GUIDE TO SOURCING
MARGINAL EMISSIONS FACTOR DATA

CEBI
Clean Energy Buyers Institute

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About the Next Generation Carbon-Free Electricity Procurement Activation Guide

This guide is meant as a supplementary reader to the Clean Energy Buyers Institute's brief on applying the consequential emissions framework for emissions-based energy procurement. This guide is intended to help analysts and decision-makers identify sources of marginal emissions data, understand how they are calculated, and weigh the strengths and limitations of using these data. The first section describes the different types of data sources and summarizes some of the most widely available sources of data. The second section provides an overview of the methodologies used to estimate marginal emissions factors. The third section summarizes several considerations that should be kept in mind when using pre-calculated marginal emissions factors. The final section provides detailed information about each source of marginal emissions factor data identified in section 1.

SOURCES OF MARGINAL EMISSIONS FACTORS

Although marginal emissions factors (MEFs) have been calculated for over two decades in academic literature, such data were typically developed for the context of a specific study and are not applicable for general use in business decision-making. More recently, however, a growing number of both public and proprietary sources of marginal emissions data have been developed to aid in decision-making. This section provides an overview of most of the more widely used sources of MEFs and is supplemented by a more detailed overview of each data source in the appendix. This information is provided not to rate or rank these data sources, but rather to help the reader better understand the differences between each source and the types of decisions to which each source is tailored.

There are four major types of sources of MEF data: academia, commercial products, government sources, and grid operators. Academic estimates are generally peer-reviewed with documented methodologies and assumptions, but they are typically created for historical analysis of a specific use case and generally are not going to be relevant for general decision-making. However, the methodologies developed in academic literature have often been adapted for use in commercial and public estimates. Public sources are provided by government agencies, such as the Environmental Protection Agency (EPA) or Department of Energy, and provide free access to the data with generally well-documented methodologies and assumptions. Many of these government sources, such as the EPA's eGRID database or AVERT tool, have been around for decades. Commercial data products are typically only available behind a paywall and often use proprietary and black-box methods. Recently, some independent system operators (ISOs) have started directly providing historical marginal emission rate data, which may more accurately identify the marginal generators in specific markets but may not necessarily represent the "true" consequential impact of a specific decision.

These data sources typically consist of both a data layer, which includes the MEF, and a software or feature layer, which includes applications and interfaces designed to help a user interact with, apply, and interpret the data. Selecting marginal emissions data is analogous to shopping for cars: different vehicles are built for different purposes (like pickup trucks or sedans). Each car is going to have different technology under the hood and will have different features that affect the quality of the drive, but any car of the same type should be able to allow you to arrive at the intended destination. Likewise, each MEF will be built for a slightly different purpose, have a different methodology and technical approach, and will have different features in its software layer, but all of them (if calculated accurately and used appropriately) should allow you to arrive at the same decarbonization decision. However, one challenge that the carbon data industry must overcome is the lack of standardization of the data layer, which means that today, in some cases analogous MEFs from different sources may point toward different optimal emissions-based decisions.

Table 1 summarizes the data sources that are described in more detail in the appendix. Most of these sources provide operating or short-run marginal emission rates, while only a single source provides long-run marginal emission rates.

TABLE 1:
Overview of the major sources of MEFs. More details about each data source can be found in the appendix.

MEF TYPE	SOURCE	CATEGORY	METHOD APPROACH	METHODOLOGY	GEOGRAPHIC COVERAGE
Operating	PJM	ISO	Operator-reported	Proprietary	PJM
Operating	REsurety	Commercial	Statistical dispatch	Proprietary	ERCOT
Operating	SGIP Signal	Government	LMP-based	Public	California
Operating	Carbonara	Commercial	Operator-reported	Proprietary	Contiguous U.S.
Short-run	Electricity Maps	Commercial	Statistical dispatch	Proprietary	On-demand global
Short-run	WattTime	Commercial	Statistical emissions	Proprietary	U.S., Canada, Europe, Australia
Short-run	AVERT	Government	Statistical dispatch	Public	Contiguous U.S.
Short-run	eGRID	Government	Non-baseload	Public	U.S.
Long-run	NREL Cambium	Government	Simulation	Public	Contiguous U.S.

HOW ARE MARGINAL EMISSIONS FACTORS CALCULATED?

