described in the remainder of this document.

2 Changes to Scenarios, Metrics, and Methods Relative to Cambium 2022

This section highlights the major differences between the 2022 and 2023 Cambium data releases, in terms of the scenarios, metrics and methods. For a list of other modeling changes not mentioned here see section A.2 in the Standard Scenarios 2023 report:

- **GEA Regions Updated:** The Cambium 2022 data set used Generation and Emission Assessment (GEA) regions that were based on the U.S. Environmental Protection Agency’s eGRID subregions. The fact that the Cambium regions were similar, but not identical, to the eGRID subregions caused confusion, and in some cases, inaccurate use of the data. In response to this, the Cambium 2023 data sets use new definitions of GEA regions. See section 4.2 for further discussion. Mappings of the new regions to ZIP codes and counties are available for download in the Scenario Viewer in the Download section of the Cambium 2023 project (<https://scenarioviewer.nrel.gov/>).
- **Historical Emissions Intensity Data Now Provided:** Historical annual in-region emission intensity data is now provided for the new GEA regions, both to provide context to the projections as well as facilitate analyses that wish to be grounded in recent empirical observations. The data is created by aggregating eGRID plant-level data. See section 4.2. for further discussion. The data can be obtained in the Scenario Viewer in the Download section of the Cambium 2023 project (<https://scenarioviewer.nrel.gov/>).
- **New Demand Trajectories:** The 2023 Cambium scenarios include new end-use electric demand trajectories. The new trajectories assume greater rates of load growth and a trend towards increasing winter peak demands. Unlike the previous demand trajectories, which only scaled over time but retained their same shape, the new trajectories’ hourly shape evolves over time.
- **General Updating of Assumptions:** The 2023 Cambium scenarios include a general updating of major inputs such as state policies, technology and fuel costs, and technology performance assumptions. The new inputs are documented in section 3.1 of this report.
- **Year Set Changed:** The 2022 Cambium release had biennial data through 2030 and then five-year time steps from 2035 through 2050. The 2023 release has five-year time steps from 2025 through 2050.
- **Removal of State-level Data:** Due to the increasing difficulty in modeling near-term operational decisions of small states (e.g., Delaware, Rhode Island, Vermont), state-level aggregations have been removed from the 2023 Cambium data release. Analysts are encouraged to use GEA level regional aggregations where feasible. Where state-level data is required, analysts may create it by aggregating the Balancing Area data, which is still available.
- **Updated Natural Gas Precombustion CH₄ Assumption:** To align with the default values in the ReEDS model, the precombustion CH₄ assumption for natural gas now starts at 0.57 kg/MMBTU in 2022, declining to 0.40 kg/MMBTU by 2030 (Alvarez et al. 2018). The decline over time is based on goals stated by the Biden administration (Jeff Mason and Alexandra Alper 2021).
- **Curtailment Metrics Added:** The 2023 Cambium data sets reports curtailment of wind, solar, geothermal, non-dispatchable hydropower, and nuclear generators.

- **Higher Interconnection Costs:** The Cambium 2023 release had network reinforcement costs, which were not represented in prior releases. These increase the costs of interconnecting generators to the grid, impacting renewable energy technologies more than other technologies.
- **IRA Clean Generation Tax Credits Persist:** In the Cambium 2022 release, some scenarios (including the Mid-case) had their greenhouse gas emissions cross the threshold set in IRA, and consequently had their clean generation tax credits phase out. In the Cambium 2023 scenarios the majority of scenarios, including the Mid-case, did not see the threshold crossed and consequently the clean generation tax credits persist through the modeled horizon. The difference is primarily caused by greater load growth assumptions and higher interconnection costs for renewables. For consistency across scenarios, all scenarios in the 2023 data set were assumed to have the tax credits persist. This eliminated two of the scenarios from the 2022 release which only varied clean generation tax credit availability. For additional discussion of this phaseout phenomenon, see the 2023 Standard Scenarios report (Gagnon et al. 2024).
- **Inclusion of Hydrogen Combustion Turbines:** In the two decarbonization scenarios in the 2023 release there is now a representation of hydrogen combustion turbines, fueled by hydrogen created endogenously within the model through low temperature electrolysis. In prior releases there was a generic renewable fuel combustion turbine technology with a fixed fuel cost. As this technology is classified as a nascent technology, it is not available for investment in the non-decarbonization scenarios.

3 2023 Cambium Scenario Definitions

The 2023 Cambium data set contains 8 scenarios that project the possible evolution of the contiguous United States' electricity sector through 2050. The scenarios are based on the NREL's companion data product, the Standard Scenarios (Gagnon et al. 2024), which contains a broader suite of future projections (but fewer metrics and only reports annual results).

Scenario assumptions have been updated since 2022 to reflect the technology, market, and policy changes that have occurred in the electricity sector, and many modeling enhancements have been made (see section A.2 in the Standard Scenarios 2023 report for a list of model enhancements). Additionally, the ReEDS and dGen models and inputs we used to generate these scenarios are publicly available.⁶

The 8 scenarios are built around a base set of assumptions that contain central or median values for inputs such as technology costs and fuel prices, demand growth averaging 1.8% per year, and electricity sector policies as they existed in September 2023 (including the Inflation Reduction Act of 2022, IRA).

Additionally, the base set of assumptions excludes currently-nascent generation technologies.⁷ This exclusion is not intended to pass judgement on the difficulty or likelihood of the technologies ultimately achieving commercial adoption, and is driven primarily by material uncertainties in the data needed to represent the technologies—for example, the current omission of IRA's production tax credit for clean hydrogen production (the implementation of which had not been decided on when these data sets were created) makes the inclusion of hydrogen combustion turbines in the Mid-case of the Cambium data sets undesirable. Both of the scenarios with national decarbonization trajectories include nascent technologies.

A notable difference between the Cambium 2023 scenario set and the Cambium 2022 scenario set is that the clean generation tax credits do not phase out in the 2023 scenarios. This change is due to the fact that in the 2022 Standard Scenarios the majority of scenarios with current policies saw the threshold specified in IRA passed and consequently the tax credits phased out. In the 2023 scenarios, the majority of scenarios with current policies (including the Mid-case scenario) do not cross the threshold, and therefore the IRA tax credits do not phase out. This assumption (persistence of the clean generation tax credits) is held constant across all Cambium 2023 scenarios, for the sake of comparability between scenarios.⁸ For a more detailed discussion of this phenomena, see the Standard Scenarios 2023 report.

⁶ See www.nrel.gov/analysis/reeds and www.nrel.gov/analysis/dgen/.

⁷ Nascent technologies are defined here as enhanced geothermal systems, floating offshore wind, coal CCS, natural gas CCS, biopower CCS, small modular nuclear reactors, and hydrogen combustion turbines. See Section 6.1 for more discussion about technology classification and the listing both nascent and established technologies.

⁸ The Low Renewable Energy and Battery Costs and the 100% Decarbonization by 2035 scenario both pass the IRA threshold and therefore the tax credits could phase out if not extended. The High Natural Gas Prices and the 95% Decarbonization by 2050 scenarios both also cross the IRA threshold but at a sufficiently late year that, given the delayed phase-out schedule and safe harbor periods, would not impact these modeling results.

Summary of the 8 Scenarios in Cambium 2023

1. **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.
2. **Low Renewable Energy and Battery Costs:** the same set of base assumptions as the first scenario, but where renewable energy and battery costs are assumed to be lower and performance improvements greater.
3. **High Renewable Energy and Battery Costs:** the same set of base assumptions as the first scenario, but where renewable energy and battery costs are assumed to be higher and performance improvements lesser.
4. **High Demand Growth:** the same set of base assumptions as the first scenario, but where demand growth is assumed to average 2.8% from 2024 through 2050, consistent with 100% economy-wide decarbonization.
5. **Low Natural Gas Prices:** the same set of base assumptions as the first scenario, but where natural gas prices are assumed to be lower.
6. **High Natural Gas Prices:** the same set of base assumptions as the first scenario, but where natural gas prices are assumed to be higher.
7. **95% Decarbonization by 2050:** the same set of base assumptions as the first scenario, but nascent technologies are included and there is a national electricity sector decarbonization constraint that linearly declines to 5% of 2005 emissions on net by 2050.
8. **100% Decarbonization by 2035:** the same set of base assumptions as the first scenario, but nascent technologies are included and there is a national electricity sector decarbonization constraint that linearly declines to zero on net by 2035.

Note that the IRA clean hydrogen production tax credit, 45V, is not represented in any of these scenarios, as the rules for determining the criteria for receiving the credit had not yet been finalized at the time these data sets were created. Given that the tax credit is significant, we would expect this credit to influence results once represented in the modeling, both by increasing the use of hydrogen in the power sector while also increasing electricity demand from electrolyzers producing hydrogen for non-power-sector uses.

Although the 2023 Cambium scenario set covers a wide range of futures, it is not exhaustive. Other NREL analyses have studied particular aspects of power sector evolution in more depth than is covered in this suite of scenarios. See <https://www.nrel.gov/analysis/future-system-scenarios.html> for a more complete list of NREL's other future power systems analyses.

3.1 Cambium Input Assumptions

This section contains a high-level summary of the input assumptions that vary within the 2023 Cambium scenarios (Table 1), followed by a more detailed discussion of the inputs.

For details about the structure and assumptions in the models not mentioned here, see the companion Standard Scenarios 2023 report, as well as the documentation for ReEDS (Ho et al.

2021) and dGen (Sigrin et al. 2016b). Both models are publicly available,⁹ and inputs are viewable within the model repositories.

Table 1. Summary of Inputs that Vary within the 2023 Cambium Scenarios

The scenario settings listed in *blue italics* correspond to those used in the base set of assumptions.

Group	Scenario Setting	Notes
Electricity Demand Growth	<i>Reference Demand Growth</i>	<i>End-use electricity trajectory reaching 6,509 TWh/year of demand (1.8% compound annual growth rate [CAGR]) with conservative assumptions about the impact of demand-side provisions in IRA</i>
	High Demand Growth	End-use electricity trajectory reaching 8,354 TWh/year (2.8% CAGR) consistent with 100% economy-wide decarbonization by 2050
Fuel Prices	<i>Reference Natural Gas Prices</i>	<i>AEO2023 reference^a</i>
	Low Natural Gas Prices	AEO2023 high oil and gas resource and technology ^a
	High Natural Gas Prices	AEO2023 low oil and gas resource and technology ^a
Electricity Generation Technology Costs and Performance	<i>Mid Technology Cost</i>	<i>2023 Annual Technology Baseline (ATB) moderate projections</i>
	Advanced RE and Battery Costs and Performance	2023 ATB renewable energy and battery advanced projections
	Conservative RE and Battery Costs and Performance	2023 ATB renewable energy and battery conservative projections
Policy/Regulatory Environment	<i>Current Law</i>	<i>Includes state, regional, and federal policies as of September 2023</i>
	<i>95% by 2050</i>	<i>95% net reduction in electricity sector CO₂ emissions by 2050 (relative to 2005)</i>
	<i>100% by 2035</i>	<i>Net zero electricity sector CO₂ emissions by 2035</i>

^a Natural gas prices are based on AEO electricity sector natural gas prices but are not identical because of the application of natural gas price elasticities in the modeling. See the Fuel Prices section below for details.

⁹ See <https://github.com/NREL/ReEDS-2.0> and www.nrel.gov/analysis/dgen/model-access.html.

Demand Growth and Flexibility

This year's Cambium scenario suite includes two different end-use electricity demand trajectories, both produced through modeling by Evolved Energy Research (EER). The Reference Demand Growth trajectory reaches 6,509 TWh/year of electric load by 2050 (a CAGR of 1.8% from 2024 through 2050, see Figure 1). It reflects relatively conservative assumptions about the impact of demand-side provisions in the Inflation Reduction Act (relative, compared to other scenarios developed by EER). More information about EER's outlook can be found in (Haley et al. 2022), although their published material does not yet describe their modeling of the impacts of IRA. The Reference Demand Growth trajectory is used for all scenarios except the High Demand Growth scenario.

The High Demand Growth trajectory reaches 8,354 TWh/year of electric load by 2050 (a CAGR of 2.8% from 2024 to 2050). It is largely similar, but not identical, to EER's Central scenario from (Haley et al. 2022). EER describes the scenario as achieving least-cost economy-wide net-zero greenhouse gas emissions for the U.S. by 2050, inclusive of energy and industrial CO₂, non-CO₂ greenhouse gases, and the land CO₂ sink. It does not directly include representations of IRA's demand-side provisions, although many of IRA's provisions would prompt directionally similar changes in demand. The High Demand Growth trajectory is only used in the High Demand Growth scenario.

Both demand scenarios do not include electric load from hydrogen electrolysis. When present, demand from electrolyzers is determined endogenously within the ReEDS model and added to the loads specified here. This technology is only available in the two decarbonization scenarios.

We assume inelastic, inflexible end-use electricity demand in all scenarios. This is a poor assumption—grid-responsive flexible loads currently exist in practice, and the increasing value of energy arbitrage in many of the futures modeled would likely induce more loads to become grid-responsive, especially with the electrification of certain end-uses (such as vehicles). The omission of elastic and flexible loads from this modeling would tend to create systems that are more expensive and more difficult to integrate variable generators into, relative to situations where load is elastic and flexible.

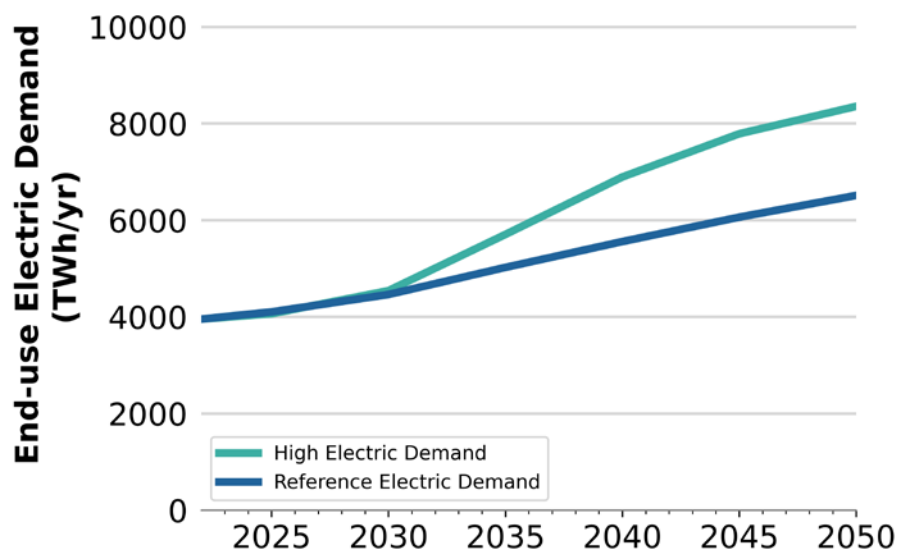


Figure 1. End-use electric demand trajectories used in Cambium 2023

Figures 2 through 4 show average national end-use electricity demand patterns by hour and month (excluding any demand for hydrogen production). Note that the figures show the national demand patterns in Eastern Time, which has the effect of smoothing the diurnal patterns—the diurnal pattern for any specific region would tend to be peakier.

Figure 2 shows the month-hour demand patterns for the Reference trajectory in 2024. To give a sense of how the patterns evolve over time, Figure 3 and 4 show the month-hour demand patterns for the Reference and High demand trajectories respectively.

Note that both trajectories have higher winter peaks in 2050 relative to 2024, with the High demand trajectory having a winter peak approximately the same magnitude as the summer peak, driven in large part by the electrification of heating. The patterns shown below are for the nation—individual regions can have winter peaks that exceed summer peaks.

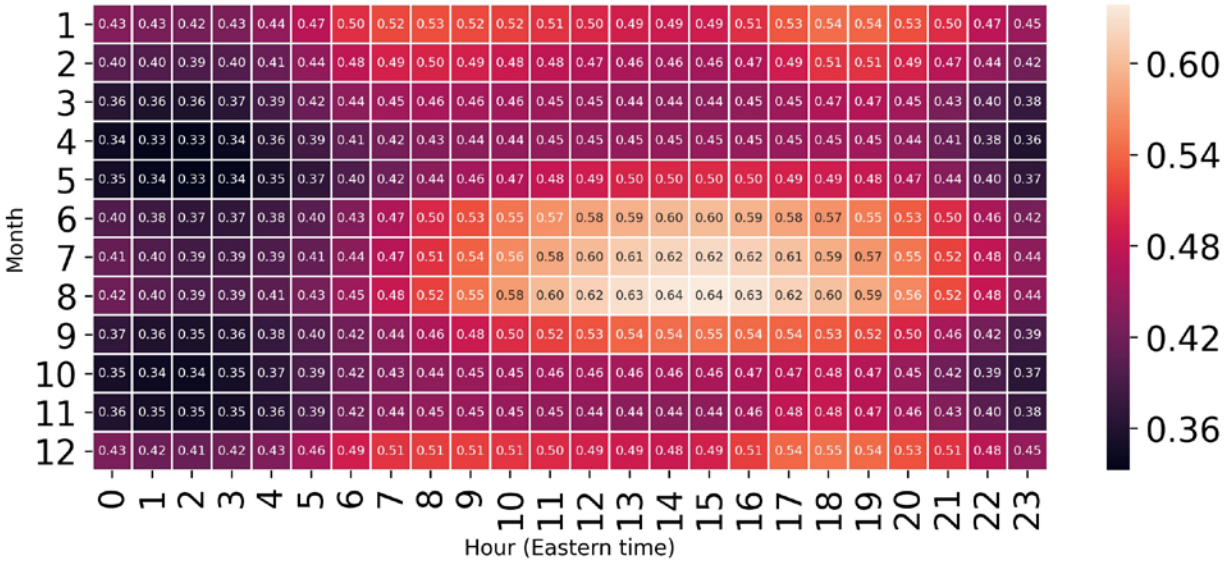


Figure 2. Month-hour average end-use national demand, in TWh, in 2024 for the Reference demand trajectory

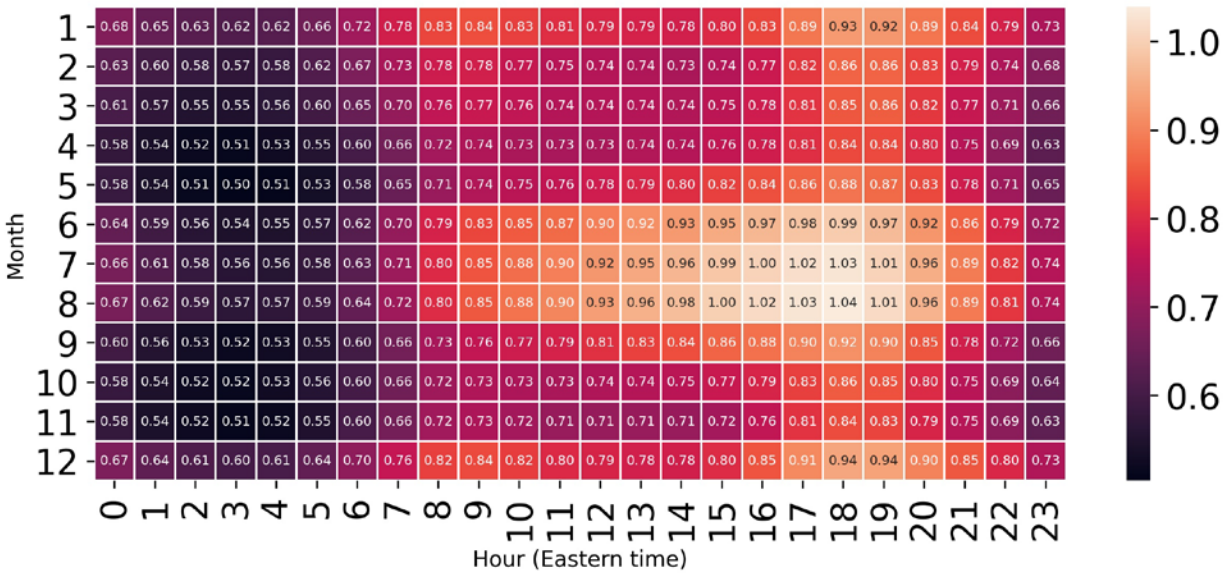


Figure 3. Month-hour average end-use national demand, in TWh, in 2050 for the Reference demand trajectory

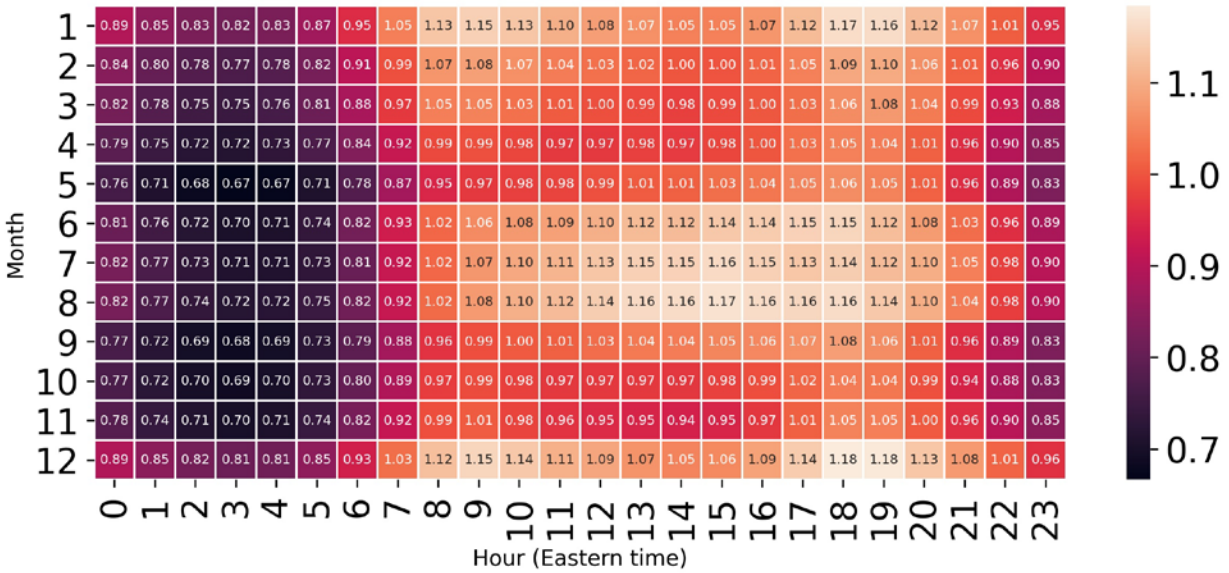


Figure 4. Month-hour average end-use national demand, in TWh, in 2050, for the High demand trajectory

Fuel Prices

Natural gas input price points are based on the trajectories from AEO2023 (EIA 2023). The input price points are drawn from the AEO2023 Reference scenario, the AEO2023 Low Oil and Gas Supply scenario, and the AEO2023 High Oil and Gas Supply scenario. Actual natural gas prices in ReEDS are based on the AEO scenarios, but they are not exactly the same; instead, they are price-responsive to ReEDS natural gas demand in the electric sector. Each census region includes a natural gas supply curve that adjusts the natural gas input price based on both regional and national demand (Cole, Medlock III, and Jani 2016). Figure 5 shows the output natural gas prices from the suite of scenarios.

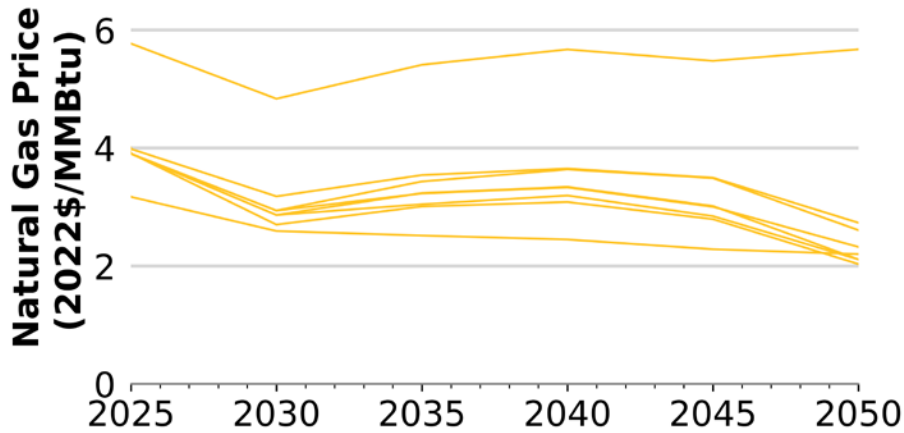


Figure 5. National average natural gas price outputs from the suite of scenarios

The coal and uranium price trajectories are from the AEO2023 Reference scenario and are shown in Figure 6. Both coal and uranium prices are assumed to be fully inelastic. Coal prices vary by census region (using the AEO2023 census region projections). Figure 6 shows the coal prices across the census regions. Uranium prices are the same across the United States.

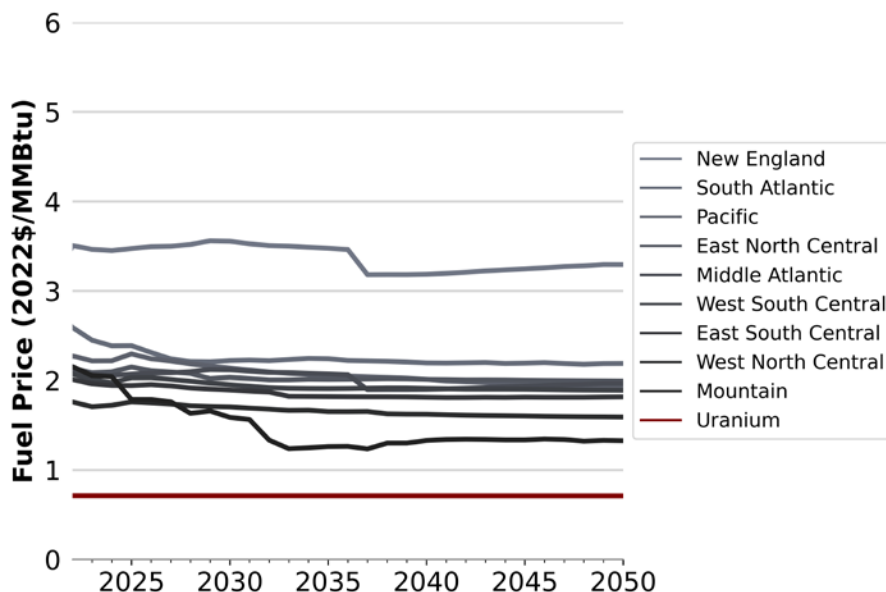


Figure 6. Input coal and uranium fuel prices used in Cambium 2022

Uranium prices are the same across the United States. Coal prices vary by census region, and as listed in descending order of average price in the legend in this figure.

Hydrogen combustion turbines (H2-CT) are available as an investment option for the two decarbonization scenarios and are represented consistent with the RE-CT technology in the Solar Futures Study (DOE 2021). These H2-CT generators are fueled by hydrogen created through low temperature electrolysis with electrolyzers that are represented endogenously within the ReEDS model (i.e., the electrolyzer load is represented within the modeling and the cost of the hydrogen is endogenously determined by the model). Notably, this modeling does not include a representation of the clean hydrogen production tax credit, 45V, as the Treasury Department had not released guidance on the rules for determining clean hydrogen when this work was being performed. As the clean hydrogen tax credit is significant, it will likely affect the projected role of hydrogen in future modeling.

Technology Cost and Performance

Technology cost and performance assumptions for newly built generators are taken from the 2023 ATB (NREL 2023), and performance assumptions for existing generators are drawn from EIA-NEMS data (available through the open access ReEDS repository). The ATB includes advanced, moderate, and conservative cost and performance projections through 2050 for the generating and storage technologies used in the ReEDS and dGen models. The low renewable energy (RE) and battery cost and performance scenarios use the advanced projections for all renewable energy and battery technologies, and the high RE and battery cost and performance

scenarios use the conservative projections (for these scenarios, RE technologies include all solar, geothermal, hydropower, and wind generators).

In the scenarios that include nascent technologies, coal, natural gas, and biopower CCS generators are available for investment as either greenfields or retrofits. Greenfield capital costs for gas and coal CCS technologies are taken from the conservative, reference, and advanced trajectories of the 2023 ATB. Variable and fixed O&M cost estimates are both taken from the 2023 ATB’s three trajectories.

Plant-level retrofit capital cost estimates are provided in the EIA-NEMS data set used to initialize the generator fleet in ReEDS (this file can be viewed in the ReEDS GitHub repository). This value was implemented as the cost for retrofitting a generator in 2028. Beyond 2028, that cost declines at the rate of the CCS retrofit capital cost declines for the corresponding technology in the 2023 ATB.

Biomass with CCS cost and performance values are from EPRI (2020). Hydrogen combustion turbine retrofits are represented consistent with the RE-CT technology in the Solar Futures Study (DOE 2021). Natural gas turbines can be upgraded to H2-CTs for 33% the cost of a new gas turbine or be built new at a cost 3% higher than natural gas turbines. Heat rates and operation and maintenance costs are the same as natural gas turbines. All H2-CT units are assumed to be clutched to allow them to also act as synchronous condensers.

Generator lifetimes are shown in Table 2 and Table 3. These lifetimes represent that maximum lifetimes generators are allowed to remain online in the ReEDS. ReEDS will retire generators before these lifetimes if their value to the system is less than 50% of their ongoing fixed maintenance and operational costs (50% is assumed, instead of 100%, to roughly approximate the friction of plant retirements, as retirement decisions in practice are often not strictly economic decisions). If a retirement date has been announced for a generator, ReEDS will retire the capacity retiring that generator at that date or earlier.

Table 2. Lifetimes of Renewable Energy Generators and Batteries

Technology	Lifetime (Years)	Source
Land-based wind	30	Wind Vision (DOE 2015)
Offshore wind	30	Wind Vision (DOE 2015)
Solar PV	30	SunShot Vision (DOE 2012)
CSP	30	SunShot Vision (DOE 2012)
Geothermal	30	GeoVision (DOE 2019)
Hydropower	100	Hydropower Vision (DOE 2016)
Biopower	50	2021 National Energy Modeling System plant database (EIA 2021)
Battery	15	Cole, Frazier, and Augustine (2021)
H2-CT	50	Matching natural gas combustion turbines

Table 3. Lifetimes of Nonrenewable Energy Generators

Technology	Lifetime for Units Less than 100 MW (Years)	Lifetime for Units Greater than or Equal to 100 MW (Years)
Natural gas combustion turbine	50	50
Natural gas combined cycle and CCS	60	60
Coal, all technologies, including cofired	65	75
Oil-gas-steam (OGS)	50	75
Nuclear	80	80

3.2 Definition of Decarbonization Scenarios

In the 2023 Cambium data set there are two scenarios with national electricity sector decarbonization trajectories: the 95% Reduction by 2050 and the 100% Reduction by 2035 scenarios. These trajectories correspond to a percentage reduction in net U.S. electricity sector CO₂ emissions relative to 2005 emissions. These scenarios are drawn from the companion 2023 Standard Scenarios analysis.

These trajectories are implemented as a national electricity sector CO₂ constraint. The CO₂ constraint only apply to the U.S. electricity sector. None of the scenarios in this analysis model international or economy-wide decarbonization, which would impact factors such as fuel prices, generator costs, and the magnitude and shape of electricity demand.

The trajectories limit the net electricity sector emissions, meaning that the constraint is applied to CO₂ emissions from the direct combustion of fuel for electricity generation, less any CO₂ captured and stored through carbon capture technologies. The emission limit does not incorporate other greenhouse gases, emissions from precombustion or post-combustion activities such as fuel extraction and transport (other than the CO₂ removed from the atmosphere during feedstock growth for biopower with CCS), or the emissions induced by construction or decommissioning activities.

The definition of a CO₂ constraint given above is only one possible definition—others may include the CO₂ equivalence of other greenhouse gasses or include noncombustion emissions (e.g., emissions from fuel extraction, processing, and transport). Furthermore, other definitions may involve different approaches to the accounting around carbon removal, including completely prohibiting offsets. Other possible definitions of power sector decarbonization were explored in NREL’s 100% Clean Electricity by 2035 Study.

4 User Guidance, Caveats, and Limitations of Cambium Databases

4.1 Limitations and Caveats

When projecting the expansion and operation of the U.S. electric system in coming decades, it is necessary to make various simplifications. Here, we list some important limitations and caveats that result from these simplifications:

- **Cambium Data Should Not Be the Sole Basis for Decisions:** Cambium data sets contain modeled projections of the future under a range of possible scenarios. Although we strive to capture relevant phenomena as comprehensively as possible, the models used to create the data are unavoidably imperfect, and the future is highly uncertain. Consequentially, these data should not be used as the sole basis for making decisions. In addition to drawing from multiple scenarios within a single Cambium set, we encourage analysts to draw on projections or perspectives from other sources, to benefit from diverse analytical frameworks when forming their conclusions about the future of the power sector.
- **Cambium Is Primarily Designed for Long-term Forward-looking Analysis:** Consequently, it is not recommended to use Cambium data for real-time decision-making or historical accounting.
- **Relevant Phenomena May Not Be Reflected in Cambium:** When using Cambium data for estimating intervention impacts, such as induced or avoided emissions, it is important to recognize that phenomena relevant to the specific project being analyzed may not be represented in the Cambium workflow. As one of many possible examples, how a particular renewable generator’s deployment influences the progress of other projects in the interconnection queue is not represented in this modeling. Expert judgement is strongly encouraged in interpreting whether such non-modeled phenomena may be present for a particular intervention being studied, and if so, how the omission may influence the results.
- **Cambium’s Metrics are Derived from System-Wide, Cost-Minimizing Optimization Models:** The models that Cambium draws from take system-wide, cost-minimizing perspectives that do not necessarily reflect the decision-making of individual actors, whose actions may not align with system-wide cost-minimization because of differing incentives or information deficits.
- **The Spatial and Temporal Resolution of the Underlying Models is Coarse:** Though the models that Cambium draws from have high spatial and temporal resolution for models of their scope, they do require simplifications and aggregations along those dimensions.¹⁰ Perhaps most critically, the United States is represented as 134 “copperplate” balancing areas (BA). This lack of transmission losses and constraints

¹⁰ See (Cole et al. 2017) for a multimodel analysis that, in part, explores the impact of spatial and temporal resolution in long-term planning models.

within BAs tends to produce lower and less variable marginal costs than what is observed in practice.

- **Cambium Reports Marginal Costs, Which Can Differ from Market Prices:** Cambium databases contain estimates of various marginal costs (i.e., how much the costs of building and operating the power sector increases with an increase in demand). Importantly, market prices in practice can deviate from marginal costs due to market design, contract structures, cost recovery for nonvariable costs, and bidding strategies. We strongly encourage users to read the descriptions of each marginal cost metric reported in Cambium (Section 5.6) for an understanding of the limitations of each metric.
- **Cambium’s Marginal Costs are Not Estimates of Retail Rates:** The marginal costs in Cambium should not be directly used as estimates of retail electricity prices because (1) retail rates typically include cost recovery for administrative, distribution infrastructure, and other expenses that are not represented in Cambium databases and (2) retail rates are often set through a ratemaking process that, while sometimes reflecting temporal patterns in the marginal costs of electricity, are generally not priced directly at marginal costs but rather seek to balance cost-recovery, equity, and cost-causation.
- **The Full Range of Uncertainty is Not Captured:** The models that Cambium draws from compute deterministic least-cost solutions for a particular set of assumptions—each scenario, therefore, does not fully reflect the uncertainties in the underlying assumptions and data. Cambium, through the Standard Scenarios, tries to address this by providing a suite of possible futures, although the full range of possible outcomes can never be fully captured; for example, no scenario includes a severe economic depression as one of many possible futures that are not modeled.
- **Cambium is Not Designed to Assess Grid Reliability or Resource Adequacy:** Although the models that Cambium draws from can recognize dropped load when insufficient capacity is available to meet demand, these runs should not be considered as assessing grid reliability or resource adequacy, because, among other reasons, (1) only a specific set of conditions (weather, load, and renewable resource quality) is simulated, (2) important temperature effects on generator efficiencies and transmission losses are not represented, (3) transmission line outages are not represented, and (4) intra-BA transmission line constraints are not captured.
- **ReEDS’ Capacity Expansion Decisions Have Limited Foresight:** Except when it runs with intertemporal optimization, ReEDS has limited long-term foresight and therefore model decision-making in a particular modeled year does not account for anticipated changes to markets or policies in future years. For example, when running without intertemporal optimization, ReEDS would not anticipate or react to the upcoming expiration of an incentive program. Unless otherwise specified, scenarios in Cambium databases are not run with intertemporal optimization.
- **Cambium’s Production Cost Modeling Does Not Have Forecast Error:** Although PLEXOS, the production cost model used to create Cambium data sets, is capable of representing load and variable generator forecast error, we do not deploy this feature in the runs from which Cambium draws.

- **Cambium Databases Do Not Contain Elasticity Data:** There are no estimates of the elasticity of the metrics reported in Cambium databases (i.e., how much a metric’s value would change if load or generation changed). Though many metrics may change little across a wide range of intervention sizes, some metrics may be highly elastic, particularly at certain points in time. Hours with a marginal energy cost of zero, for example, could become nonzero with small increases in demand. In general, the larger an intervention being analyzed, the more likely it is that the Cambium values are not accurate for that specific intervention.
- **Flexible Loads are Not Currently Represented in Cambium:** Although the models that Cambium draws from have the ability to represent flexible load, this capability is not currently used for Cambium. Grid-responsive buildings and intelligent charging of electrical vehicles are two of many potential examples of electric loads that may play a meaningful role in operation of the grid in the future—for example, by absorbing otherwise-curtailed energy or shifting load away from high-demand periods.
- **The Project Pipeline and Retirements Data Are Likely Incomplete:** Although ReEDS incorporates data of planned or under-construction projects, these data are unlikely to include *all* projects in progress, and it is possible that some planned projects included in ReEDS will not be finished. Similarly, scheduled near-term retirements are represented, but may be incomplete or reversed.
- **Possible Constraints on Rates of Changes are Not Fully Represented:** The Cambium 2023 data sets newly contains constraints on the rates of generator deployment, primarily slowing the rate of wind and solar deployment in the 2020’s. Other possible barriers or constraints on the rates of change, such as the rate of generator decommissioning or the rate at which coordination and trade between different regions could increase are not restricted in this modeling. This may result in overly rapid near-term rates of change.
- **Only the U.S. Electric Sector is Represented in Cambium:** The models that Cambium draws from only represent the electric sector of the conterminous United States, not adjacent sectors nor the global energy economy. For example, competing uses of natural gas or financial capital across sectors and countries are not dynamically represented.
- **A Single Year of Weather Data is Used for Most Cambium Metrics:** The PLEXOS runs that Cambium draws from use weather data from a single year, 2012. Therefore, most metrics in Cambium databases (e.g., the marginal cost and variable generator patterns) are not “expected values,” although they do capture realistic weather-induced hourly variations.

We point interested users to a review of Cambium’s 2020 marginal cost patterns performed by Lawrence Berkley National Laboratory (Seel and Mills 2021). The report describes the 2020 Cambium data release, and there have been various incremental improvements since then, but the general findings and recommendations of the report still hold.

4.2 Comparing Cambium Projections to Historical Emissions Data

To place Cambium’s emissions intensity projections in context, this section compares the 2023 Cambium Mid-case in-region CO₂ emissions intensity projections (the *aer_gen_co2_c* metric) against historical emissions data (Figure 8). The historical data is derived from eGRID, where

the plant-level emissions and generation values have been aggregated to the GEA regions used for reporting Cambium data (shown in Figure 7). Note that, although plant-level eGRID data is used, these regions differ from eGRID's subregions.

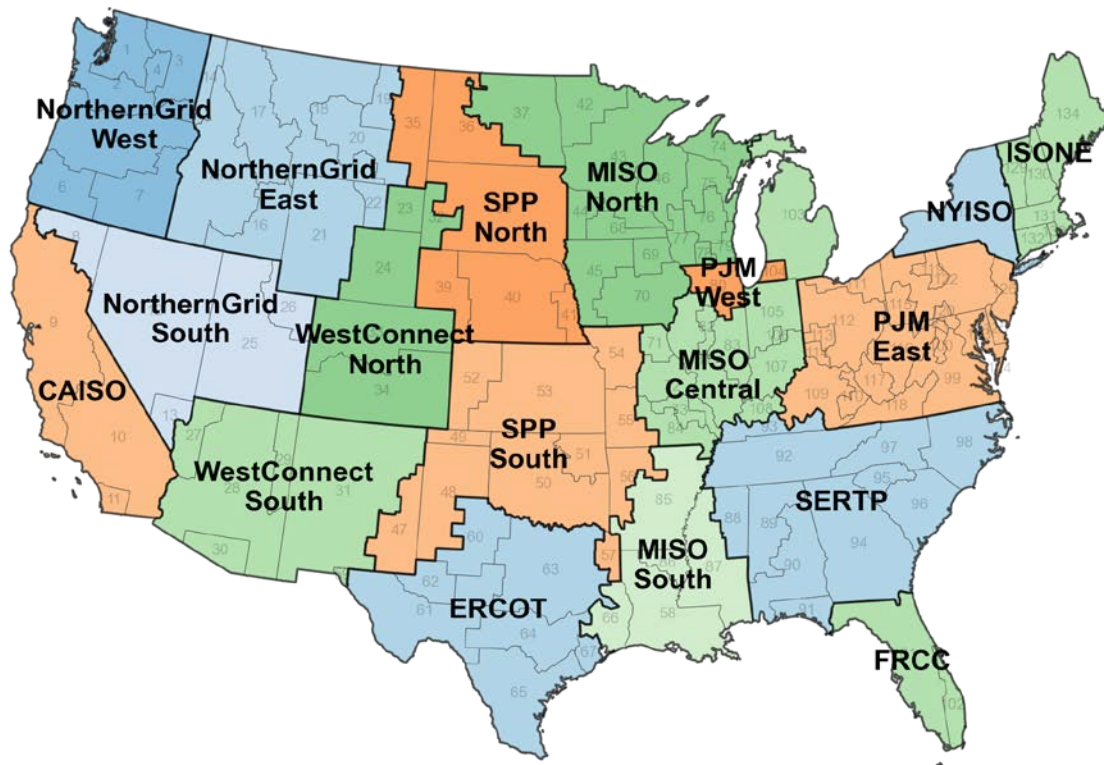


Figure 7: Cambium's generation and emission assessment (GEA) regions, 2023 version

Note that there is a difference between how the eGRID and Cambium emissions intensities are calculated, in that Cambium's emissions intensity calculation includes generation from behind-the-meter PV, storage, and electricity imported from Canada, whereas eGRID does not. The native Cambium calculation is shown in dark blue in Figure 8 whereas a replication of the eGRID calculation with Cambium projections is shown in light blue. The effect in most regions and years is small, at less than 10 kg/MWh. The greatest difference is ISONE in 2025, with the Cambium calculation yielding a value 35 kg/MWh lower than the eGRID version.

Examining Figure 8, we see that all of the GEA regions have seen a historical decline in emissions intensity, with the Cambium data often projecting an increase in the rate of decline in the near term. The projected decline comes primarily from reduced coal generation and increased wind and solar generation.

Note that, to facilitate analyses that wish to be anchored on an empirical or recent starting point, a file with the historical emissions intensities for the Cambium GEA regions is available for download with the rest of the Cambium data in the Download section of the Cambium 2023 project in the NREL Scenario Viewer (<https://scenarioviewer.nrel.gov/>).