Calculating MEFs requires a solid understanding of power system dynamics, access to large amounts of data, and the application of data science, statistical, or modeling techniques. Most energy customers use pre-calculated MEFs rather than conducting their own bespoke modeling of marginal emissions impact. It is nevertheless helpful for a consumer of these data to have at least a basic understanding of the methodologies and assumptions behind the data to evaluate the quality of each MEF and to apply them correctly.

The primary challenge of calculating MEFs is that they attempt to quantify a counterfactual: how different would grid-wide emissions be if a hypothetical intervention occurs versus if it doesn't occur. MEFs do not represent measured emissions reductions; rather, they represent estimates derived from the difference between baseline and counterfactual emission scenarios. Over the past several decades, many different methodologies have been developed to estimate the marginal impact of an intervention on the grid. These methods have evolved in response to the amount of data that is available about the grid and emissions, evolving market structures, and generator fleet composition.

There is tremendous variation in the way that MEFs can be estimated. Depending on the specific methodology, data sources, and assumptions used, no one estimate is likely to match another. Even two approaches using the same methodology could use different input data or assumptions to estimate marginal emissions impact, leading to two different and sometimes inconsistent estimates.[1,2] This means that there is no single source of "truth" for marginal emissions impact. However, several characteristics may be used to evaluate the relative quality of different factors based on the methodologies and assumptions they use:[3]

01

The method should minimize the number of assumptions and rely on measured data as much as possible. For example, one common assumption made by all methods is which generator fuel types can respond to an intervention. Some methods assume that only a single fuel type (often natural gas) can be on the margin, that only generators above a certain size (generally 25 MW) can be on the margin, or that only fossil fuel-based generators can be on the margin. As we can see from the data in Figure 1, these assumptions are likely not very accurate: a wide variety of resources, including renewables and energy storage, can be marginal. This assumption is important, because if a method assumes that only fossil fuels are marginal, it means that it can only send a signal about whether to use cleaner fossil fuels, rather than whether to use clean energy.

02

The factor should be available at a high temporal resolution (at least hourly) to account for variability in emission rates from period to period. The generator on the operating margin can, and often does, change every five minutes, and differences in the availability of certain resources, especially renewables, throughout the day mean that the factor needs to be able to reflect this variability.[4] This is particularly important if you are trying to dynamically optimize emissions in real time.

03

The method should account for the physical flows of electricity, including import and export of electricity between regions, and transmission constraints within regions. Because regions often exchange electricity with one another, imported generation could be the source of marginal emissions. Likewise, because there are sometimes transmission constraints within grid regions that prevent electricity from freely flowing from one part of a region to another, different parts of the same region may be served by different marginal generators. Thus, methods that ignore inter-regional interchange or intra-regional congestion may not accurately represent the marginal emissions impact of an intervention. Consumers of these data should note that while creating factors for smaller geographic regions is one strategy to address this, factors that represent smaller regions are not *necessarily* more accurate than those that represent larger regions. What is important is that they represent the topology and power flow of the grid.

In this section, we summarize the seven categories of methods that are used to estimate MEFs, and highlight the strengths and limitations of each.