Note also that not all constraints, barriers, or frictions that exist in practice are reflected in the models underlying the Cambium data. While the Cambium 2023 data set newly includes growth constraints to moderate near-term rates of generator deployment (primarily slowing down the rate of wind and solar deployment in the 2020's), rates of generator decommissioning and increased coordination between regions are not restricted. In practice, the rates of change may be slower than projected here for reasons not yet characterized and reflected in our models. The effects of this are most prominent in ISONE, CAISO and NorthernGrid West, which the models have as relying less on in-region fossil generators and more on imported electricity, then has been observed in historical operation for those systems. Because the Cambium data sets are focused primarily on future projections, an analysis seeking to be conservative about near-term rates of change may choose to ignore the 2025 projection and instead interpolate between the most recent (2022) empirical data and the 2030 Cambium data point.

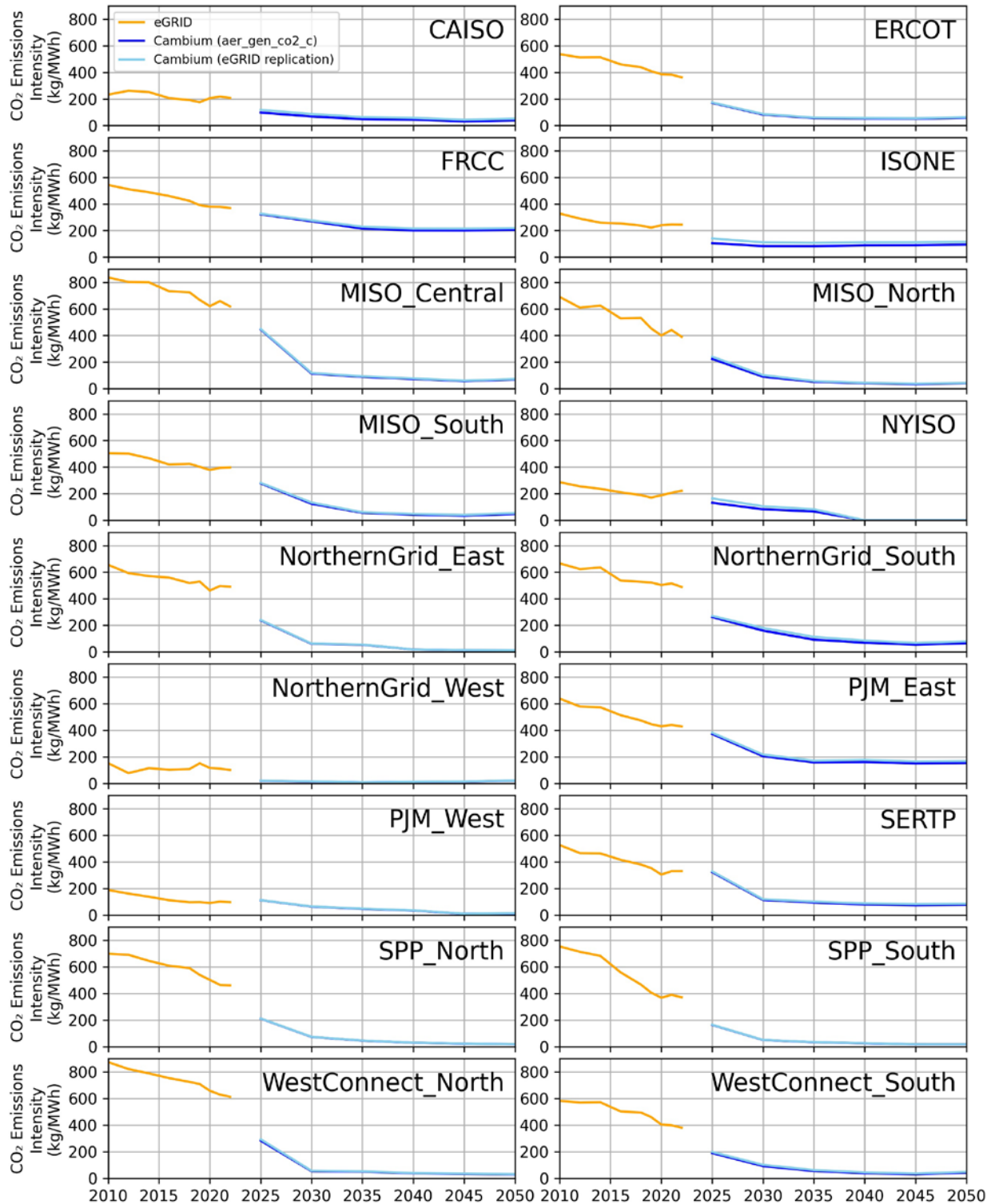


Figure 8: Comparison of Cambium CO₂ emission intensity projections against historical data

5 Cambium Metric Definitions

In this section, we briefly define all the metrics in Cambium databases. The outputs from ReEDS and PLEXOS are the starting point for Cambium’s processing; some of the metrics are direct reports from those models, but others involve extensive post-processing. We describe the Cambium-specific post-processing methods in Section 6.

5.1 Busbar and End-Use Values

Metrics in Cambium databases are reported at either the busbar or end-use level, depending on their most common usage (and indicated in the “Units” header information throughout this section, for each family of metrics). Busbar refers to the point where bulk generating stations connect to the grid, whereas end use refers to the point of consumption. Analyses of bulk generators would typically use busbar values, whereas analyses of electricity consumers would typically use end-use values. In Cambium databases, busbar and end-use values differ by the distribution loss rates between the two points.

There are two distribution loss rates: an average and a marginal. The relevant distribution loss metric for the emission and cost metrics are indicated in each metric’s section below. Short-run marginal metrics (i.e., cost metrics and the short-run marginal emission rates) use marginal loss metrics, whereas average or long-run marginal metrics use average loss metrics.¹¹

An analyst may wish to transform a Cambium busbar metric into its end-use value, or vice versa. For example, marginal emission rates are given in end-use terms as they are most commonly used to assess the change in emissions associated with a change in end-use electric demand. However, if an analyst wishes to use a marginal emission rate to estimate the change in emissions from a change in load or generation at the busbar level, they could apply the following equation to change the marginal emission rate into its busbar equivalent value.

For a generic metric X , the end-use and busbar values are related by the equation below, where the relevant distribution loss rate is α .

$$X_{end-use} = \frac{X_{busbar}}{(1 - \alpha)}$$

Hourly α are given in Cambium databases as *distloss_rate_avg* and *distloss_rate_marg* respectively. See Section 6.7 for our approach and assumptions for calculating these metrics.

¹¹ We apply average loss rates to the long-run marginal emissions rates because the metric assumes that generation and transmission assets can vary, and therefore we extend the assumption to distribution assets also varying. If an analyst wishes to assume that distribution assets are held fixed, they can apply a marginal distribution loss rate to the busbar version of long-run marginal emissions rates.

5.2 Time and Geographic Identifiers

Metric Family: timestamp

Metric Names: *timestamp* and *timestamp_local*

The *timestamp* metric is the time in Eastern Standard Time. The *timestamp_local* variable is the time in the local Standard Time. If no *timestamp_local* variable is in a file, the data are in Eastern Standard Time (and therefore indicated with the *timestamp* variable).

Both timestamp variables are hour-beginning, meaning a 1:00 timestamp indicates data for 1:00–2:00. Neither timestamp variable includes the effects of Daylight Savings Time. Every year in a Cambium data set has 8,760 hours and preserves the 7-day weekday/weekend pattern throughout the full time period. Leap days are omitted in the timestamps during leap years, although the 7-day weekday/weekend pattern is not broken—i.e., leap years are modeled as if they were not leap years.¹²

Every time series—and the underlying data—in a Cambium data set starts on a Sunday, regardless of the actual day of the week for January 1 of that year.¹³ This keeps the weekend/weekday patterns and hour positions consistent between years in the data, which facilitates analysis that spans across multiple years.

Metric Family: time zone

Metric Name: *tz*

The *tz* variable in the metadata indicates the time zone used for the *timestamp_local* variable. For regions that contain multiple time zones, the data are reported using the time zone where the majority of the load is located.

Metric Family: ReEDS model balancing area (BA)

Metric Names: *r*

The balancing area (*r*) is the finest geographic unit for which Cambium data are reported (Figure 9). There are 134 BAs, which are used as the nodes for balancing supply and demand in both the ReEDS and PLEXOS models that Cambium draws from.

¹² If users wish to represent the additional 24 hours in leap years, we recommend they copy the data from the third day from each year (a Tuesday in Cambium) and add it to the end of the year's time series and then rename the dates to incorporate February 29. If, instead, 24 hours of data are added between February 28 and March 1, the weekday/weekend pattern of the time series would be disrupted.

¹³ Cambium data starts on a Sunday because the underlying weather and load data are from 2012, which also start on a Sunday.

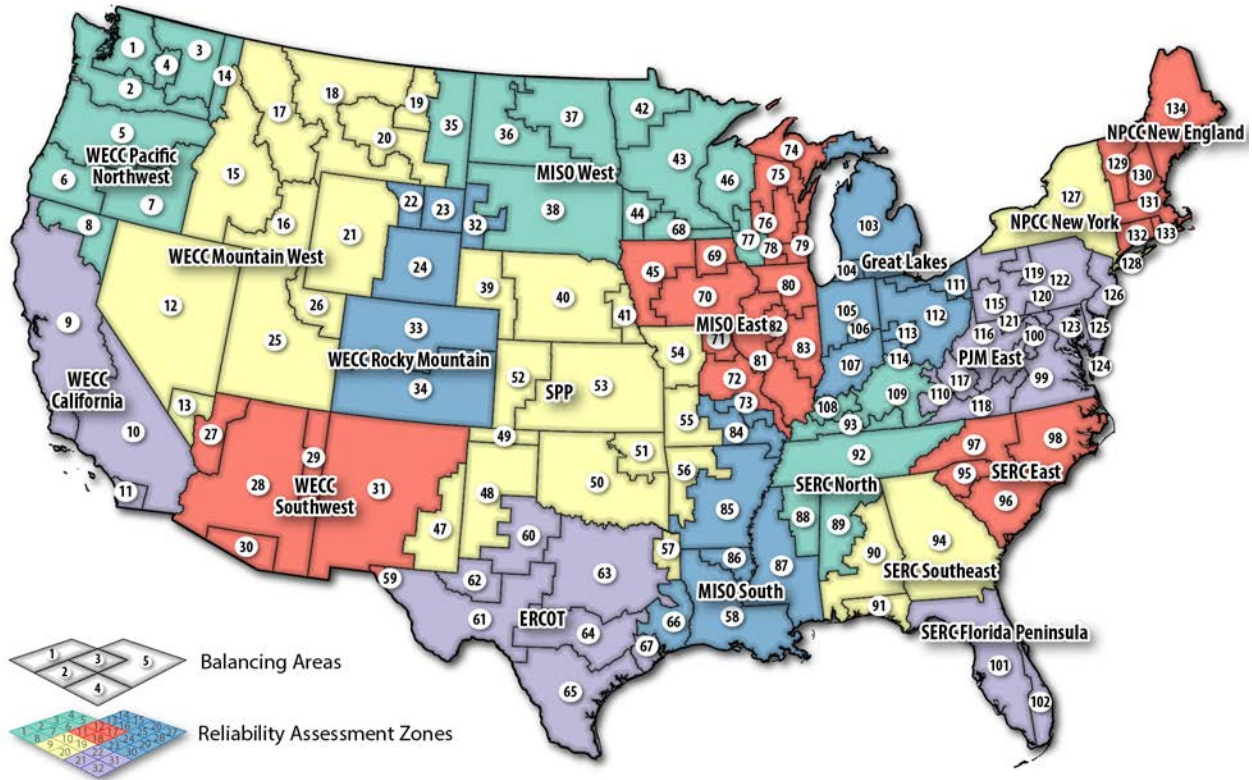


Figure 9. Balancing areas and reliability assessment zones

MISO: Midcontinent Independent System Operator; NPCC: Northeast Power Coordinating Council; SERC: SERC Reliability Corporation; SPP: Southwest Power Pool; WECC: Western Electricity Coordinating Council. Reliability assessment zones are used for enforcing operating reserve requirements in this modeling workflow.

Metric Family: Cambium Generation and Emission Assessment region (GEA)

Metric Names: *gea*

Cambium’s GEA regions are 18 regions covering the contiguous United States (Figure 10). Note that the GEA regions in the 2023 Cambium data release are different from the GEA regions in the prior release, which were previously based on the U.S. Environmental Protection Agency’s (EPA’s) eGRID regions. The regions were changed primarily for two reasons: First, to better align the regions with the coverage of electric grid system operators, and secondly, the fact that the Cambium GEA regions were similar, but not identical, to the eGRID subregions caused some confusion.

For analyses that wish to use historical emissions intensities for GEA regions, data has been provided for these regions by aggregating eGRID plant-level data. This data can be obtained in the NREL Scenario Viewer, in the Download tab of the Cambium 2023 project (<https://scenarioviewer.nrel.gov/>).

Shapefiles, mappings of GEA regions to ZIP codes, and mappings of GEA regions to counties can also be obtained in the NREL Scenario Viewer.

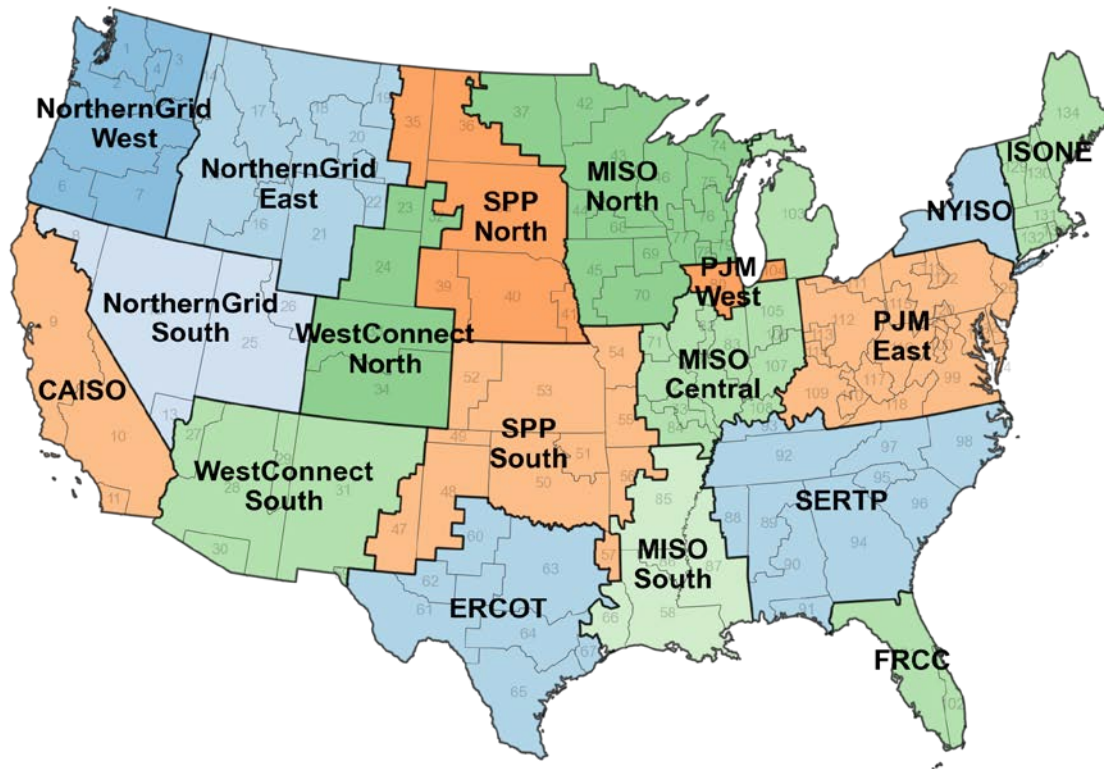


Figure 10. Cambium's generation and emission assessment (GEA) regions, 2023 version

5.3 Generation and Capacity Metrics

Metric Family: total generation

Metric Name: *generation*

Units: MWh_{busbar}

The *generation* metric reports the total generation from all generators within a region. It includes generation from storage (e.g., batteries or pumped hydropower storage). It does not include curtailed energy. If there are net imports or exports from a region, generation will not match load.

Behind-the-meter PV generation is included in the *generation* metric and is reported as the equivalent amount of busbar generation (i.e., it is increased to reflect the assumption that it does not incur distribution losses).

Metric Family: variable generation

Metric Name: *variable_generation*

Units: MWh_{busbar}

The *variable_generation* metric reports the total generation from all variable generators within a region, which includes PV, concentrating solar power (CSP) without storage, and wind. It does

not include curtailed energy. Behind-the-meter PV generation is included, and as with *generation*, is reported as the equivalent amount of busbar generation.

Metric Family: generation by technology

Metric Name: *technology_MWh*

Units: MWh_{busbar}

These metrics report the total generation within a region from each of the technologies listed in Table 4. These generation values do not include curtailed energy. Generation from behind-the-meter PV, which is assumed to occur at the point of end use, is reported as an equivalent amount of busbar generation.

These generation metrics should not be confused with the *battery_energy_cap_MWh*, *phs_energy_cap_MWh*, and *csp_energy_cap_MWh*, which report energy storage capacity, not generation.

Metric Family: nameplate capacity by technology

Metric Name: *technology_MW*

Units: MW

These metrics report the total nameplate capacity within a region from each of the technologies listed in Table 4 (except for Canadian imports). Behind-the-meter PV is reported as the AC inverter capacity—it is not adjusted to a busbar equivalent capacity, unlike generation from the same technology. The capacities of wind and solar generation are reported at their original nameplate capacities when they were installed (i.e., their reported capacity is not reduced over time by degradation). Outages are represented by derating the installed capacity to an effective capacity—these *technology_MWh* metrics report the original installed capacities, not the derated capacities.

Metric Family: nameplate energy storage capacity by technology

Metric Name: *technology_energy_cap_MWh*

Units: MWh

These metrics report the total nameplate energy storage capacity within a region for batteries, pumped hydropower storage, and concentrating solar power.

5.4 Clean Energy Metrics

Two “clean” energy fraction metrics are reported, one for the in-region generation mixture, another for the mixture ascribed to in-region load. “Clean” generation sources are defined as those whose net life cycle CO₂ emissions associated with fuel combustion are zero or negative, and includes nuclear, hydropower, Canadian imports, geothermal, biomass with and without CCS, hydrogen combustion turbines, wind, and solar. In the *cef_gen* metric, storage technologies are designated as clean, whereas in the *cef_load* metric storage technologies are assigned a clean fraction based on the mixture when they charged.

We note that all generation sources induce emissions, such as during manufacturing and construction activities or maintenance and operational activities beyond the direct combustion of

fuels. These metrics use the above definition for classifying technologies and are therefore only considering emissions associated with fuel combustion.

Metric Family: clean energy fraction of in-region generation

Metric Name: *cef_gen*

Units: MWh/MWh

The *cef_gen* metric is the fraction of generation that is clean within a region for the specified duration of time. No adjustment is made for imported or exported electricity. The designation of clean technologies is given at the beginning of this section. Storage generation is classified as clean for this metric. No adjustment is made to reflect policy-related accounting (i.e., this reports the actual generation mixtures in the given region and time frame, and the effects of any credit trading for portfolio standard compliance is not reflected).

Metric Family: clean energy fraction of generation induced by a region's load

Metric Name: *cef_load*

Units: MWh/MWh

The *cef_load* metric is the fraction of generation that is clean, for the generation that is allocated to a region's end-use load. Unlike the clean energy fraction of in-region generation, this metric includes the effects of imported and exported power. For example, if the power for a region's load is being supplied in equal parts from in-region gas generation and out-of-region wind generation, the *cef_load* would be 0.5.

This metric assigns a clean energy fraction to storage generation based on the weighted average clean energy fraction from when the storage generators were charging. Unlike *cef_gen*, *cef_load* reflects credit trading for state portfolio standards.

Cambium allocates generation, by assuming perfect mixing through nodes. For a description of the method employed in Cambium for power flow accounting, and its limitations, see Section 6.3.

The PLEXOS runs that Cambium draws from do not restrict which generators can provide power to which locations. In practice, some states have restrictions on the types of out-of-state power that can be imported, such as California's limits on long-term contracts for out-of-state coal power. Additionally, utilities often contract with specific suppliers that may justify them claiming power mixtures that are different from the estimates produced by the perfect-mixing approach implemented in Cambium. Cambium does not currently capture these state or utility accounting effects; it just assumes perfect mixing through all nodes. This assumption, and therefore this metric, may not be appropriate for some analyses.

5.5 Emission Metrics

Emissions are reported for three gasses: carbon dioxide (CO₂), methane (CH₄), and nitrous oxides (N₂O). CO₂ equivalent (CO_{2e}) values are also given that combine the three emissions using 100-year global warming potential (GWP) values from the Intergovernmental Panel on Climate Change (IPCC) *Sixth Assessment Report*. CH₄ and N₂O rate metrics are reported in g/MWh, whereas CO₂ and CO_{2e} rate metrics are reported in kg/MWh.

Additionally, emissions are reported for direct combustion (indicated with “_c” in the metric name) and precombustion processes (indicated with “_p” in the metric name). Precombustion processes include fuel extraction, processing, and transport (including fugitive emissions).

Emission metrics with “_co2e” and no “_c” or “_p” report the combined CO_{2e} value from both combustion and precombustion.

For the fuel-specific emissions factors used in all emissions calculations, see Section 6.2.

Metric Family: average emission rates of in-region generation

Metric Name: *aer_gen_co2_c*, *aer_gen_ch4_c*, *aer_gen_n2o_c*, *aer_gen_co2_p*, *aer_gen_ch4_p*, *aer_gen_n2o_p*, *aer_gen_co2e_c*, *aer_gen_co2e_p*, *aer_gen_co2e*

Units: kg/MWh_{generation} for CO₂ and CO_{2e}, g/MWh_{generation} for CH₄ and N₂O

Distribution Loss Metric: average

The *aer_gen* family of metrics is the average emission rate of all generation within a region for the specified duration of time, in either kilograms (kg) or grams (g) of emissions per megawatt-hour (MWh) of busbar generation. No adjustment is made for imported or exported electricity. Start-up and shut-down emissions are not included. Generation from batteries and pumped hydropower storage are assigned zero emissions (i.e., any emissions induced by storage technologies are reported when the storage is charged, not when discharged).

No adjustment is made to reflect policy-related accounting (i.e., this reports the actual emissions in the given region and time frame, and the effects of any credit trading for portfolio standard compliance is not reflected).

The CH₄ and N₂O metrics are reported in g/MWh, whereas CO₂ and CO_{2e} rate metrics are reported in kg/MWh. “_c” indicates emissions from direct combustion, whereas “_p” indicates emissions from precombustion processes. *aer_gen_co2e* reports combined combustion and precombustion rates.

Metric Family: average emission rates of generation induced by a region’s load

Metric Name: *aer_load_co2_c*, *aer_load_ch4_c*, *aer_load_n2o_c*, *aer_load_co2_p*, *aer_load_ch4_p*, *aer_load_n2o_p*, *aer_load_co2e_c*, *aer_load_co2e_p*, *aer_load_co2e*

Units: kg/MWh_{enduse} for CO₂ and CO_{2e}, g/MWh_{enduse} for CH₄ and N₂O

Distribution Loss Metric: average

The *aer_load* family of metrics is the average emission rate of the generation that is allocated to a region’s end-use load, in either kilograms or grams of emissions per megawatt-hour of end-use load. Unlike the average emission rate of in-region generation, this metric includes the effects of

imported and exported power. For example, if the power for a region’s load is being supplied in equal parts from in-region generation with a CO₂ emission rate of 400 kg/MWh and out-of-region generation with a CO₂ emission rate of 1,000 kg/MWh, the average CO₂ rate for generation supplying the power for that load would be 700 kg/MWh. If distribution losses were 5%, this metric would report the average CO₂ rate as 737 kg/MWh of end-use load.

The *aer_load* family assigns emissions to storage technologies based on the weighted average emission rates when the storage generators were charging. Unlike the *aer_gen* family, the *aer_load* family reflects credit trading for state portfolio standards.

Cambium allocates generation, and therefore the emissions from generation, by assuming perfect mixing through nodes. For a description of the method employed in Cambium for power flow accounting, and its limitations, see Section 6.3.

The PLEXOS runs that Cambium draws from do not restrict which generators can provide power to which locations. In practice, some states have restrictions on the types of out-of-state power that can be imported, such as California’s limits on long-term contracts for out-of-state coal power. Additionally, utilities often contract with specific suppliers that may justify them claiming power mixtures that are different from the estimates produced by the perfect-mixing approach implemented in Cambium. Cambium does not currently capture these state or utility accounting effects; it just assumes perfect mixing through all nodes. This assumption, and therefore this metric, may not be appropriate for some analyses.

The CH₄ and N₂O metrics are reported in g/MWh, whereas CO₂ and CO_{2e} rate metrics are reported in kg/MWh. “*_c*” indicates emissions from direct combustion, whereas “*_p*” indicates emissions from precombustion processes. *aer_load_co2e* reports combined combustion and precombustion rates.

Metric Family: short-run marginal emission rates for a region’s load

Metric Name: *srmer_co2_c*, *srmer_ch4_c*, *srmer_n2o_c*, *srmer_co2_p*, *srmer_ch4_p*, *srmer_n2o_p*, *srmer_co2e_c*, *srmer_co2e_p*, *srmer_co2e*

Units: kg/MWh_{enduse} for CO₂ and CO_{2e}, g/MWh_{enduse} for CH₄ and N₂O

Distribution Loss Metric: marginal

These metrics are the short-run marginal emission rates (SRMER) for end-use load, which is the rate of emissions that would be induced by a marginal increase in a region’s load at a specific point in time. The value is the emission rate of whichever generator would have served the marginal increase in load, modified by any relevant transmission, distribution, and efficiency losses.¹⁴ For an overview of the method that Cambium uses to interpret PLEXOS results and estimate which generator was on the margin at every point in time, see Section 6.5.

SRMER only describes the immediate operational response of the electric grid to a perturbation. It does not capture how the perturbation may influence the structure of the grid at a later point

¹⁴ If the marginal generator is not the initial source of energy (e.g., when the marginal generator is a battery), the marginal emission rate is derived from the emission rate of the actual marginal source of energy and is further modified by the efficiency of the energy-storing generator. For a discussion of how Cambium determines what the marginal energy source is in these circumstances, see Section 6.5.

(e.g., a when a fleet of electric vehicles charged, the SRMER will describe the operational impact of the charging, but not capture how the additional load from the fleet may prompt additional electric generators to be built). Therefore, a SRMER alone is typically unsuitable if an analyst wishes to comprehensively describe the impact of an intervention. Instead, it is often more suitable to use a long-run marginal emission rate (LRMER) or a blend of a SRMER and LRMER. See (Gagnon and Cole 2022) for more detailed discussion of this concept.

These metrics are reported as rates per MWh of end-use load. If a user wishes to obtain the SRMER at the busbar level (if they are estimating the emissions avoided by an alternative generation source injected at the busbar level, for example), they should adjust by the marginal distribution loss rate, as described in Section 5.1.

For every balancing area and every hour, the Cambium method identifies a single marginal generator, although multiple regions can have the same marginal generator if they are connected by a partially utilized transmission line. In practice, which generator is on the margin can (and typically does) switch much more frequently than the 1-hour resolution of the Cambium data sets.

SRMER depends on proper identification of the marginal generator (and energy source). As we discuss in Section 6.5, identification of marginal generators and energy sources is an ongoing area of research. We encourage any researcher working with this metric to approach it with a critical eye.

Cambium’s modeled SRMER values are not appropriate for real-time operational decision-making. The primary intended use of this metric is to inform research questions that depend on anticipating the patterns of SRMER in potential futures (e.g., what the patterns of SRMER might look like in a future with high variable generator deployment).

The CH₄ and N₂O metrics are reported in g/MWh, whereas CO₂ and CO_{2e} rate metrics are reported in kg/MWh. “_c” indicates emissions from direct combustion, whereas “_p” indicates emissions from precombustion processes. *srmer_co2e* reports combined combustion and precombustion rates.

Metric Family: long-run marginal emission rates for a region’s load

Metric Name: *lrmer_co2_c*, *lrmer_ch4_c*, *lrmer_n2o_c*, *lrmer_co2_p*, *lrmer_ch4_p*, *lrmer_n2o_p*, *lrmer_co2e_c*, *lrmer_co2e_p*, *lrmer_co2e*

Units: kg/MWh_{enduse} for CO₂ and CO_{2e}, g/MWh_{enduse} for CH₄ and N₂O

Distribution Loss Metric: average

The long-run marginal emission rate (LRMER) is the emission rate of the mixture of generation that would be either induced or avoided by an electric sector intervention, taking into account how the intervention may influence the structure of the grid (i.e., the building and retiring of capital assets, such as generators and transmission lines). It incorporates both the operational and structural consequences of an intervention and is therefore distinct from the short-run marginal emission rate, which treats grid assets as fixed. The units are kilograms or grams of emission per megawatt-hour of end-use load. For a description of the methodology used to calculate LRMER, see Section 6.4.

The LRMER in Cambium is designed to characterize the emissions consequences of interventions during the period of time where the intervention is in effect and structural responses to the intervention are likely to have occurred (i.e., when in long-run equilibrium). For interventions that were anticipated by resource planners (such as electric generators incorporated in resource plans or large energy efficiency campaigns), it may be appropriate to apply a LRMER to the entire duration of an intervention. For unanticipated interventions, it may be appropriate to blend a SRMER (for the first several years, prior to a structural response to the intervention occurring) and LRMER (for later years) to estimate the impact of an intervention.

These metrics are reported as rates per MWh of end-use load. If a user wishes to obtain the LRMER at the busbar level (if they are estimating the emissions avoided by an alternative generation source injected at the busbar level, for example), they should adjust by the average distribution loss rate, as described in Section 5.1.

LRMER can be applied to either load increases or decreases. Load increases could be estimating the electric-sector emissions that would be induced by increased electric vehicle charging or replacing a natural gas furnace with a heat pump. Load decreases might be estimating the emissions avoided by installing a more efficient cooling technology. The LRMER in Cambium databases was created with a scalar increase in load across all hours—for an exploration of how the metric might err for interventions of different shapes, see (Gagnon and Cole 2022).

The CH₄ and N₂O metrics are reported in g/MWh, whereas CO₂ and CO₂e rate metrics are reported in kg/MWh. “_c” indicates emissions from direct combustion, whereas “_p” indicates emissions from precombustion processes. *lrmer_co2e* reports combined combustion and precombustion rates.

Note that we apply average distribution loss rates to the long-run marginal emissions metrics, unlike the SRMER, to which we apply marginal loss rates. We do this because the LRMER assumes that generation and transmission assets can vary, and we therefore consider it appropriate to assume that distribution infrastructure will also vary, making an average loss rate a more appropriate metric. For example, if applying a LRMER to a load increase, the use of an average loss metric would implicitly assume the distribution infrastructure is expanding in response to the new load. If an analyst wishes to instead assume that distribution assets are held fixed, they can apply a marginal distribution loss rate to the busbar version of LRMER.

LRMER values are not calculated for solve years 2035 and later, for the 100% decarbonization by 2035 scenario. Note that, although combustion emissions would nominally net to zero during those years, there would still be non-zero precombustion values, as the decarbonization trajectories are defined in terms of net zero combustion emissions.

Metric Family: total emissions by region

Metric Name: *total_gen_co2_c*, *total_gen_ch4_c*, *total_gen_n2o_c*, *total_gen_co2_p*, *total_gen_ch4_p*, *total_gen_n2o_p*, *total_gen_co2e_c*, *total_gen_co2e_p*, *total_gen_co2e*

Units: metric tons

The *total_gen* family of metrics reports the total emissions from all generation within a region, in metric tons. No adjustment is made for imported or exported electricity. Start-up and shut-down

emissions are not included. The effect of carbon capture from CCS technologies is included (i.e., the emissions from CCS generators is net of their capture).

The CH₄ and N₂O metrics are reported in g/MWh, whereas CO₂ and CO_{2e} rate metrics are reported in kg/MWh. “*_c*” indicates emissions from direct combustion, whereas “*_p*” indicates emissions from precombustion processes. *aer_gen_co2e* reports combined combustion and precombustion rates.

Metric Family: carbon capture

Metric Name: *co2_captured_ccs*

Units: metric tons

This metric reports the CO₂ captured by Carbon Capture and Storage generation technologies (CCS), within a given region during a given timestep, in metric tons.

5.6 Cost Metrics

The metrics in this section are estimates of the marginal costs induced by an increase in demand (or avoided costs from a decrease in demand). In some instances, it may be appropriate to use these values as approximations of market prices for corresponding electric services, but it is important for users to understand the limitations of using marginal costs from least-cost optimization models as estimates of market prices. We strongly recommend users read Section 4, as well as the methods sections that discuss each cost metric in more detail than do the brief summaries given in this section.

All dollar values are in real terms for a constant dollar year. For the annual Cambium data sets, the dollar year is the year preceding the release (e.g., the 2023 Cambium dollar values are in 2022 dollars).

Metric Family: marginal energy costs

Metric Names: *energy_cost_busbar* and *energy_cost_enduse*

Units: \$/MWh_{busbar} and \$/MWh_{end-use}

Distribution Loss Metric: marginal

The *energy_cost_busbar* and *energy_cost_enduse* metrics report the short-run marginal costs of providing the energy for a marginal increase in load, in dollars per megawatt-hour of either busbar or end-use load. These metrics are derived using the shadow price of an energy constraint in the PLEXOS model. They include short-run costs that vary as a function of load (fuel and variable costs), but they do not reflect other operational costs that are fixed or vary as “steps,” such as start-up costs or fixed operation and maintenance costs. In practice it is possible for marginal energy costs to be negative, but due to incomplete representation of relevant phenomena (e.g., representation of all relevant tax credits in the production cost modeling step, and other phenomena such as self-scheduling and bidding strategies), marginal energy costs in Cambium have a floor of zero.

These metrics are conceptually similar to a day-ahead locational marginal price, given the limitations discussed in Section 4. Specifically, the coarse geographic resolution, lack of temperature effects on generator heat rates and transmission losses, and fact that these are derived

from the shadow prices out of a system-wide least-cost optimization model all contribute to these marginal costs tending to be less variable than observed prices in energy markets.

These marginal costs include the effects of generator short-run marginal costs, inter-BA transmission losses, and inter-BA transmission congestion. In the case of *energy_cost_enduse*, distribution loss effects are also included. Cost-recovery for start-up costs are not reflected in these values, as these are marginal costs and start-up costs are step changes. Debt service and fixed operation and maintenance costs are likewise not reflected in these marginal costs.

As a least-cost optimization model, PLEXOS can sometimes find solutions that result in exceptionally high marginal costs. For example, PLEXOS will sometimes drop a small amount of a reserve product and incur the associated penalty rather than incur the costs of starting up a generator that could have provided those reserves. This results in the marginal energy cost being set by the \$/MWh penalty for dropping the reserve product in that hour. Though this is a technically correct description of the least-cost solution as defined in the model, it does not correspond well to observed behavior of markets, and we find it generally misaligned for the types of analyses for which Cambium data are used. Therefore, for each BA and each time-step, we post-process the load constraint's shadow price to remove these types of price spikes.¹⁵ As discussed in Section 4, the models that Cambium draws from are not set up to assess resource adequacy or reliability, and the implementation of these caps reflects that limitation.

For scenarios that include national carbon constraints (the Mid-case 95% decarbonization by 2050 and Mid-case 100% decarbonization by 2035 scenarios in the 2022 Cambium release), the shadow price on the carbon constraint for the corresponding year in the underlying ReEDS model run is added to the operating costs of emitting generators for the corresponding PLEXOS run. This tends to meaningfully increase the marginal energy costs in the decarbonization scenarios.

Metric Family: marginal capacity costs

Metric Names: *capacity_cost_busbar* and *capacity_cost_enduse*

Units: \$/MWh_{busbar} and \$/MWh_{end-use}

Distribution Loss Metric: marginal

The *capacity_cost_busbar* and *capacity_cost_enduse* metrics report the long-run cost of additional capital investment necessary to maintain a target planning reserve margin when demand is increased. An annual marginal capacity cost is derived from the shadow price off of the capacity constraint in the ReEDS model, which is set by the least-cost option for obtaining a marginal increase in firm capacity within each BA. The increase in firm capacity can be achieved by building new generation capacity, by holding on to existing generation capacity that would

¹⁵ The shadow prices are processed by identifying hours where the shadow price in a region is more than twice the shadow price of both the preceding and following hours. In those instances, the shadow price is reduced to 20% of the average of the preceding and following hours. Additionally, shadow prices are capped across all regions and hours at the short-run marginal cost of the most expensive natural gas combustion turbine in the national fleet. This post-processing method was selected by comparing the results of post-processed modeled values against observed day-ahead locational marginal prices, with this method outperforming several other candidate methods.

otherwise have been retired, or by building new inter-BA transmission capacity, whichever is the least-cost solution.

The annual shadow price is then increased by the planning reserve margin and allocated to the highest net-load hours within the year. The use of net-load is a heuristic for identifying the hours with the highest loss of load probability, and therefore the hours in which increased demand would induce a need for more firm capacity. For a detailed discussion of these methods and their limitations see Section 6.8.

The annual planning reserve margin and shadow price on the capacity constraint are also provided in Cambium databases as the metrics *prm* and *capacity_shadow_price* respectively. The quantity of firm capacity set by the planning reserve margin is reported as *planning_capacity_MW*.

Metric Family: marginal costs of renewable and clean energy portfolio standards

Metric Names: *portfolio_cost_busbar* and *portfolio_cost_enduse*

Units: \$/MWh_{busbar} and \$/MWh_{end-use}

Distribution Loss Metric: marginal

The *portfolio_cost_busbar* and *portfolio_cost_enduse* metrics report the marginal cost of staying in compliance with a state's portfolio standard policies—both renewable portfolio standards (RPS) and clean energy standards (CES)—when end use demand is increased. For Cambium databases, unless otherwise noted in a scenario, enacted state-level RPS and CES are included.

For example, if a noncompliant technology (e.g., a natural gas generator for an RPS) is on the margin during a particular hour, additional consumption during that hour would require an increase in compliant generation at another point in the year for the standard to still be met. This cost reflects the cost of obtaining the required generation or credits through either operations or purchase.

In contrast, if a compliant technology is on the margin (e.g., a curtailing solar photovoltaic generator under most portfolio standards), there would be a value (i.e., negative cost) to additional consumption during that hour, as additional consumption would create credits from the otherwise-curtailed-generator, decreasing the need to acquire them through other means.

These costs are zero if either there are no portfolio standard policies or the policies that exist are not binding at that point in time.

For a discussion of how these metrics are calculated for Cambium databases, see Section 6.9. For a discussion of which policies are represented, and how they are represented in ReEDS, see (Ho et al. 2021).

Cambium databases also include the annual shadow prices on the policy constraints (see *rps_shadow_price* and *ces_shadow_price*), as well as the fraction of end-use load covered by each policy (see *rps_f* and *ces_f*).

Metric Family: total marginal cost
Metric Names: *total_cost_busbar* and *total_cost_enduse*
Units: \$/MWh_{busbar} and \$/MWh_{end-use}
Distribution Loss Metric: marginal

The *total_cost_busbar* and *total_cost_enduse* metrics are the sum of energy, capacity, and portfolio costs. These are only the costs that are currently included in Cambium databases, and they do not include costs for distribution capacity, transmission capacity, administrative and general expenses, and other electric sector expenses. Therefore, this metric does not capture all the costs of building and operating the electric system. If the intervention being analyzed would influence costs beyond the ones currently included in the Cambium database, those additional costs may need to be estimated through other methods for a complete analysis. As with marginal energy costs, this metric has a floor of zero, due to incomplete representation of the phenomena that can result in negative marginal energy costs.

Additionally, we emphasize that these costs are estimates of the costs incurred by the bulk power system by marginal consumption, and they are not estimates of retail electricity prices. Retail prices typically include cost recovery for other expenses and are often set by ratemaking methods designed to collect target revenue amounts from various customer classes, instead of adhering strictly to marginal cost pricing.

5.7 Interregional Transmission Metrics

These transmission metrics include only transmission between BAs, not within BAs. They also do not include Canadian imports and exports, which are represented as generation and end-use loads in the respective border regions.

Metric Family: total imports and total exports
Metric Names: *imports* and *exports*
Units: MWh_{busbar}

The *imports* and *exports* metrics capture the total imports and exports into and out of a region through interregional transmission lines, in megawatt-hours of energy at the busbar level.

This value is the energy sent along the transmission lines, and it is not netted by transmission losses. Transmission losses (reported in Cambium databases as additional load in the *trans_losses* metric) are allocated equally between the sending and receiving regions. For example, if 100 MWh of energy is transmitted between two regions while incurring 5 MWh of losses, the load in both the sending and receiving regions would increase by 2.5 MWh. In effect, the receiving region would receive a net of 97.5 MWh of energy while the burden on the sending region would be higher by 102.5 MWh. This would be reported as 100 MWh of *imports* in the receiving region, 100 MWh of *exports* in the sending region, and 2.5 MWh of *trans_losses* in both the sending and receiving regions.

5.8 Load Metrics

Metric Family: total load at the busbar

Metric Name: *busbar_load*

Units: MWh_{busbar}

The *busbar_load* metric reports the total electric load in a region, in megawatt-hours of busbar load. It includes the load from end uses (including the busbar equivalent of end-use load that is served by behind-the-meter PV), load incurred through transmission losses, and load from storage generators charging.

Metric Family: end-use load

Metric Names: *enduse_load* and *busbar_load_for_enduse*

Units: MWh_{enduse} and MWh_{busbar}

The *enduse_load* metric reports the amount of electricity consumed at the point of end use within a region, including end-use load that is served by behind-the-meter PV. The metric *busbar_load_for_enduse* reports the quantity of load consumed at the busbar level to meet that end-use load. Therefore, *busbar_load_for_enduse* is larger because it is prior to incurring distribution losses whereas *enduse_load* is smaller because it is after incurring distribution losses.

Neither of these metrics includes transmission losses or storage load, which are both loads induced at the busbar.

In border regions, Canadian exports are included in the end-use load metric.

Metric Family: load from transmission losses

Metric Name: *trans_losses*

Units: MWh_{busbar}

The *trans_losses* metric reports the amount of energy that is lost due to inter-BA transmission losses. The losses are represented as an additional load at the busbar level, split equally between the sending and receiving BA.

Metric Family: load from storage generators that are charging

Metric Names: *battery_charging* and *phs_charging*

Units: MWh_{busbar}

The metrics *battery_charging* and *phs_charging* report the busbar load caused by the charging of electric battery storage and pumped hydropower storage respectively. The *battery_charging* metric includes charging from the McIntosh compressed air energy storage plant in McIntosh, Alabama.

Metric Family: net load

Metric Name: *net_load_busbar*

Units: MWh_{busbar}

The metric *net_load_busbar* reports the *busbar_load* minus *variable_generation*.

5.9 Operational Metrics

Metric Family: Curtailment

Metric Names: *curt_wind_MWh*, *curt_solar_MWh*, *curtailment_MWh*

Units: MWh_{busbar_load}

These metrics reflect the curtailed generation from wind, solar, geothermal, non-dispatchable hydropower, and nuclear generators. It is the difference between the available generation and actual generation over the given time period. *curt_wind_MWh* and *curt_solar_MWh* report curtailment of those respective technology classes, while *curtailment_MWh* reports the total curtailment from all of the technology classes listed above.