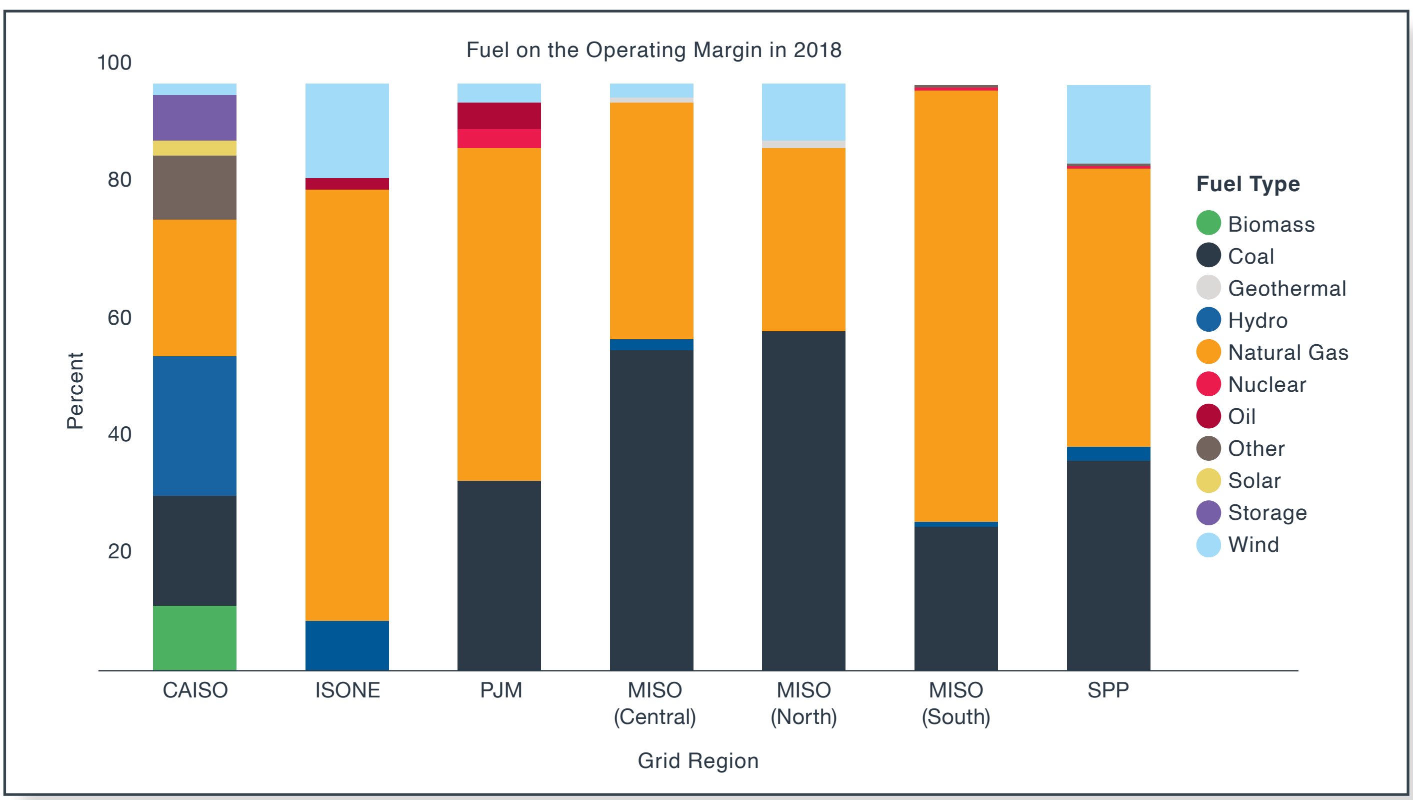
The **non-baseload approach** attempts to identify which generators are least likely to be baseload generators, and thus more likely to be able to respond to changing load. This is done by examining the capacity factor of each generator (the ratio of actual generation to maximum generation capacity): baseload generators generally operate at a high capacity factor, near their maximum output level, so cannot respond to changes in demand.[5–7] Generators that operate at low capacity factors are thus more likely to be “load following” or “peaker” plants that can ramp up or down in response to changing load. This method is most applicable to calculating operating or short-run factors. Although non-baseload MEFs are useful for first-order approximations of marginal impact, they are currently published only at the annual resolution as part of the EPA’s eGRID database and may not be as precise as other estimates.

Merit order or load duration curve analysis simulates the economic dispatch of generators in real-time markets by creating a supply stack of generators ordered from lowest to highest marginal cost and identifying the marginal generator by determining where the demand curve intersects this supply curve.[7–15] A limitation of this method is that precise merit order or economic dispatch is often not observed in practice because of transmission constraints, plant operating constraints, and market structures.[16] In addition, this method cannot be used to estimate long-run factors because it assumes that the generation stack is fixed.

In wholesale power markets, locational marginal prices (LMPs) describe the marginal cost of wholesale electricity at each node on the grid. Because LMPs are already locational and marginal, and are available in real time, the **locational marginal price-based method** uses LMPs as a proxy for locational marginal emissions. This method depends on the assumption that LMPs are correlated with the fuel consumption, and thus emissions of the marginal generator.[17–20] The idea is that the price that a generator bids into a market (which becomes the LMP if that generator is marginal) mostly reflects that generator's variable operating cost, which is primarily the cost of fuel. However, this method works best when there is primarily a single marginal fuel type (such as natural gas or coal) in real-time markets, which is not always the case (see Figure 1). Because this method relies on real-time market data, it is inherently an operating marginal emission rate.