Note that, in practice, the relative order of curtailment between different technology types (e.g., nuclear versus variable renewables) or generators of the same technology (e.g., two solar generators located in neighboring balancing areas) may depend on market characteristics or specifics of a region's generator dispatch procedure not captured here. Analysts are encouraged to keep this in mind when interpreting these curtailment metrics: wind and solar curtailment values are given in order for analysts to determine what occurred in this modeling, and to reconstruct the before-curtailment generation values, but it should be recognized that the actual preferences of the order of curtailment may be different in practice. Therefore, analysts may wish to use the *curtailment_MWh* metrics as a more general estimation of the curtailment of low-or-zero-marginal-cost clean generators as a group.

Metric Family: distribution loss rates

Metric Names: *distloss_rate_avg* and *distloss_rate_marg*

Units: MWh_{losses}/MWh_{busbar_load}

The metric *distloss_rate_avg* is the average distribution loss rate (i.e., the rate of losses incurred in the distribution of electricity to end uses in a region). The metric *distloss_rate_marg* is the marginal distribution loss rate (i.e., the rate of losses incurred in the distribution system by a marginal increase in the end-use load in the region). Both marginal and average loss rates increase as the end-use load in a region increases.

The average loss rate (α) is defined as losses (L) per busbar load consumed for end use (D):

$$\alpha = \frac{L}{D}$$

For example, if 100 MWh of energy were consumed at the busbar for end uses, and 5 MWh were lost in distribution, the total consumption at the end use would be 95 MWh and the average loss rate would be 5%. Similarly, the marginal loss rate (μ) is defined as the increase in losses per marginal increase in busbar load consumed for end use.

See Section 6.7 for our approach and assumptions for calculating average and marginal distribution loss rates.

Metric Family: planning reserve margin

Metric Name: *prm*

Units: MW_{firm}/MW_{peak}

The *prm* metric reports the planning reserve margin (PRM) used within ReEDS. Utilities, regulators, and system operators use the PRM as a heuristic for procuring sufficient firm capacity to achieve a desired level of resource adequacy, where resource adequacy is defined as “the ability of supply- and demand-side resources to meet the aggregate electrical demand” (NERC 2020).

The PRM is defined as the fraction of firm capacity above peak demand:

$$PRM = \frac{\text{Firm Capacity} - \text{Peak Demand}}{\text{Peak Demand}}$$

For example, in a region with a peak demand of 100 MW and a PRM of 0.15, the planned capacity would be 115 MW.

The PRMs applied in ReEDS are based on reserve margin requirements for North American Electric Reliability Corporation reliability subregions (NERC 2010).

Metric Family: planning capacity

Metric Name: *planning_capacity_MW*

Units: MW_{firm}

The *planning_capacity_MW* metric reports how much firm capacity is called for in each region to meet the planning reserve margin, where firm capacity is defined as capacity that can reliably contribute to meeting the region’s peak demand. For documentation of how ReEDS assesses the ability of different generators to contribute firm capacity, see (Ho et al. 2021).

The sum of the BA-level planning capacities will exceed the maximum amount of firm capacity available in the conterminous United States, because peak demand periods are noncoincident across the country, and therefore capacity trading can reduce the total capacity needed to below the sum of the BA’s requirements. Relatedly, a BA’s maximum demand may exceed its planning capacity, if its maximum demand occurs at a different time than the region’s peak demand.

Metric Family: shadow price on the capacity constraint

Metric Name: *capacity_shadow_price*

Units: \$/MW_{firm}

The *capacity_shadow_price*, which is an annual value from the ReEDS model, is the marginal cost of procuring another megawatt of firm generation capacity. It is used in the calculation of the marginal capacity cost.

The shadow price off of this constraint is the \$/MW-year marginal cost for obtaining additional firm capacity. The model will find the least-cost option amongst the options of increasing generation capacity, increasing transmission capacity, or delaying the retirement of an existing

generator. See Section 6.8 for more discussion about the capacity shadow price and its translation into hourly marginal capacity costs.

Because of the prevalence of retiring generators, and the ability of wind and solar to contribute firm capacity, Cambium results for the 2020s often show capacity shadow prices that are substantially lower than what they would be if the shadow price were only being set by the net cost of new entry (CONE) of a natural gas combustion turbine (a common benchmark in practice). For some analyses, it may be appropriate for an analyst to substitute Cambium's shadow price with a different estimate of the marginal cost of capacity (e.g., annualized cost of a new combustion turbine) if there is reason to believe such an estimate describes the behavior of the region being analyzed better than the solution found by Cambium.

Metric Family: technology of the short-run marginal generator and short-run marginal energy source

Metric Names: *marg_gen_tech* and *marg_es_tech*

The *marg_gen_tech* and *marg_es_tech* are the technologies of the short-run marginal generator and the short-run marginal energy source for a given location and time. These metrics only refer to the short-run marginal generator. In the long run, a marginal increase in demand is typically served by a mixture of generators. These metrics are only reported at the hourly balancing area resolution.

The marginal generator is the generator that would provide the power to cover an increase in load, precisely when the load is increased. However, we differentiate between the marginal generator and the marginal energy source because some generators are energy-constrained and would therefore be unable to create new electrical energy if they were the marginal generator. We call these generators energy-constrained generators, and they include both generators that never have the ability to create new energy (e.g., batteries) and generators that have a limited budget of energy that they would dispatch entirely under expected conditions (e.g., dispatchable hydropower).

If an energy-constrained generator provides power, a different generator—one that can create new electric energy—must increase its generation at a different time. The generator that would ultimately increase its generation in response to the energy-constrained generator providing power as a marginal generator is the generator we consider to be the marginal energy source.

Each balancing area can only have a single marginal generator and marginal energy source during each time-step, although multiple balancing areas can share the same generators through transmission.

We note that the relative priority of curtailing zero or near-zero marginal cost generators (PV, wind, CSP without storage, geothermal, non-dispatchable hydropower, and nuclear generators) is, in practice, influenced by market and generator operations that may not be well captured by Cambium's production cost modeling. For example, the short-run marginal cost assigned to nuclear plants in Cambium modeling averages \$6/MWh, non-dispatchable hydropower \$1/MWh, and the rest of the mentioned technologies \$0/MWh. Therefore, Cambium's production cost modeling will generally curtail nuclear first, followed by hydropower, followed by a degenerate

selection between the remaining technologies after that point. Whether such a rank-ordering would actually occur would depend on, amongst other things, whether nuclear generators ramp their outputs, water conditions for hydropower generators, and production incentives for any generators that may result in negative cost bids. Although we report when each of these technologies was identified on the short-run margin, we encourage analysts to generally view them as amongst the same class of zero-or-near-zero-marginal-cost, zero-emissions generators, where the actual one that would be on the short-run margin at a specific point in practice would depend on specific operational details.

For a discussion of how the marginal generators and marginal energy sources are identified for Cambium databases, see Sections 6.5 and 6.6.

5.10 Policy Metrics

Metric Family: shadow price on portfolio standard constraints

Metric Names: *rps_shadow_price* and *ces_shadow_price*

Units: \$/MWh_{credit}

These metrics are the shadow prices on portfolio standard constraints from the ReEDS model. Unless otherwise specified in a scenario's description, the ReEDS runs that Cambium draws from represents both renewable portfolio standards and clean energy standards.

These metrics are annual values, and they represent the marginal cost of procuring another megawatt-hour of generation (or an unbundled credit from eligible generation, where allowed) that is eligible to satisfy the requirements of the policy.

Although these metrics are conceptually similar to the price of policy credits (e.g., RECs), important limitations to our representation mean these values are unlikely to be good estimates of the market price of these credits in practice. These limitations include the lack of inter-year credit banking, imperfect representations of policies, no representation of other consumers of policy credits, and the fact that these are long-run not short-run values (i.e., the shadow price reflects the option of building additional capacity to generate more credits).

For a discussion about how these values are used in calculating the marginal portfolio costs, see Section 6.9. For documentation of how these policies are represented in ReEDS, see (Ho et al. 2021).

Metric Family: portfolio standard fractions

Metric Names: *rps_f* and *ces_f*

Units: MWh_{credit}/MWh_{end-use}

These metrics are the requirements of state-level portfolio standard constraints from the ReEDS model. Unless otherwise specified in a scenario's description, the ReEDS runs that Cambium draws from represent both renewable portfolio standards and clean energy standards.

These fractions are the average requirement for the end-use load within the region covered by the policy. Defined in this way, these fractions are frequently lower than the nominal top-line number of the policy they represent, as many policies exclude certain types of load from being

covered. For example, many states exempt utilities below a certain size from their policies. Such exemptions would result in a fraction that is lower than the nominal RPS goal.

For a discussion about how these values are used in calculating the marginal portfolio costs, see Section 6.9. For documentation of how these policies are represented in ReEDS, see (Ho et al. 2021).

Metric Family: shadow price on CO₂ constraint

Metric Names: *co2_shadow_price*

Units: \$/metric ton

This metric reports the shadow price on the CO₂ constraint, if such a constraint is present for a particular scenario. As the shadow price is derived in the ReEDS model, it is a long-run value, not a short-run value (i.e., the shadow price reflects the option of building additional capacity).

6 Cambium Methods

Cambium draws from the outputs of ReEDS and PLEXOS when creating its output database. This section documents the methods that Cambium implements to process the outputs from ReEDS and PLEXOS into the final Cambium database.

6.1 Technologies Represented in Cambium

Data are reported for technology groups in Cambium (Table 4). The actual number of discrete technologies in both the ReEDS and PLEXOS runs is greater, but the data are grouped to reduce the size of the database. The ReEDS and PLEXOS technologies that are within each of Cambium’s technology groups is given in Table 4. Within each ReEDS and PLEXOS technology, there can be generators with varying performance characteristics (e.g., heat rates), based on improvement over time, but we do not consider those as distinct technologies. For a detailed discussion of how each technology is represented, see (Ho et al. 2021).

Table 4 also indicates whether the technology is classified as either established or nascent. Six of the eight scenarios in Cambium 2023 only include established technologies. The two scenarios with national decarbonization trajectories also include the nascent technologies.

The classification of technologies as either nascent or established was an analytical judgement call based on the technology’s readiness level, the current installed capacity globally, the current presence or absence of the technology in resource plans in the United States, the level of understanding of permitting and siting challenges, and the breadth and quality of future performance and cost estimates from multiple institutions.

The designation of a technology as nascent is not intended to pass judgement on the difficulty or likelihood of the technology ultimately achieving commercial adoption. Indeed, many of the technologies have high technology readiness levels, and some have operational demonstration plants. Nonetheless, even if a technology is technically viable, there can still be great uncertainty about its future cost and performance, as well as a lack of understanding of other considerations relevant to projecting their adoption, such as siting preferences and restrictions. Given these uncertainties, Cambium data sets rely to a greater extent on scenarios that do not include such technologies.

Table 4. Cambium Technologies

Technology Name in Cambium Database	Technologies in ReEDS and PLEXOS	Technology Classification
battery	Electric batteries	Established
beccs	Bioenergy with carbon capture and storage	Nascent
biomass	Biopower and landfill gas	Established
canada	Canadian imports	Established
coal	Coal (scrubbed and unscrubbed, integrated gasification combined cycle, and biomass cofired)	Established
coal-ccs	Coal with carbon capture and storage	Nascent

Technology Name in Cambium Database	Technologies in ReEDS and PLEXOS	Technology Classification
csp	Concentrating solar power (with and without thermal energy storage)	Established
distpv	Behind-the-meter PV	Established
gas-cc	Natural gas combined cycle	Established
gas-cc-ccs	Natural gas combined cycle with carbon capture and storage	Nascent
gas-ct	Natural gas combustion turbine	Established
geothermal	Geothermal (hydrothermal, near-field enhanced geothermal, and deep enhanced geothermal systems)	Established (conventional geothermal), nascent (enhanced geothermal)
hydro	Hydropower (existing and undiscovered, dispatchable and nondispatchable)	Established
nuclear	Nuclear (both conventional and small modular reactors)	Established (conventional), nascent (SMRs)
o-g-s	Oil-gas-steam	Established
phs	Pumped hydropower storage	Established
h2-ct	Hydrogen combustion turbine	Nascent
upv	Utility-scale and distributed-utility-scale PV	Established
wind-ofs	Offshore wind (fixed-bottom and floating)	Established (fixed-bottom), nascent (floating)
wind-ons	Onshore wind	Established

6.2 Emissions Factors by Fuel

Cambium emission metrics are calculated using the fuel-specific emissions factors given in Table 5. The resulting emissions per MWh of electric generation is a function of the generator’s heat rate (i.e., the rate at which fuel is converted into electricity), which can vary by generator. Heat rates for newly built generators in Cambium data sets generally follow the projections in NREL’s Annual Technology Baseline, unless otherwise specified. Heat rates for existing generators draw from U.S. Energy Information Administration (EIA) data and are available in the publicly available ReEDS repository.

The precombustion emission factors include fuel extraction, processing, and transport, including fugitive emissions. Because these activities occur prior to combustion, it should be noted that the precombustion emissions associated with a particular timestep are not actually occurring at that timestep.

The precombustion emissions for natural gas are drawn from (Alvarez et al. 2018). Power plants are assumed to avoid local distribution losses, resulting in a fugitive methane emissions rate that starts at 2.2% in 2022 and decreases linearly by 30% by 2030 based on Biden administration goals (Jeff Mason and Alexandra Alper 2021). If an analyst wished to make a consistent

assumption for a technology that incurs local distribution losses (e.g., gas-powered home appliances), the value would start at 2.3% in 2022 and likewise linearly decrease by 30% by 2030.

Emissions from ongoing, noncombustion activities (e.g., the emissions induced by operation and maintenance activities) are not included in Cambium emissions metrics. Emissions from commissioning or decommissioning generators or other physical infrastructure are also not included.

Bioenergy with carbon capture and storage technologies are assumed to have a net capture rate of 60 kg of CO₂ per MMBtu of fuel, following the assumption in ReEDS. That value is for CO₂ from direct combustion, and the rest of the emission factors take the same values as the biomass category.

Natural gas and coal generators with carbon capture are assumed to have a 95% reduction in their CO₂ from direct combustion. All other emissions factors for those generating technologies following their fuel-specific values.

Sources:

- USLCI: *U.S. Life Cycle Inventory Database*, (National Renewable Energy Laboratory 2021)
- EPA 2016: *Greenhouse Gas Inventory Guidance: Direct Emissions from Stationary Combustion Sources*, (United States Environmental Protection Agency 2016).
- ATB 2023: *Annual Technology Baseline 2023*, (NREL 2023).
- CARB 11-307: *Assessment of the Emissions and Energy Impacts of Biomass and Biogas Use in California*, (Carreras-Sospedra et al. 2015).
- Alvarez et al. 2018: Assessment of methane emissions from the U.S. oil and gas supply chain.

Table 5. Emission Factors by Fuel

Fuel	Type	Emission	Emission Factor	Units	Source
Coal	Precombustion	CO ₂	2.94	kg/MMBtu	USLCI, Bituminous Coal at power plant
		CH ₄	208.26	g/MMBtu	USLCI, Bituminous Coal at power plant
		N ₂ O	0.05	g/MMBtu	USLCI, Bituminous Coal at power plant
	Combustion	CO ₂	95.52	kg/MMBtu	EPA 2016, Table A-3, Coal and Coke, Mixed (Electric Power Sector)
		CH ₄	11.00	g/MMBtu	EPA 2016, Table A-3, Coal and Coke, Mixed (Electric Power Sector)

Fuel	Type	Emission	Emission Factor	Units	Source
		N ₂ O	1.60	g/MMBtu	EPA 2016, Table A-3, Coal and Coke, Mixed (Electric Power Sector)
Natural Gas	Precombustion	CO ₂	6.27	kg/MMBtu	USLCI, Natural Gas at power plant
		CH ₄	571.6 – 400.2	g/MMBtu	(Alvarez et al. 2018; Jeff Mason and Alexandra Alper 2021) 571.6 g/MMBtu in 2022 decreasing linearly to 400.2 g/MMBtu in 2030, constant thereafter
		N ₂ O	0.02	g/MMBtu	USLCI, Natural Gas at power plant
	Combustion	CO ₂	53.06	kg/MMBtu	EPA 2016, Table A-3, Natural Gas
		CH ₄	1.00	g/MMBtu	EPA 2016, Table A-3, Natural Gas
		N ₂ O	0.10	g/MMBtu	EPA 2016, Table A-3, Natural Gas
Residual Fuel Oil	Precombustion	CO ₂	9.91	kg/MMBtu	USLCI at power plant
		CH ₄	153.45	g/MMBtu	USLCI at power plant
		N ₂ O	0.17	g/MMBtu	USLCI at power plant
	Combustion	CO ₂	75.10	kg/MMBtu	EPA 2016, Table A-3, Petroleum Products, Residual Fuel Oil No. 6
		CH ₄	3.00	g/MMBtu	EPA 2016, Table A-3, Petroleum Products, Residual Fuel Oil No. 6
		N ₂ O	0.60	g/MMBtu	EPA 2016, Table A-3, Petroleum Products, Residual Fuel Oil No. 6
Uranium	Precombustion	CO ₂	0.84	kg/MMBtu	USLCI, Uranium at power plant
		CH ₄	2.10	g/MMBtu	USLCI, Uranium at power plant
		N ₂ O	0.02	g/MMBtu	USLCI, Uranium at power plant
	Combustion	CO ₂	0.00	kg/MMBtu	ATB 2023
		CH ₄	0.00	g/MMBtu	-
		N ₂ O	0.00	g/MMBtu	-
Biomass	Precombustion	CO ₂	2.46	kg/MMBtu	CARB 11-307, Table 15
		CH ₄	2.94	g/MMBtu	CARB 11-307, Table 15
		N ₂ O	0.01	g/MMBtu	CARB 11-307, Table 15
	Combustion	CO ₂	0.00	kg/MMBtu	ATB 2023
		CH ₄	0.00	g/MMBtu	-
		N ₂ O	0.00	g/MMBtu	-

6.3 Coloring Power Flows

When calculating the characteristics of the generation allocated to load at a certain point—such as the average emission rate of the generators serving end-use consumption at a specific node—the composition of the source generation must be determined, including the contribution of

generators in different regions that may be sending power through transmission lines. Therefore, we need a method for allocating the generation from each generator to loads—or, from the other perspective, finding where the power for a given node’s end use originally came from. To do so, we take the network of nodes and transmission flows in each PLEXOS solution that Cambium draws from, and assume each node is a “perfect mixer” (i.e., that any electricity consumed or exported from a node is a perfect mixture of the electricity being supplied to the node).

Consider the network in Figure 11.

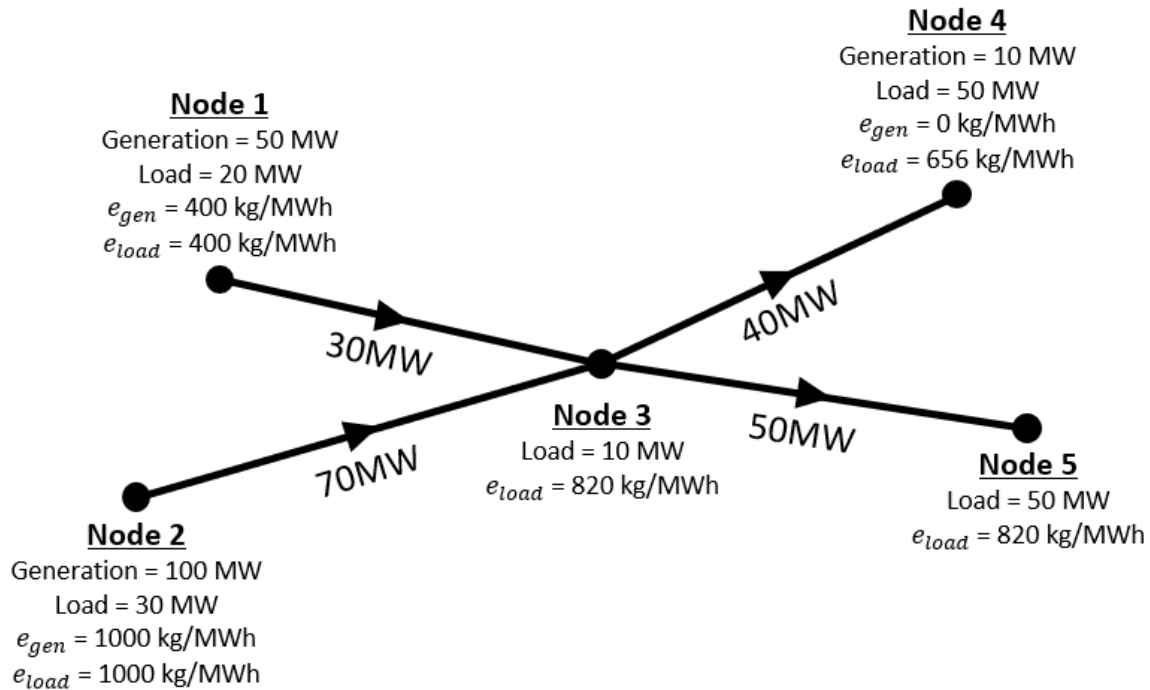


Figure 11. Simple network for illustrating power flow coloring

In this toy example shown in Figure 11, we have a system with five nodes (N_1 – N_5), connected by four transmission lines. Only nodes N_1 , N_2 , and N_3 have generation, with emission rates for in-region generation (e_{gen}) of 400, 1,000, and 0 kg/MWh respectively. For this example, we assume there are no transmission losses.

The question we are trying to answer is: What is the emission rate that you could ascribe to each of the five nodes’ load (e_{load})?

For N_1 and N_2 , the only power flowing into the node is from their own generation (they are not importing any power), and therefore we consider the emission rates induced by their load to be the rates of their in-region generation, which are 400 kg/MWh and 1,000 kg/MWh respectively.

For N_3 , we see that 30% of the power it is receiving is coming from N_1 , and 70% is coming from N_2 . The weighted average of those two sources is 820 kg/MWh, and therefore we take that as the emission rate induced by the load at N_3 .

Given the assumption of perfect mixing through N_3 , we assume the power that both N_4 and N_5 are receiving from N_3 must be identical, and of the same character as the power that was consumed within N_3 itself. Therefore, the transmission from N_3 to N_4 and from N_3 to N_5 is assumed to have an emission rate of 820 kg/MWh.

N_4 is receiving 40 MW of power from N_3 at 820 kg/MWh and 10 MW of power from its own generation at 0 kg/MWh. The result is an emission rate of 656 kg/MWh ascribed to the load in N_4 .

N_5 is only importing power from N_3 , and therefore its load is ascribed the emission rate of 820 kg/MWh.

The example above is a trivial network: to calculate the contribution of each BA's generation to each BA's loads for the 134 BAs in Cambium (which are the nodes in our models), we use the downstream-looking algorithm from Bialek (1996), which we summarize next for our application here.

For each BA and each time-step, we take the generation in the node (g_i), total imports into the node ($f_{in,i}$), and total exports from the node ($f_{out,i}$), and derive the load (l_i):¹⁶

$$l_i = g_i + f_{in,i} - f_{out,i}$$

We then calculate the nodal through-flow P_i as the sum of the node's load and outflow.

$$P_i = l_i + f_{out,i}$$

We then calculate the values for the downstream distribution matrix (\mathbf{A}_d), which is a square matrix whose length and width is the number of nodes. The (i, l) element of \mathbf{A}_d is:

$$[\mathbf{A}_d]_{i,l} = \begin{cases} 1, & i = l \\ -|f_{i-l}|/P_i, & l \in \alpha_i^{(d)} \\ 0, & otherwise \end{cases}$$

Where $\alpha_i^{(d)}$ is the set of nodes that are directly supplied by node i and f_{i-l} is the total flow into node l directly from node i .

We then take the inverse of \mathbf{A}_d to obtain \mathbf{A}_d^{-1} . Using each (i, l) element of \mathbf{A}_d^{-1} , we calculate the amount of generation from source BA i that can be allocated to the load in destination BA l (g_{i-l}):

$$g_{i-l} = g_i * l_i * [\mathbf{A}_d^{-1}]_{i,l}/P_i$$

Note that this can also be expressed as an allocation factor f_{i-l} which can be used to allocate any quantity from node i to node l , if it is assumed to flow proportionally with generation:

¹⁶ We derive the load, instead of using the output from PLEXOS, to avoid violations of Kirchhoff's current law that could arise from rounding errors in the outputs.

$$f_{i-l} = l_i * [A_d^{-1}]_{i,l} / P_i$$

Lastly, we use the allocation of generation to determine the weighted average of the characteristics of the generation sources supplying each BA. For example, for generic attribute X_l :

$$X_l = \frac{\sum_{i=1}^n g_{i-l} * X_i}{l_i} \quad i = 1, 2, \dots, n$$

This is the general form of the method we described above for our trivial network in Figure 11.

In Cambium, we iterate through every time-step, calculating the allocation factors g_{i-l} between every pair of the 134 BAs (i.e., what fraction of the generation from one BA is allocated to the load in another BA). With these allocation factors, we can calculate the characteristics of the generation that is supplying every BA, at every time-step.

Caveats and Limitations

Allocating generation based on the assumption of perfect mixing through every node is not always appropriate. If load in one BA contracted to have generation of a certain type produced in a neighboring BA and shipped to them (e.g., with a power purchase agreement), it may be appropriate to assign all that generation to the BA that contracted for that specific type of energy. Similarly, some states, like California, have restrictions on importing power from certain fuel types (e.g., coal), and these restrictions would not necessarily be respected with this perfect-mixing implementation.

Additionally, because transmission losses are represented as load in our models, we are not accurately capturing their impact. Our current approach slightly dilutes the emission rate ascribed to end-use load, because it is not separated from the load induced by transmission losses. In future iterations of Cambium, we intend on improving this algorithm to properly reflect the effects of transmission losses, which our current implementation does not do.

6.4 Calculating Long-Run Marginal Emission Rates

The long-run marginal emission rate (LRMER) is the emission rate of the generation that would either be induced or avoided by a marginal change in electric load, including both the operational and structural (e.g., building new generation or transmission capacity) consequences of the marginal change.¹⁷ This is in contrast to the short-run marginal emission rate, which is the emission rate that would serve a marginal increase in load, but with the capital assets of the grid being fixed (i.e., the short-run marginal emission rate only reflects the immediate operational consequences of a marginal change in load).

It is worth noting explicitly that the LRMER is not simply the SRMER in the future (or averaged over a long period of time). Because the LRMER incorporates the potential for structural change into its formulation, whereas the SRMER is strictly an operational metric, they are fundamentally different metrics, not the same metric for different time periods. In situations

¹⁷ The terms “short-run” and “long-run” do not refer to specific lengths in time, but instead are just referring to whether the equilibrium solution is evaluated with fixed capital assets (short-run), or by allowing capital assets to vary as part of the solution (long-run).

where an intervention would induce structural change, SRMER is an incomplete characterization of the consequences of an intervention (often overestimating the emissions consequences of the action). See (Gagnon and Cole 2022) for a more thorough exploration of the difference between the two metrics.

For Cambium, we estimate the LRMER by solving each modeled year twice: once with the projected conditions (the “Base” solve) and again with everything the same except for a scalar increase in end-use electricity demand (the “Perturb” solve). As the perturb solve includes both operational as well as structural changes to serve the additional demand (at least cost subject to policy and operational constraints), it represents a long-run solution, not a short-run. By comparing the generation mixtures between the two solves, we can derive a long-run marginal emission rate.

At a high level, the approach is:

1. Run each solve year twice, a Base and Perturb solve.
2. Use power flow accounting to allocate any increases in generation to the regions that consume the increases, and then subtract any decreases in generation to derive a net change in consumed generation of each technology type.
3. Assign origination mixtures for energy-constrained generators (e.g., battery storage and dispatchable hydropower).
4. Examine the resulting mixtures by state. Where the resulting mixtures would not be in compliance with a state policy, trade credits with states that have excess to reflect accounting transfers.
5. Apply distribution losses.

We walk through our methodology in more detail below. We discuss the limitations of our current method at the end of this section.

Step 1: Run Each Solve Year Twice

The objective of the long-run marginal emission rate metric is to estimate the change in emissions that would result from a change in end-use electric demand, taking into account both operational and structural responses to the change in demand. Therefore, to calculate the LRMER, we run both our ReEDS and PLEXOS models twice for each solve year. The first run (the “Base” run) is the same run that we use for all other metrics in the database (i.e., all of the inputs take their projected values for that point in time). The second run (the “Perturb” run) is identical for every input except for one: end-use load is scaled up from the base run.

Because the only difference between the two runs is the end-use electrical demand, we can then examine the differences between the two runs and ascribe any changes as being induced by the higher demand.

Crucially, because both ReEDS (a capacity expansion model) and PLEXOS (a production cost model) were rerun for each year, the resulting generation mixtures include potential structural responses to changes in load. If only a production cost model was perturbed, the generator fleet between the two mixtures would be the same, and the results would therefore only be short-run values.

Step 2: Allocate Changes in Generation to Regions

In this step, the changes in generation between the Base and Perturb model runs are allocated to GEA regions, along with the fuel consumption of that generation. This approach is based on the work of Bialek (1996), previously described in Section 6.3, but modified for allocating differences instead of absolute values.

First, the generation mixtures for both the Base and Perturb model solves are aggregated by GEA regions (g) and technology (t), and their difference calculated ($\Delta g_{g,t}$). The changes in generation are split into generation increases $\Delta g_{g,t,+}$ and generation decreases $\Delta g_{g,t,-}$ for region g and technology t (in the set of technologies with n technologies), and the sum of all technologies with nonnegative generation is calculated as $\Delta g_{g,+}$. The corresponding fuel consumption is also calculated.

$$\Delta g_{g,+} = \sum_{t=1}^n \begin{cases} 0, & \Delta g_{g,t} < 0 \\ \Delta g_{g,t}, & \Delta g_{g,t} \geq 0 \end{cases}$$

Transmission flows are also aggregated to the interfaces between GEA regions and their differences calculated. $\Delta f_{in,g}$ indicates the change in flows into GEA region g , whereas $\Delta f_{out,g}$ indicates the change in flows out.

The change in load Δl_g in region g is then calculated as the sum of increased generation and new imports less new exports.

$$\Delta l_g = \begin{cases} 1, & \Delta g_{g,+} + \Delta f_{in,g} - \Delta f_{out,g} < 0 \\ \Delta g_{g,+} + \Delta f_{in,g} - \Delta f_{out,g}, & \Delta g_{g,+} + \Delta f_{in,g} - \Delta f_{out,g} \geq 0 \end{cases}$$

Note that it is possible for the derived load changes Δl_g to be negative (if a large charging load in the Base run is not present at that time in the Perturb run). The value l_g is restricted to being positive (with a lower bound of 1 MWh). Additional treatment for regions where the l_g value would have been negative are explained later when we are handling energy storage generators in the following step.

As with the original form of the power flow algorithm, we then calculate the nodal through-flow P_g , but using Δl_g and $\Delta f_{out,g}$

$$P_g = \Delta l_g + \Delta f_{out,g}$$

We then calculate the values for the downstream distribution matrix (\mathbf{A}_d), which is a square matrix whose length and width is the number of GEA regions. The (g, l) element of \mathbf{A}_d is:

$$[\mathbf{A}_d]_{g,l} = \begin{cases} 1, & g = l \\ -|\Delta f_{g-l}|/P_g, & l \in \alpha_g^{(d)} \\ 0, & otherwise \end{cases}$$

Where $\alpha_g^{(d)}$ is the set of nodes that are directly supplied by node g and Δf_{g-l} is the difference in the total flow into node l directly from node g .

We then take the inverse of \mathbf{A}_d to obtain \mathbf{A}_d^{-1} . Using each (g, l) element of \mathbf{A}_d^{-1} , we calculate an allocation factor that gives us the fraction of $\Delta g_{g,+}$ (and therefore the technology-specific $\Delta g_{g,t,+}$, as well as any attributes of $\Delta g_{g,t,+}$ that flow with it proportionally, such as fuel consumed) that can be allocated to GEA region l .

$$\omega_{g-l} = \Delta l_l * [\mathbf{A}_d^{-1}]_{g,l} / P_g$$

The allocated generation increases are aggregated together by technology and GEA region, and then any generation decreases ($\Delta g_{g,t,-}$) from each GEA region are subtracted from that aggregation. For example, if a region decreased its coal generation by 10 MWh but increased the amount of coal generation it was importing by 10 MWh, the net change in consumed coal generation would be zero. This is expressed in the following equation, where i is the number of GEA regions.

$$\Delta g_{l,t,net} = \left(\sum_{g=1}^i \Delta g_{g,t,+} * \omega_{g-l} \right) - \Delta g_{g,t,-}$$

$\Delta g_{l,t,net}$ is therefore the generation mixtures by technology t that is allocated to consuming GEA region l . The corresponding fuel differences that follow the generation differences are likewise calculated.

Lastly, any negative values (i.e., technologies whose generation decreased on net) are removed from the $\Delta g_{l,t,net}$ generation mixtures (and the corresponding fuel mixtures). Although perhaps counterintuitive, this is necessary when producing hourly LRMER values, due to interhour effects: net generation decreases in particular hours tend to be a consequence of conditions in a different hour, and therefore misleading to report in the hour that saw the decrease. For example, in the Perturb solution for a particular year, more solar may be built to serve midday electricity demand. A shoulder daylight hour may subsequently have a net decrease in a different technology's generation (coal, perhaps) not primarily because of conditions in the shoulder hour, but as a spillover from conditions in the midday hours. Said differently, we would not expect a further reduction in coal generation if there was additional demand in the shoulder hour, and therefore reporting a negative value for coal in the LRMER would be misleading.

Further research into interhour effects may develop methods for allocating the net decreases back to the hours that induced them, which may improve the results.

The method described in this step is for a single hour—it is repeated for each hour in a Cambium data set.

Step 3: Assign Originating Mixtures for Storage and Other Energy-Constrained Generators

The process in Step 2 derives mixtures ($\Delta g_{l,t,net}$) that include the contribution of energy storage technologies (electric batteries and pumped hydropower storage) as well as energy-constrained technologies (dispatchable hydropower and Canadian imports, which are treated as dispatchable hydropower in Cambium’s simulations). Each of these technology groups requires special treatment.

First, energy storage technologies: Energy storage technologies, such as batteries, do not create electrical energy. In order for an energy storage generator to help meet a marginal increase in demand, it would be necessary for a different generator to supply the original energy. Therefore, to determine the emissions that were induced by a change in load in an hour where energy storage was part of the $\Delta g_{l,t,net}$ mixture, it is necessary for us to estimate the mixtures from other source generators that enabled the energy storage generator’s behavior.

As of the 2022 Cambium release, the approach for energy storage generators was relatively simple: energy storage and energy-constrained generators are removed from the $\Delta g_{l,t,net}$ term calculated in Step 2, and the result is grouped by receiving GEA region (l) and month, and the proportion each technology type within that monthly mixture is calculated. That fractional mixture is then assigned to the generation from any energy storage generator located in the receiving GEA region, associated fuel consumption is inflated by that generator’s monthly round-trip efficiency, and then allocated using the allocation factors ω_{r-l} that were calculated in Step 2. For example, if a battery located in CAISO discharges 10 MWh during a particular timestep, and the nonstorage and non-energy-constrained receiving mixture of CAISO during that month was half natural gas and half photovoltaics, then the discharge of that battery is colored as 5 MWh natural gas and 5 MWh photovoltaics. The fuel consumption associated with that discharge would be the fuel consumption of the natural gas, inflated by the losses within the battery.

Next, for energy-constrained generators: these generators are represented in the Cambium workflow as having monthly energy budgets that are dispatched, respecting certain operational constraints, in order to minimize total system operational costs. Their treatment for the LRMER calculation is similar to energy storage, but with an additional step. Whereas energy storing generators cannot be the originating sources of energy, it is possible for energy-constrained generators to be. For example, an increase in dispatchable hydropower generation for a particular timestep could either come from a change in the dispatch of the same energy budget, or from more investment in hydropower capacity that results in the perturb run having a higher energy budget. If the increase came from more hydropower capacity, the generation should take the characteristics of the hydropower generation itself. If the increase came as a consequence of decreasing generation in a different hour, the mixture of generation that is induced by the other-hour decrease should be assigned to the hydropower generation.

Therefore, for energy-constrained generators, we first sum the monthly generation for each technology type between the Base and Perturb solves, calculate the difference, and reflect any increase in the allocation of that technology’s generation ($\Delta g_{g,t,+}$). For example, if the monthly generation from hydropower in a particular GEA region increased by 100 MWh between the

Base and the Perturb solves, and the summation of all increases from that technology (i.e., $\Delta g_{g,t,+}$ summed for the month, where t corresponds to hydropower) equal 200 MWh, then we apply that fraction (0.5, in this example) to the generation and allocate it using the ω_{g-l} factors from Step 2. The remaining component of $\Delta g_{g,t,+}$ must be differently-dispatched energy from the same budget, and is treated the same as energy storage, where it is assigned the monthly mixture from the originating region (but without an efficiency loss, since it is just re-dispatch, not charging and discharging). Conceptually, this is an approximation of the mixture that must have been induced to cover the re-dispatch of any energy-constrained generation.

For both these technology classifications, it would likely slightly improve the answer if the replacement mixtures were derived based on the charging patterns (for storage) or based on the hours where the re-dispatch was drawn from (for the energy-constrained technologies). This step was not implemented in Cambium at this time because of time constraints.

During Step 2, we mentioned that calculated busbar loads used for power flow allocations can be lower in the Perturb run than the Base run, despite the fact that the end-use load is always greater in the Perturb runs. As this only occurs when there was a large charging load in the Base run that was reduced significantly in the Perturb run, we know that the end-use load increase was, in effect, met by either charging a storage device in a different hour, or not charging it altogether. In either case, it would have been necessary for different generators to increase their generation during different hours, to enable such behavior. Therefore, we approximate the mixture that serves those hours with the same monthly average mixture that was used for storage and energy-constrained generators explained previously in this section.

Step 4: Calculate the LRMER and Adjust to Respect State Policies

Steps 2 and 3 produce a received generation mixture $\Delta g_{l,t,net}$ for each GEA region that is based on the physical flow of power and assuming perfect mixing through each node. In the presence of state policies, such as clean energy portfolio requirements, it may be necessary to take further action capture the effects of the policy.

To determine if further action is necessary, after completing Step 3, we calculate state-level mixtures by combining the GEA region mixtures, weighted by the how much load from each state is located within each GEA mixture. The emissions intensity of those received generation mixtures is calculated, based on the fuel consumption associated with those mixtures and implementing the fuel-specific emissions rates given in Section 6.2.

Portfolio standards and national carbon policies are handled sequentially in Cambium. We will first describe the treatment of portfolio standards.

States are sorted by whether their allocated mixtures either meet their most stringent portfolio standard, or fail to meet it, based on the fraction of qualified generation that was originally allocated to it. For any states with a shortfall (i.e., whose receiving generation mixtures would not be in compliance with their portfolio standard), the fraction of their generation that would have to be offset in order to be in compliance is calculated. The original emissions intensity for each hour is then decreased by that fraction. Note that this implicitly makes the assumption that all emitting generation during all hours of the year is equally offset by accounting transfers.

The sum of all emissions subtracted in this way is calculated for each interconnect, and then allocated to all states within each interconnect that had an excess of clean generation. The emissions are added based on the fraction of non-emitting generation in each hour (e.g., an hour with 100% clean generation would be allocated twice as much emissions as an hour with 50% clean generation).

Note that, in practice, these transfers would likely be more specific (e.g., a wind generator in a particular state may be selling all of its renewable energy credits to a utility in a neighboring state). Both the fractional decreases and subsequent reallocation of emissions in Cambium implicitly assume an averaged treatment at the interconnect level—all emitting generation is equally offset in states with a shortfall, and all non-emitting generation in states with an excess is assumed to contribute toward covering the shortfalls within that state’s interconnect.

The treatment for national carbon policies is similar, and it is explained next.

First, it should be noted that, for the purpose of LRMER calculations, the national carbon policies in the 2022 Cambium release are interpreted as being enforced at the state level with unlimited and unrestricted trading credits allowed between states. This means that, while the in-region generation mixtures of different states may be decarbonizing at different rates, the ultimate emissions rate of received generation (when taking into account credit transfers) for each state will be the same (unless a state outpaces the national trajectory due to economics or state policies).

Given this, states whose emissions intensity of their receiving mixture are above the rate implied by the given decarbonization trajectory have their emissions rates reduced, reflecting transfers, to meet the decarbonization rate. In previous editions of Cambium databases, adjustments were made to reflect the effects of DACs and BECCS in decarbonization scenarios, but such adjustments were not necessary in Cambium 2022 because DAC was not allowed and BECCS was not further built out in the perturbation solutions, due to supply constraints.

Step 5: Adjust the LRMER for Distribution Losses

As the LRMER is currently most commonly used for assessing emissions associated with changes in end-use load, the published values are reported as kilograms or grams of emissions per MWh of end-use load. This is achieved by taking the hourly value from Step 5 and inflated it based on the marginal distribution loss rate. If a user wishes to apply the LRMER to a change in load or generation at the busbar level, they can unwind the distribution loss impact as described in Section 5.1.

How To Use the Year-Over-Year LRMER Data

Cambium databases give LRMER data in 5-year timesteps. For some analyses, it may be appropriate to utilize a single year’s worth of data, if knowing a consequence of a change in load in that specific year is desired. For most applications, however, it would likely be more appropriate to either average or levelize the year-over-year LRMER data for the lifetime of the

intervention they are analyzing.¹⁸ Interpolation may be used for years between the five-year timesteps in the Cambium databases.

Levelization is the process of using a discount rate to give greater weight to near-term years than years further out. Said differently, levelizing with a positive discount rate it is effectively stating that if damages from emissions were to occur, it would be preferable to have them occur later rather than sooner.

The equation for levelizing the LRMER for a particular unit of time h (e.g., an hour, a time-of-day, a month-hour, or a year) is given below, where n is the number of years used for the analysis horizon (often an expected lifetime of the intervention being analyzed) and d is a social discount rate. Because the underlying weather and weekday/weekend patterns are the same across the years of a Cambium database, it is coherent to levelize hourly values. Note that if a social discount rate of 0% is selected, the equation becomes a simple average, which is potentially valid if the analysis is intended to have no preference for when emissions occur.

$$LRMER_{h,levelized} = \frac{\sum_{t=0}^{n-1} \left(\frac{LRMER_{h,t}}{(1+d)^t} \right)}{\sum_{t=0}^{n-1} \left(\frac{1}{(1+d)^t} \right)}$$

Weather Alignment

The LRMER data, as with all Cambium data, is created using 2012 weather patterns, which influence electricity demand shapes and renewable energy resource quality. If using the hourly data, it is strongly recommended to ensure that other inputs into an analysis also use 2012 weather (e.g., a building energy model should use 2012 weather inputs), otherwise the misalignment of assumptions could cause inaccuracies.

If it is not feasible or desirable to use 2012 weather patterns for an entire analysis, it may sometimes be preferable to utilize either the month-hour or time-of-day temporal aggregations that are provided in the Cambium data sets. These aggregations retain much of the diurnal and seasonal trends while removing specific short-duration weather-driven patterns that might cause meaningful inaccuracies if misaligned with other weather data.

Treatment of National Decarbonization Scenarios

The 2023 Cambium data release included two scenarios with national decarbonization trajectories (the *95% decarbonization by 2050* and *100% decarbonization by 2035*). The representation of these scenarios in ReEDS is described in Section 3. Here we describe how the scenarios were treated during the calculation of the LRMER.