Statistical methods are a broad class of approaches that use regression, econometric, or machine learning techniques to estimate marginal emissions based on observed historical data. Instead of explicitly modeling power system operations and market processes, these statistical methods observe the correlation

FIGURE 1:
U.S. annual power sector CO2e emissions resulting from each decarbonization pathway and combination of pathways evaluated



between historical dispatch or emissions patterns and natural variations in load or generation throughout the day.[16] Because they are based on the observed historical response of a power system to fluctuations in load, MEFs derived from statistical methods are only valid for time periods in which the power system is structurally the same as the historical period used to train the model. The particularly rapid changes that the grid has been undergoing over the past decade can limit the accuracy of statistical methods as you look further into the future, because the historical data the models were trained on can become outdated rapidly. Another limitation is that while these methods are good at assessing correlation, assessing the causality between an intervention and the emissions outcome is not always possible, even when causal inference methods are employed. These methods come in two main varieties depending on how they approach the estimation of marginal response: **Statistical dispatch methods** observe historical generator dispatch data to predict which generators will be dispatched in response to marginal changes in net load.[21] **Statistical emissions methods** are based on regressing changes in systemwide emissions on changes in load or generation, and using the slope of that line as the marginal emissions rate.[1,16,22–32]

The **simulation or modeling methodology** is perhaps the oldest and most flexible method for estimating different types of marginal emissions. It is the only method that can be used to produce long-run marginal emission rates and explicitly model the future. It uses different types of models to simulate the marginal response of the system to a specific intervention over different timescales. These sophisticated engineering models are generally some combination of optimal power flow, security-constrained economic dispatch, and capacity expansion models, which consider not only the marginal cost of generators, but factors such as power flow, transmission constraints, policy constraints, reliability constraints, and other grid stability factors.[33–38] Generally, these models are what grid planners use to make capacity investment decisions to maintain the reliability of the grid and what ISOs use to clear wholesale power markets and dispatch generation in real time. These methods determine the marginal impact of an intervention by first simulating a baseline scenario, then making the change represented by the intervention and re-solving the simulation, and finally taking the difference between the two scenarios. The primary limitations of this approach are that it is computationally heavy, requires a lot of data, and is generally not accessible to many users. Another limitation is that the results can be sensitive to the peculiarities of the specific simulation or model assumptions being used. Consequently, users of these estimates should consider factors based on multiple scenarios that represent different assumptions or uncertainties about the future being modeled.

Finally, the **operator-reported approach** relies on data reported by ISOs or other grid operators that identify the fuel type(s) or emission rate of the actual marginal generator(s) that cleared the wholesale power market at any given time. These marginal units are identified by the ISO's own market clearing processes (which uses the simulation/modeling methodology described above), which can then be assigned a generator-specific emission rate. Several U.S. ISOs, including MISO, SPP, and ISONE, regularly publish data about the fuel types of the marginal units in each real-time market interval.[39–41] In combination with data about generator-specific or fleet-specific emission rates, a MEF can be estimated. Other ISOs, including PJM and ISONE, publish the marginal emission rate of these marginal generators.[42,43] Although some see these data as a gold standard for marginal emissions data because they take the guesswork out of identifying the marginal generators, some grid operators do not recommend using them directly to make decisions or predict consequential emission response.[4] However, using these data to validate the assumptions and estimates of other methods is a new, exciting opportunity to further improve the quality of other methods discussed previously.

CONSIDERATIONS WHEN USING MARGINAL EMISSIONS FACTORS

MEFs have certain fundamental limitations regardless of the quality of the methodology or assumptions used to estimate them. Understanding these limitations is important for accurately applying MEFs and communicating the impacts they estimate.

Pre-calculated MEFS are "one-size-fits-all" even if the impacts are not

Each type of intervention, such as a solar array, a utility-scale battery, or an electric vehicle, has a unique net demand profile. In reality, the consequential impact of each intervention is the system's response to the specific shape of an intervention across multiple time intervals, rather than just a series of independent responses to the intervention in each interval. For example, the specific shape of a project activity could impact the ramping or minimum run time of marginal generators, affecting the consequential emissions impact.[22,34] Because pre-calculated MEFs are designed to be applied universally, they are limited in this regard because they treat each time interval as independent and do not reflect the specific consequential emissions impact of each intervention's unique shape.[7] In addition, many pre-calculated MEFs are designed to be applied universally to either demand-side or generation-side interventions. However, the different shapes of these resources mean that different types of marginal resources may respond.[28] To get around this limitation, one would have to conduct a bespoke modeling effort for each project activity and the system response to each specific shape.

A more practical solution for decision-making would be for carbon data providers to provide supply-specific or demand-specific marginal emissions factors for each type of project activity.[7]

All MEFs involve some uncertainty

The consequential impact should never be thought of as a single value, but rather as a range of potential impacts. As explained above, marginal emissions data is never exact, and no two methodologies are likely to ever arrive at the same MEF, partially because of the lack of standardization. If each estimate points to similar consequential emissions outcomes, you can be more certain in a recommendation than if different estimates point to different outcomes.