First, it is important to note that although the decarbonization trajectory was expressed as an absolute mass-based constraint in ReEDS (i.e., each year had an upper limit on the annual mass of direct carbon dioxide emissions in metric tons), that constraint was interpreted as a rate-based

¹⁸ This statement implicitly assumes an analysis is being conducted using a single year to characterize a multiyear intervention, as is common. If an analysis is characterizing a multiyear intervention by explicitly analyzing each year, then it would generally be appropriate to directly use the year-over-year LRMER data without averaging or levelization.

constraint when the Perturb runs were performed for the LRMER derivation. This was done by calculating the tons/MWh annual average emissions rate from the corresponding year's Base run, and then increasing the carbon dioxide cap in the ReEDS Perturb run for that year. For both the Base and Perturb PLEXOS runs, the shadow price on the annual carbon constraint from ReEDS was applied as an adder to any emitting technologies based on their emission rates.

This interpretation of the decarbonization scenarios results in LRMER values (in both magnitude and temporal patterns) that are closest to what might be seen under a policy such as a carbon tax or support for non-emitting generators. Importantly, the magnitude and pattern of the LRMER could take meaningfully different forms under different policy designs. For example, a policy that capped the total mass of emissions would result in a LRMER of zero—any change in electric demand would not result in a change in emissions (as long as the cap was binding, and only for the type of emission being capped). As a different example, a policy that capped emissions on a rate basis (i.e., the allowed mass of emissions being based on the quantity of electricity sales) would be nonzero, but likely not have a time-varying pattern, as any change in electric demand would effect a change in emissions at the specified rate regardless of the time-of-day. Note that both these policy approaches would have time-varying policy-driven costs that might be obscured if not conveyed in tandem with the LRMER values.

Secondly, although the decarbonization policies are described as national decarbonization policies, they are interpreted here as state-level policies where every state is following the same rate-based decarbonization trajectory but unlimited and unrestricted unbundled trading of emissions credits are allowed. This manifests as the accounting transfers described in Step 4 of the LRMER methodology described above.

Caveats and Limitations

The LRMER methodology described here has several known limitations:

- **Geographic disaggregation:** The method described here takes a pair of nation-wide model runs and disaggregates the resulting data into GEA regions, and then ultimately states. This would likely produce at least slightly different results than some equally defensible alternative approaches (such as perturbing each state's load in its own separate model run, which is not feasible due to the computational costs of performing model runs). Further research into the consequences and methodologies around the geographic disaggregation is warranted.
- **Interdependency of Hours:** We treat each hour as independent, but the equilibrium build-out of the power sector is influenced by the combined shape of increasing demand across hours, and operational constraints of the electric sector means the dispatch in one hour can influence the dispatch in another hour. Ultimately, this means that Cambium's hourly LRMER values (which were derived from model runs that scaled up load in all hours equally) are only estimates of the change in emissions from changes in load that follows different hourly patterns.
- **Power Flow Allocation:** As discussed in the power flow coloring section (Section 6.3), our power flow allocation method just assumes perfect mixing of power through each node and therefore does not capture relevant restrictions or modifications of the actual allocation one might give to the power flows. For example, restrictions on the amount of

generation from coal plants that can be imported into California would not necessarily be respected. Cross-state contracts for electricity bundled with RECs, for renewable portfolio standard compliance, might also not be captured.

- **Year-Over-Year Values:** For Cambium databases, we calculate these LRMER values for every other year based on a perturbation of load during that year. The intention is that analysts would apply these year-over-year values for the duration of the intervention they are analyzing. The accuracy of using year-over-year values to estimate the lifetime impacts of interventions has not been explicitly studied.
- **Transmission Losses:** Our method does not currently accurately capture the effects of transmission losses, because those losses are represented as a load, which dilutes the actual emission rate induced by an increase in load.

This is an ongoing area of research, and we expect improvements to these methods to continue for some time.

6.5 Identifying a Region's Short-run Marginal Generator

The short-run marginal generator, for a particular location and time, is the generator whose output would increase if there were a marginal increase in demand at that location and time.¹⁹ For several of the metrics reported in Cambium databases (e.g., the short-run marginal emission rate), it is necessary to identify which generator is the marginal generator.²⁰

Unfortunately, the marginal generator is not a native output of the PLEXOS runs that Cambium draws from. It is therefore necessary for us to analyze the PLEXOS results to make reasonable judgements as to which generator was likely the marginal generator for each node during each time-step. In this section, we describe our method for doing so, which follows these five steps:

1. Identify balancing areas (BA) that share a marginal generator (T-regions)
2. Identify T-regions with dropped load
3. Evaluate non-energy-constrained generators
4. Evaluate energy-constrained generators

Step 1: Identify Regions That Share a Marginal Generator (T-Regions) in Each Hour

We run PLEXOS with inter-BA transmission represented as pipe flow with fixed loss rates. Given this, and knowing that the solution is a least-cost optimization, we assume any set of BAs that are connected by partially utilized transmission lines share a marginal generator during that

¹⁹ Note that, in Cambium, we differentiate between the marginal *generator* and the marginal *energy source*. The marginal generator is the generator that would provide the power to cover an increase in load, at the moment when the load is increased. If the marginal generator does not have the ability to create energy (e.g., an electric battery), a different generator must ultimately increase its generation at a different time for the battery to be the marginal generator. The marginal energy source refers to that generator.

²⁰ Much of the published research on short-run marginal emission rates takes an empirical approach (Siler-Evans et al. 2012), often deriving marginal emission factors based on the changes in generation mixtures between sequential hours in data from system operators. We take the approach of identifying the marginal generator from our simulations, to maintain consistency with other metrics being reported by Cambium. Though we do maintain consistency, the simulation-based method is highly sensitive to the accuracy and peculiarities of the dispatch model being used.

hour. Working with this assumption, we identify all partially utilized transmission lines during each time-step, and we then identify all groupings of BAs that are connected by those lines.²¹ We refer to these groupings of BAs as “transmission connected regions,” using the shorthand T-regions.

The BAs that make up T-regions—and therefore the BAs we assume share a marginal generator—shift every time-step. A single BA can often be its own T-region, although it is also common for them to be large, covering dozens of BAs.

Step 2: Identify T-Regions with Dropped Load

After identifying T-regions, we find which ones have dropped load. These T-regions will not have a marginal generator, so we label them as such.

Step 3: Evaluate Non-Energy-Constrained Generators

Having identified BAs we assume share a marginal generator for a given time-step, we try to estimate which generator in those BAs is the marginal generator. We first identify all the generators that were committed in those BAs at that point in time and filter out any generator that is at its maximum generation level.²² We also remove energy-constrained generators, which we evaluate later in Step 4.²³

We then identify which, of these generators, has a short-run marginal cost (SRMC) that is closest to the average shadow price on the energy constraint across that T-region, and we designate that generator the marginal generator for that T-region.

Step 4: Evaluate Energy-Constrained Generators

In some instances, no generators make it through the filters listed in Step 3. In these T-regions, the marginal generators must be an energy-constrained generator: either an energy-constrained generator that is discharging (in which case it could discharge more to serve a marginal increase in demand) or an energy-constrained generator that is charging (in which case it could charge less to free up power to serve a marginal increase in demand).

For T-regions where no marginal generator was identified in Step 3, we estimate the short-run marginal cost (SRMC) of all the energy-constrained generators that are actively charging or discharging—but not at their maximum rates. Because the energy-constrained generators cannot produce additional power, but rather only shift it, their SRMC is estimated by finding a non-energy-constrained generator that could have increased its output in a different time-step to allow the energy-constrained generator to have more available energy during the time-step being evaluated. The SRMC of the energy-constrained generator is set by the SRMC of the non-

²¹ For our implementation we use the undirected graph capabilities of the python-based networkx package.

²² For variable generators like wind and solar, this is the maximum output that they can generate during that hour, given the weather conditions, not their nameplate capacity. A variable generator would only be below its maximum generator level if it is curtailment.

²³ Technologies such as batteries and pumped hydropower storage (which cannot ever create new electricity, only shift it around) are always energy-constrained. Technologies like dispatchable hydropower CSP with thermal energy storage—which have fixed budgets of energy flowing into them—are typically energy-constrained (if, in our PLEXOS dispatch, they dispatched all the energy that was available to them), but also can be classified as non-energy-constrained (in the more rare occurrences where they did not expend all of their available energy).

energy-constrained generator, modified by any relevant transmission and efficiency losses. For a detailed explanation of how this is done, see Section 6.6.

Once we have estimated the SRMC of all the energy-constrained generators in each of the T-regions being evaluated in this step, we find the one with the SRMC closest to the average marginal energy cost in each T-region, and we designate that as the marginal generator.

If there are any region-hours where a generator was not identified, those region-hours are marked as “unknown” and assigned the mean SRMER value for that GEA region at that timestamp.

Caveats and Limitations

In addition to the general caveats discussed in Section 4, our current approach for identifying marginal generators has three significant limitations:

- Because the marginal generator is not a native output of a solution to a production cost model, our method relies on trying to post-process the results and identify which generator would most likely have been the marginal generator at any point in time. Although it is clear what the marginal generator is at some points in time, it is less clear at many other points, particularly when energy-constrained generators are involved. Our method is likely not perfectly accurate in finding the marginal generator.
- Even when the marginal generator for the PLEXOS solution is correctly identified, whether the result matches real-world marginal generator patterns depends on how well the PLEXOS solutions match real unit commitment and dispatch decisions. Because we run PLEXOS as a system-wide least-cost optimization without forecast error, the PLEXOS dispatch is likely deviating from dispatches in practice, potentially in important ways. Often, for example, PLEXOS leverages energy-constrained generators to avoid starting up thermal generators in a way that is potentially too precise and would not be realized in practice.
- Relative to other metrics that we report, the identification of the marginal generator is highly sensitive to changes in demand. Therefore, these marginal generator patterns are likely inappropriate for analyses that assume there are significant quantities of load that is being shifted in reaction to what generator is on the margin; for example, if tens of megawatts of electric vehicle charging was timed to try and minimize how much charging was done when coal was on the margin, that would likely be enough to meaningfully change the patterns of which technologies are on the margin at what times.

Altogether, as we have mentioned, we recommend analysts approach these marginal generator patterns with a critical eye, as we work to improve our understanding of the quality and usefulness of these modeled results.

6.6 Identifying the Energy Source When an Energy-Constrained Generator is on the Short-Run Margin

For some analyses, we are interested in identifying the effects of marginally increasing demand at a particular location and time. For example, the short-run marginal emission rate tells us what the increase in short-run emissions would be if demand were marginally increased. The first step in this process is identifying the marginal generator, as we discussed in Section 6.5.

For most generators that are the marginal generator, we have the information we need. If a natural gas generator is the marginal generator, for example, a marginal increase in demand would induce more generation from that generator, and we can calculate the metrics we are interested in.

For generators that are energy-constrained—meaning they cannot create their own energy (e.g., batteries or pumped hydropower storage) or they have a constrained energy budget (e.g., dispatchable hydropower or CSP with thermal energy storage)—the treatment is more complicated.²⁴ Because such generators cannot create new energy, any actions by them must induce a different generator (one that can create new energy) to increase its generation at a different point in time. If we wish to know the effects of increasing demand when an energy-constrained generator is on the margin, we must therefore also identify the non-energy-constrained generator that would be induced to increase its generation as a result of the increase in demand.

In Cambium, we use the terms *marginal generator* and *marginal energy source* to describe these two generators. In this section, we describe how we try to identify the marginal energy source when the marginal generator is an energy-constrained generator.

Consider, for example, trying to determine the short-run emissions impact of increasing demand when an electric battery is on the margin. Because the electric battery cannot create new energy, but can only shift energy, we know that our increased demand from the battery must result in a different generator—one capable of creating energy—increasing its generation in a different hour, to enable the electric battery to be a marginal generator during the hour we are increasing demand. If, by demanding more energy from the battery, a coal plant would increase its generation in a different hour, and that would clearly lead to a different emissions impact than if a natural gas plant increased its generation.

This is one example of a general situation: If an energy-constrained generator is on the margin, we must find out which source-energy generator would increase its generation, at a different point in time, to enable the energy-constrained generator to increase generation. The characteristics of the source-energy generator, modified by relevant transmission and efficiency factors, define the implications of increasing our demand during the hour when the energy-constrained generator is on the margin.

For Cambium, we developed a method for identifying the source-energy generator that would most likely increase its generation, if an energy-constrained generator is the marginal generator. Our method is specifically designed to interpret the results from a production cost model: post-processing a given pattern of unit commitment and dispatch to identify the marginal source-energy generator for every energy-constrained generator. Although many of the concepts here

²⁴ Technologies such as batteries and pumped hydropower storage (which can never create new electricity, but only shift it) are always energy-constrained. Technologies like dispatchable hydropower CSP with thermal energy storage, which have fixed budgets of energy flowing into them, are typically energy-constrained (if, in our PLEXOS dispatch, they dispatched all the energy that was available to them), but they also can be classified as non-energy-constrained (in the more rare occurrences where they have not expended all their available energy). Therefore, whether a generator is energy-constrained is not an immutable characteristic of the generator; it also depends on how it was dispatched.

likely transfer to similar situations in real-world dispatch, we discuss only the interpretation of simulated dispatches in this section.

Our method for identifying the source energy generator for an energy-constrained marginal generator is:

1. Identify the span of time the energy-constrained generator could have obtained more energy: its “opportunity window”
2. Reduce the span of the window if it extends beyond what is reasonable for the scheduling and forecasting assumptions of the run under consideration (e.g., restrict the window to +/- 24 hours from the time-step being analyzed)
3. Remove all time-steps where the energy-constrained generator is already charging fully
4. Remove all time-steps when no generator is available that could increase its own generation, to either charge the energy-constrained generator or cover its reduced discharge
5. From the remaining time-steps, calculate efficiency and transmission adjustments, to determine the energy-constrained generator’s SRMC if it drew from that time-step
6. Select the time-step (and associated generator) with the lowest resulting SRMC
7. Calculate derivative values, such as marginal emission rates.

Here we explain our method for this with a toy example: an electric battery that is charging and discharging over a 20-hour period. The battery’s charging and discharging patterns, and its state-of-charge, are shown in Figure 12. The battery has a maximum charge and discharge rate of 1 MW and a maximum energy storage level of 2 MWh. The battery has a round-trip efficiency of 80%.²⁵

For this example, we evaluate the battery’s behavior assuming it was identified as the marginal generator during the 11th hour, as indicated with the shaded area in Figure 12. Because the battery itself cannot create energy, we want to identify the source-energy generator that would have increased its generation in a different time-step, in order for the battery to have the energy required to be the marginal generator during the 11th hour. Doing so allows us to calculate the implications of a marginal increase in demand during the 11th hour, such as the short-run marginal emission rate.

For the battery to marginally increase its output during the 11th hour, one of two things must happen: the battery must either enter the 11th hour with a marginal amount more energy or exit the 11th hour with a marginal amount less energy. These actions would then necessitate the battery either charging more or discharging less during a different hour. For the method we are discussing here, we assume this action could have happened either before or after the 11th hour; in other words, we assume the increased demand (relative to the original system dispatch) during the 11th hour was anticipated and system operators could have planned accordingly. If we wanted

²⁵ For the sake of simplicity in this toy example, we apply all the losses during charging, and we treat the charge and discharge limits as limits to the rate of change of the battery’s energy level. Increasing the stored energy level by 1 MWh requires 1.25 MWh of consumed energy, for example, and is shown as a 1-MW rate of charging in the figures.

to analyze the implications of an unexpected increase in demand, this method would have to be modified, but we do not explore that scenario here.

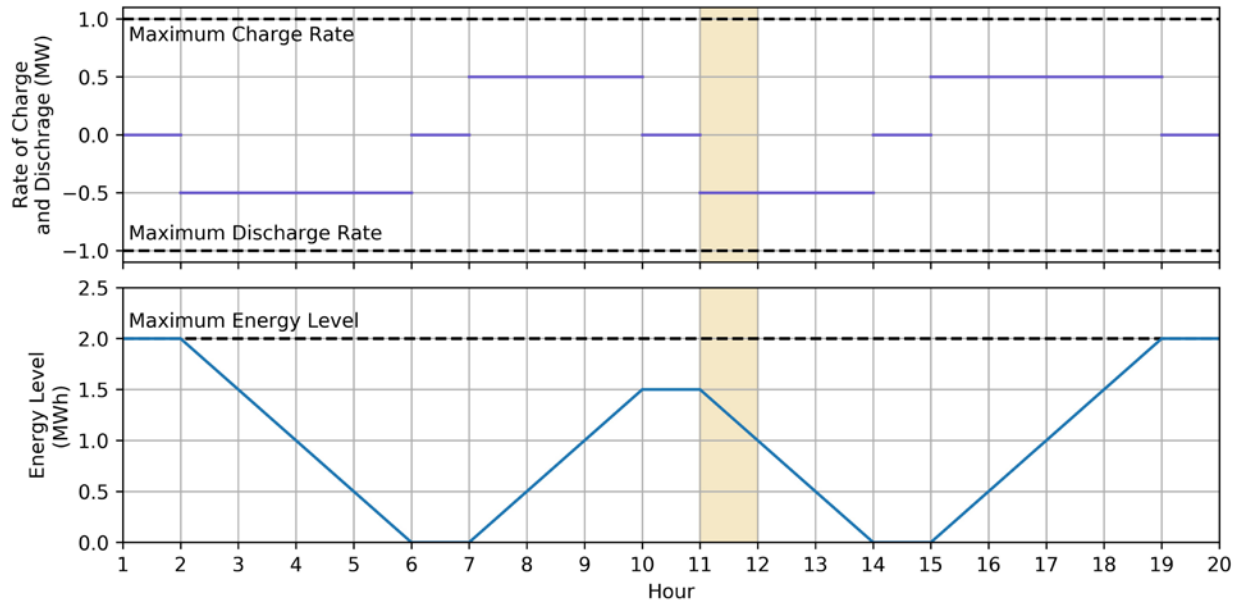


Figure 12. Charge and discharge patterns of an electrical battery

Looking before the 11th hour, we see that the battery could have obtained a marginal increase of energy at any point after the end of the 1st hour. Before the end of the 1st hour, however, it could not have obtained more energy and held it until the 10th hour, because the battery was already full during the 1st hour. A similar approach could be taken looking after the 11th hour: the battery could exit the 11th hour with an energy deficit and make it up at any point before the beginning of the 14th hour. However, once the 14th hour is reached, the battery becomes depleted, and it therefore could not hold the deficit beyond that point.²⁶

We illustrate these bounds in Figure 13. In the top panel of the figure, the 11th hour shows a marginal discharge, because that is the hour in which the battery is assumed to be on the margin. Starting at the beginning of the second hour and until the end of the 13th, the shaded area shows the span in which the battery would have been able to increase its stored energy, to enable the increased discharge during the 11th hour.

²⁶ The assessment of these bounds illustrates a fundamental assumption of our approach: we make only marginal adjustments to the original dispatch of the battery. Clearly, the battery could be entirely redispached differently to extend these bounds beyond the 1st and 14th hours; however, we assume that, if it were not cost-optimal to dispatch the battery in that manner initially, it would also not be cost-optimal to redispach it in that manner for a marginal increase.

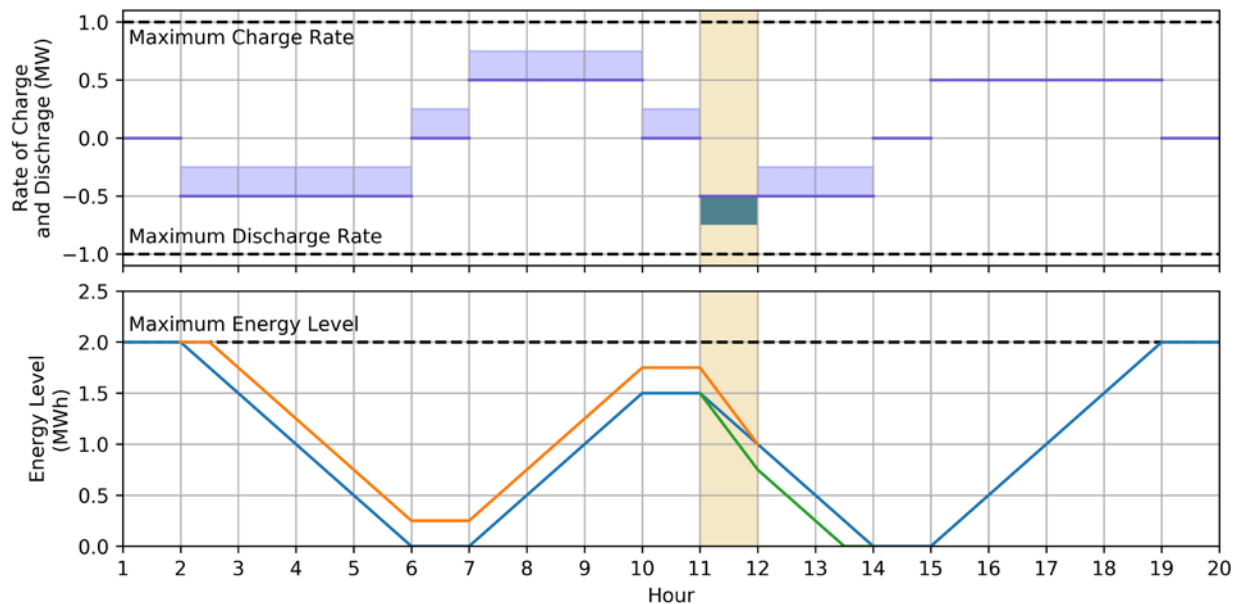


Figure 13. Example of an “opportunity window” for an electric battery

At first thought, it may seem like we are looking only for opportunities for the battery to charge (i.e., obtain more energy that it could then discharge during the 11th hour). However, this is not the case, because the increased energy does not always need to pass through the battery. For example, during the 2nd through the 5th hours and during the 12th through the 13th hours, the battery could simply have discharged less, thus reserving more energy for the 11th hour. For this to happen, a different generator would still have to increase its generation—but importantly for our purposes, there is no round-trip efficiency penalty for the scenarios where the battery discharges less, because the energy is not actually passing through the battery.

In the lower panel of Figure 13, we can visually see the general rule: the battery’s range of opportunity goes back in time as far as the most recent time that the battery was completely full, and as far forward in time as the next time that the battery is completely empty.²⁷ This establishes the bounds of an “opportunity window”—Step 1 in our list of steps given above—which is the span of time in which the battery could either charge more or discharge less. In theory, this window could extend indefinitely. For Cambium databases, however, we restrict the windows to +/- 24 hours from the hour in which the battery is the marginal generator, to reflect practical limits to dispatch scheduling (Step 2).

Having identified the opportunity window, we then filter out the hours during which the battery could not have actually drawn more energy (Steps 3 and 4).

²⁷ This is only for the situation where the battery is discharging during the hour that it is on the margin (i.e., we are considering the right-hand marginal). When the battery is charging (i.e., the left-hand marginal), the bounds are inverted: the prior bound is the most recent time the battery was empty, and the following bound is the next time the battery is full. We therefore have an interesting situation where the right-hand and left-hand marginals can be different. All Cambium values are currently generated for right-hand marginals.

First, we remove the hours where the battery was already charging at its maximum rate. If the battery were already charging as much as it could have, it clearly could not charge more.

Next, we remove the hours where we have not yet identified a marginal generator that could have increased its generation to either to charge the battery or cover the battery’s reduced discharge. For a detailed discussion of the process by which we identify marginal generators, see Section 6.5.²⁸

After applying those two filters, we end up with a set of hours where the battery is technically capable of charging and there is a generator that can either charge the battery or cover its reduced contribution. To identify which hour, and therefore which generator, would be called on, we calculate the short-run marginal cost (SRMC) of drawing from each hour.

When calculating the SRMC, four possible situations can occur, and each has different implications for applying an adjustment for the effects of efficiency. The four situations, shown in Table 6, are defined by what the energy-constrained generator is doing in (1) the time-step in which it is on the margin (the “anchor time-step”) and (2) the time-step in which it would induce an increase in another generator (the “point time-step”).

Table 6. Efficiency Adjustments

Anchor Time-Step Behavior	Point Time-Step Behavior	Description	Efficiency Adjustment
Charging	Charging	Energy-constrained generator reduces its charging during the anchor time-step and increases its charging during the point time-step.	1.0
Charging	Discharging	Energy-constrained generator reduces its charging during the anchor time-step and reduces its discharging during the point time-step.	RTE
Discharging	Charging	Energy-constrained generator increases its discharge during the anchor time-step and increases its charging during the point time-step.	1/RTE
Discharging	Discharging	Energy-constrained generator increases its discharge during the anchor time-step and reduces its discharge during the point time-step.	1.0

RTE is the round-trip efficiency of the energy-constrained generator.

To better understand the contents of Table 6, and to show how the efficiency adjustment is applied (Step 5), we return to our toy example. We assume the only hours that had available generators were the 8th hour and the 12th hour. Because the battery is discharging during the anchor time-step, these hours correspond to the discharging-charging and discharging-discharging situations respectively. To put some numbers on our example, we assume the battery was called on to discharge 0.25 MWh during the 11th hour, that the SRMC of the marginal

²⁸ Typically, an hour will be missing a marginal generator if the marginal generator in that hour is itself an energy-constrained generator; for this reason, we must iterate through the steps we are describing here, to find the situations where energy-constrained generators chain off of each other.

generator in the 8th hour was \$10/MWh, and the SRMC of the generator in the 12th hour was \$11/MWh. As mentioned before, the round-trip efficiency of the battery is assumed to be 80%.

If the battery increased its stored energy during the 8th hour, it would have to increase its rate of charging. Therefore, the marginal generator in that hour would have to generate 0.3125 MWh more, for a cost of \$3.125. Because of losses in the battery, the delivered 0.25 MWh would have an effective SRMC of \$12.5/MWh, which is the SRMC of the marginal generator in the point time-step multiplied by the efficiency adjustment of 1/RTE.²⁹

Looking to the 12th hour, we see that because the battery was already discharging, it could increase its stored energy by simply discharging less, not charging more. Therefore, the 0.25 MWh of energy could be provided to the 11th hour at a cost of \$2.75/MWh. This is an effective cost of \$11/MWh, which is the SRMC of the marginal generator in the point time-step multiplied by the efficiency adjustment of 1; in other words, there was no efficiency penalty, because the additional energy did not pass through the battery.

Of the two hours being considered, the costs are lower if the battery draws from the 12th hour, and therefore we assume it would do so (Step 6). Note that the SRMC of the marginal generator in the 12th hour was greater than the SRMC of the marginal generator in the 8th hour, but because the energy from the 8th hour would have had to take an efficiency penalty, the 12th hour was the lower-cost solution.

If the marginal generator in the hour that was selected is a source-energy generator, we have the information we want: the characteristics of the source-energy generator will allow us to calculate the impacts of a marginal increase in demand during the 11th hour (after applying the same transmission and efficiency adjustments that we previously used for the SRMCs).

If, however, the marginal generator is another energy-constrained generator, we have a chain, and we must follow the chain until we ultimately reach a source-energy generator. When deriving values for Cambium databases, we iterate over this step several times, to identify these chains.

6.7 Calculating Time-Varying Distribution Loss Rates

Both ReEDS and PLEXOS balance load and generation at the busbar level (i.e., before distributing electricity to end users). However, Cambium databases include end-use values, so to get end-use metrics from busbar metrics, we need time-varying distribution loss rates.

Our method for calculating both average and marginal hourly distribution loss rates draws primarily from Borenstein and Bushnell (2019). As in their work, we assume 25% of annual distribution losses are fixed losses that do not vary with load (e.g., losses in transformers), and 75% are resistive losses that scale with the square of the flow on a line.

We assumed that the annual average distribution loss rate is 3.6% for each BA. This was derived by taking the national average Grid Gross Loss from eGRID data for 2018 (EPA 2020) (which

²⁹ If transmission losses would occur as a result of the energy-constrained generator drawing from this hour, the SRMC of the marginal generator in that hour should also be modified by the transmission losses. For this example, we assume there are no transmission losses.

includes all forms of losses), performing a ReEDS model run for 2018 and calculating a loss rate from that run for nondistribution losses, and subtracting those from the eGRID Grid Gross Loss rate.

We start by calculating the total annual fixed ($L_{f,a}$) and variable ($L_{v,a}$) losses for each BA as a function of the annual busbar load consumed for end uses ($Q_{b,a}$), the aforementioned no-load loss fraction (π) and annual loss rate (r_a).

$$L_{f,a} = Q_{b,a} * r_a * \pi$$

$$L_{v,a} = Q_{b,a} * r_a * (1 - \pi)$$

We then calculate an annual variable loss factor $f_{v,a}$:

$$f_{v,a} = L_{v,a}/Q_{b,a}^2$$

We then calculate each BA's hourly variable losses ($L_{v,h}$), using the annual variable loss factor ($f_{v,a}$) and the hourly busbar load consumed for end uses ($Q_{b,h}$):

$$L_{v,h} = f_{v,a} * Q_{b,h}^2$$

The total hourly losses ($L_{t,h}$) are then the sum of the hourly variable losses and one hour's worth of the fixed no-load losses:

$$L_{t,h} = L_{v,h} + L_{f,a}/8760$$

We can then calculate each hour's average distribution loss rate (α_h):

$$\alpha_h = L_{t,h}/Q_{b,h}$$

and each hour's marginal distribution loss rate (μ_h) as the derivative of the square of the hour's busbar load times the annual variable loss factor:

$$\mu_h = Q_{b,h} * 2 * f_{v,a}$$

6.8 Calculating Hourly Marginal Capacity Costs

The marginal capacity costs in Cambium are estimates of the costs of acquiring sufficient firm capacity to meet a system's planning reserve margin if there is a marginal increase in peak demand. The annual marginal cost of firm capacity is determined by our ReEDS model, which is then allocated to the highest net-load hours to produce an hourly marginal capacity cost pattern. We first explain how ReEDS determines the annual marginal cost of firm capacity, and we then explain how we allocate that value to specific hours.

Calculating an Annual Marginal Cost of Firm Capacity with ReEDS

ReEDS has a constraint that requires sufficient firm capacity to be procured in each balancing area (BA) to exceed a year's peak demand by a planning reserve margin (e.g., if the peak busbar

demand in a BA is 100 MW and the planning reserve margin is 0.15, ReEDS will require 115 MW of firm capacity).³⁰

The shadow price off of this constraint is the \$/MW-year marginal cost for obtaining additional firm capacity. ReEDS will find the least-cost option through three possible decision variables within the model:

- **New Generation Capacity:** Referred to as net cost of new entry (net CONE), the shadow price of the capacity constraint may be set by the annualized revenue needed to recover the costs of the generator that can provide firm capacity at the lowest cost, minus any revenue that generator could obtain by providing other services (e.g., energy or operating reserves). This is often a natural gas combustion turbine plant, although in certain regions it can also be variable resources like wind and solar, if their generation aligns well with peak demand.³¹
- **New Transmission Capacity:** If a neighboring BA has excess generation capacity, the shadow price of the capacity constraint may be set by the annualized cost of building additional transmission capacity, minus the revenue that the line would obtain from transmitting energy or operating reserve products.
- **Delayed Retirement:** ReEDS will choose to retire generation capacity if the capacity generator is not providing sufficient value to the system to cover its fixed costs (amplified by a multiplier to represent the “stickiness” of retirement). When this is happening, the shadow price of the capacity constraint can be set by the revenue that would have been required to keep that capacity online, minus the revenue it would have received for any other services.

Because of the prevalence of retiring generators, and the ability of wind and solar to contribute firm capacity, Cambium results in the 2020s often show capacity shadow prices that are substantially lower than what they would be if the shadow price were only being set by the net CONE of a natural gas combustion turbine.

If the capacity constraint in ReEDS is not binding, the shadow price on the constraint will be zero.

³⁰ Planning reserve margins are heuristics for the amount of capacity required to maintain a desired level of reliability in the electric system. Probabilistic resource assessments and the associated metrics, like loss-of-load probabilities, can give a more accurate assessment of the reliability of an electric grid. Cambium relies on planning reserve margins, however, because of shortcomings in the integration of these more sophisticated methods into our capacity expansion models, particularly in the presence of large amounts of variable generation and storage generators.

³¹ ReEDS assesses the ability of variable generators (wind and solar) to provide firm capacity through a net load duration curve approach. Doing so tends to result in variable generators being able to provide firm capacity in the near term, which eventually goes to zero as net load peaks shift away from times of peak variable generation. See (Ho et al. 2021) and the forthcoming documentation of the 2021 version of ReEDS for a more detailed discussion of this.

Allocating the Annual Shadow Price to Individual Hours

Having obtained an estimate of the annual marginal cost of additional firm capacity (i.e., the shadow price on the capacity constraint from ReEDS), we want to allocate that value to individual hours. Our method follows these steps:

1. Obtain each BA's shadow price (ρ_{BA}) off of the annual capacity constraint in ReEDS.
2. Multiply the annual shadow price by (1 + planning reserve margin), to obtain the marginal cost of procuring the firm capacity that would be required by an increase in peak busbar load (δ_{BA}):³²

$$\delta_{BA} = \rho_{BA} * (1 + prm_{BA})$$

3. Calculate the hourly net load ($\eta_{gea,h}$) for the 18 GEA regions. The net load in Cambium is given by *net_load_busbar* and is the *busbar_demand_for_enduse* less generation from nondispatchable wind and solar generators.³³
4. Determine a threshold MW value ($\eta_{gea,threshold}$) for each GEA region that is either the net load during the 101st greatest net-load hour ($\eta_{gea,41}$) or 95% of the GEA region's annual peak net load ($\eta_{gea,1}$), whichever is lower:

$$\eta_{gea,threshold} = MIN(\eta_{gea,101}, \eta_{gea,1} * 0.95)$$

5. Calculate the total amount of each GEA region's net load that exceeds its threshold value (N_{gea}):

$$N_{gea} = \sum_{h=1}^{8760} MAX(\eta_{gea,h} - \eta_{gea,threshold}, 0)$$

6. Calculate a weight for each hour ($w_{gea,h}$) whose net load exceeds the threshold value, defined as the amount that hour's net load exceeds the threshold value divided by the total amount of load exceeding the threshold in that GEA region in that year; the weights will sum to 1.

$$w_{gea,h} = \frac{MAX(\eta_{gea,h} - \eta_{gea,threshold}, 0)}{N_{gea}}$$

³² For example, if the planning reserve margin is 15%, 1 MW more of peak busbar demand will require 1.15 MW more firm capacity. If the shadow price for firm capacity was \$10/MW-year, the capacity cost per MW of additional peak load would be \$11.50/MW-year.

³³ Load from storage generators charging is not included in the net load, with the idea being that that load is flexible and in most instances the charging could be reduced (without impacting reliability) if there were a capacity shortage. However, it is possible that in certain futures there could be situations where storage would need to charge during certain periods of time for reliability reasons (e.g., charging during the day after providing required firm capacity during a morning peak, in anticipation of being needed during an evening peak). We do not capture that possibility.

7. Allocate each BA's annual marginal capacity cost (δ_{BA}) from Step 2 using the hourly weights of the GEA region that that BA is in:

$$c_{ba,h} = w_{gea,h} * \delta_{BA}$$

Caveats and Limitations

Our method of calculating marginal capacity costs has an important limitation and two important caveats.

First, *our method relies on heuristics*. The use of a planning reserve margin, and the subsequent allocation of the annual capacity cost based on a net-load threshold, are heuristics. They are meant to approximately capture the costs induced by increased demand during high-net load hours, but they do not represent the most sophisticated techniques for resource adequacy assessment.

The use of the 101st-hour/95%-peak threshold, in particular, is only an approximation, although it is similar to the top-hour counts used by other models. The 2020 version of ReEDS uses the top 10 net-load hours in each of 4 seasons for assessing the capacity credit of variable resources. Hale, Stoll, and Mai (2016) used the top 100 net-load hours for estimating the capacity value of flexible resource in the Resource Planning Model. In the publicly available Avoided Cost Calculator (Energy+Environmental Economics 2016), which was developed for use in California, the default values for 2020 has 334 hours with nonzero weights for generation capacity costs, although 80% of the weight was in the top 40 hours and 99% in the top 90 hours.³⁴

We selected this approach because it has three attractive features:

- The hours with the highest net loads have the greatest marginal capacity costs.
- The marginal capacity costs phase out, instead of cutting out sharply at a threshold (which would occur if costs were allocated evenly to a number of top hours).
- The sum across a year's hourly capacity costs will equal the \$/MW-year shadow price, amplified by the PRM.

A more technically sophisticated approach could involve the derivation of hourly probabilistic loss metrics (e.g., loss of load probability). These probabilistic metrics could be used to assign weights to individual hours, or to directly calculate a marginal cost of capacity by using the rate of change of the loss metrics as a function of increased load and a cost of lost load. Currently, however, we do not have a method for calculating hourly probabilistic loss metrics that can be deployed coherently with our ReEDS model. Given that the ReEDS model makes capacity investment decisions based on a combination of a planning reserve margin and net load duration curve techniques, more-sophisticated assessments of the reliability of the systems that ReEDS builds could produce nonsensical results—for example, consistently showing negligible loss of load probabilities (if ReEDS tends to over-build the electric system), and therefore showing

³⁴ The default generation capacity value allocation factors in the Avoided Cost Calculator were based on loss-of-load-probability calculations within the Renewable Energy Capacity Planning, or RECAP, model developed by Energy + Environmental Economics.

negligible capacity costs. The use of heuristics to allocate the ReEDS-derived shadow price is a tractable solution to a complex problem.

The first significant caveat for our method of calculating marginal capacity costs is that *Cambium capacity costs can be lower than conceptually similar values used in practice, such as Net CONE derived assuming a natural gas combustion turbine (NGCT)*. The ReEDS capacity shadow price can often be meaningfully lower than the annualized cost of an NGCT, which is sometimes taken as a benchmark value for additional firm capacity in practice. These low values are generally driven by the fact that the pool the model can draw from when calculating the incremental cost of firm capacity includes 1) otherwise-retiring generators, 2) batteries, and 3) variable generators, commiserate with their ability to provide generation during the highest net load hours.

If a marginal capacity cost derived from such an inclusive pool of resources is not suitable for a given analysis (e.g., if the expectation is that the marginal capacity cost is derived from a Net CONE value of a NGCT), the marginal costs provided in Cambium may not be suitable. If a different annual marginal cost of firm capacity is known or available, it is possible to use the hourly marginal capacity costs in Cambium to allocate that different annual value. This could enable an analyst to use their own estimate of the annual cost of firm capacity while respecting the temporal patterns of the Cambium data set.

As the second caveat, as with all marginal costs in Cambium databases, we do not provide elasticities for these marginal capacity costs. Large interventions (e.g., widespread electrification of transportation) could change load patterns sufficiently to change these marginal capacity costs: the annual capacity cost, the hourly pattern, or both. If an analysis includes a large intervention, we encourage analysts to consider directly calculating changes in peak net load using the *net_load_busbar* values in Cambium, instead of relying on these marginal price-taking values.

6.9 Calculating Marginal Portfolio Costs

Marginal portfolio costs are the costs associated with staying in compliance with renewable portfolio standards (RPS) and clean energy standards (CES), when end-use demand is increased. Treating this in post-processing is necessary for Cambium because RPS and CES are represented in our ReEDS runs but not our PLEXOS runs, which means the marginal energy costs do not have these costs embedded in them (i.e., the marginal unit of energy may not be in compliance with a state's RPS or CES policy, necessitating remedial action to stay in compliance). In this section, we discuss how we calculate the cost of that remedial action, when necessary.

Depending on the scenario, Cambium databases can include state RPS (including technology-specific carveouts), national RPS, and CES policies. They are all handled the same way, however, so we just generically refer to policies in this section.

Calculating a Marginal Portfolio Cost

Each policy in Cambium databases is represented in ReEDS as a constraint. The shadow price on that constraint is the dollar cost of obtaining one more credit for the policy; for example, a \$10/credit shadow price on a RPS constraint is conceptually equivalent to a price of \$10 per 1

MWh of renewable energy credits (REC); however, it is different in important ways, as we explain at the end of this section.³⁵ If the policy is not binding in given state and year, the shadow price would be zero, and therefore the marginal cost would also be zero.

For documentation of how the various policies are represented in ReEDS, see (Ho et al. 2021).

Using the shadow price for each policy, we calculate the cost of staying in compliance with each of the policies as end-use demand is increased. The marginal cost can change from hour to hour, depending on whether the marginal generator at that point in time can contribute to the policy (a generator needs to be an eligible technology and either be in a location that within the region covered by the policy or be able to trade credits with the region covered by the policy).

If the marginal generator is unable to contribute to the policy (because it is either not an eligible technology or it is not in a location that can trade credits with the region covered by the policy), the marginal cost of policy n (C_n) in \$/MWh of end-use demand is given by:

$$C_n = f_n * p_n$$

where f_n is the fraction of end-use demand that must be covered by generation from an eligible technology, and p_n is the annual shadow price for policy n .

We emphasize that, when calculating f_n , we calculate the average fraction for the region covered by the policy. That can result in f_n values that deviate from the nominal top-line numbers used to describe a policy, as some load within a region is often excluded from the policy. Many states, for example, exempt utilities below a certain size from their RPS. This would result in a f_n that is lower than the nominal RPS goal.

The equation given above is straightforward: if a state has a policy where, say, 30% of end-use load must be covered by a credit, and the shadow price on credits is \$10/MWh, a 1-MWh increase in end-use demand when a noneligible generator is on the margin means 0.3 credits must be obtained for a marginal cost of \$3/MWh of end-use demand.

Notably, if the marginal generator can contribute to the policy (i.e., it is both an eligible technology and in a region that can trade with the region covered by the policy), the marginal cost can be negative (i.e., there is actually a marginal benefit to increasing consumption):

$$C_n = -\left(\frac{1}{1 - \mu_h} - f_n\right) * p_n$$

where μ_h is the marginal distribution loss rate at that point in time, as explained in Section 6.7.

Conceptually, the reason the cost can be negative is because the additional consumption can create more credits than are required by the policy to cover that additional consumption. Because the credits have value, the excess credits count as a benefit.

³⁵ We use the term “credit” to refer to the mechanism by which policy compliance is tracked, although it should be noted that different policies use various terms and have various tracking mechanisms in practice.

Consider a situation where an eligible technology is on the margin (e.g., an in-region solar generator is currently curtailing), the marginal distribution loss rate is 5%, the policy covers 30% of end-use demand, and the shadow price is \$10/MWh. In this case, an increase in end-use demand of 1 MWh increases generation from the solar plant by 1.053 MWh (amplified slightly because of the distribution losses). However, only 0.3 MWh of credits are needed to cover the additional load, so 0.753 MWh of credits remain and they are valued at \$10 per credit. Therefore, there is a marginal benefit of \$7.53/MWh of end-use demand.

For busbar marginal costs, we modify the end-use marginal costs by the marginal distribution loss rate.

Caveats and Limitations

Our representations of marginal portfolio costs have two important limitations:

- **Incomplete policy representations:** The shadow prices used to calculate marginal portfolio costs are driven by the representations of the policies in ReEDS, which can be incomplete. Though significant effort is put into correctly categorizing technology eligibility, fractions of load covered, and trading restrictions, there are still missing components (e.g., inter-year REC banking and technology-specific multipliers).
- **Shadow prices are long-run values.** Because the annual shadow prices on each policy come from ReEDS, which solves for the long-run equilibrium position, the shadow prices themselves are long-run values. In other words, they incorporate the option of building new capacity to generate credits. Where credits are traded in practice, their prices would potentially be better described as a short-run prices, although the ability of banking RECs better years makes the distinction less clear. Altogether, we recommend the policy shadow prices not be used directly as forecasts of future prices of these credits, as the markets for the credits likely deviate in significant ways from our modeled representations.

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