MEFS are only relevant to a specific time period

MEFs are only valid for a specific time period. For example, some factors may only be applicable to a single five-minute period, while others may provide some predictive insights into consequential emissions response at a general time of day, or for some range of time into the future. Factors should only ever be applied to the time(s) to which they are relevant. For example, if you only have access to short-run factors but are trying to evaluate the consequential emissions impact of a 20-year solar PPA, you might be able to estimate the avoided emissions impact for the first year of the solar plant's operation, but not for its entire lifetime.

APPENDIX: DETAILED COMPARISON OF MARGINAL EMISSIONS RATE DATA

This appendix presents more detailed information about each of the major sources of marginal emissions data. These sources are presented in alphabetical order. Each table was completed based on publicly available information and survey responses from each of the data providers and is current as of September 2022.

For each of these data sources, information is provided for three categories of data: historical, real-time, and forecasted. This paper defines these categories as follows:

- **Historical data: data that represent the marginal emissions rate in a time period that occurred in the past or which are not linked to a specific date/time but are estimated using historical data.**

- **Real-time data: data that are provided on a continuous basis (typically via an API) for a period occurring within an hour of the data being released. These data are generally operating marginal emissions rates intended for use in algorithms that optimize decisions in real time.**

- **Forecasted data: data that are forecasted for a specific date/time in the future, based on anticipated power system conditions at that time.**

We note that these categories describe how the data are released, but not necessarily how they must be used. For example, some "historical" data may be relevant to estimating consequential emissions impacts in the near future, or some "real time" data, if archived, can be used for analysis of past activities.

AVERT

Data Provider: U.S. Environmental Protection Agency
Data Product: Avoided Emissions and Generation Tool (AVERT)
Website
Link to access data

Factor type	Short-run
Methodological approach	Statistical dispatch
Pollutant types included	CO2, NOx, SO2, PM2.5, NH3, and VOC
Input data used in calculations	EPA Continuous Emissions Monitoring System (CEMS) and National Emissions Inventory (NEI)
Link to documentation about methodology	**https://www.epa.gov/avert/how-avert-works** **https://www.epa.gov/avert/avert-user-manual**
Link to external peer review or validation of estimates	**"Assessing the Emission Benefits of Renewable Energy and Energy Efficiency using EPA's AVoided Emissions and geneRation Tool (AVERT)"** (Note: Synapse Energy Economics, which developed this report, is the consultant that originally developed the AVERT model for the EPA.)
Approach to considering power flow between and within regions	Does not account for imports/exports between regions
Assumptions about what resources can be marginal	Fossil-only generators with capacity > 25 MW

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Public/Free	N/A	N/A
Data format	Excel file	N/A	N/A
Geographic coverage	Continental U.S.	N/A	N/A
Geographic resolution	"AVERT Regions" generally aligning with ISO boundaries	N/A	N/A
Temporal coverage	2007–2021	N/A	N/A
Temporal resolution	Hourly	N/A	N/A
Data release lag	1–2 years	N/A	N/A

CAMBIUM

Data Provider: U.S. National Renewable Energy Laboratory (NREL)
Data Product: Cambium Long-Run Marginal Emission Rate (LRMER) and Short-Run Marginal Emission Rate (SRMER)
Website
Link to access data

Factor type	Long-run and short-run
Methodological approach	Simulation (Capacity Expansion/Production Cost Model)
Pollutant types included	CO_2, CH_4, N_2O, CO_2e
Input data used in calculations	NREL Annual Technology Baseline Weather data National Energy Modeling System
Link to documentation about methodology	**https://www.nrel.gov/docs/fy22osti/81611.pdf**
Link to external peer review or validation of estimates	**"Planning for the evolution of the electric grid with a long-run marginal emission rate"**
Approach to considering power flow between and within regions	Simulates interchange between regions
Assumptions about what resources can be marginal	Any generator can be marginal. Generators that don't create energy (batteries, pumped hydro) are identified, but their contribution is replaced with an estimate of the original source energy from which they would have charged.

CAMBIUM: CONTINUED

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	N/A	N/A	Public/Free
Data format	N/A	N/A	Excel file, CSV
Geographic coverage	N/A	N/A	Contiguous U.S.
Geographic resolution	N/A	N/A	"Generation and Emission Assessment Regions" (i.e., our approximation of eGRID regions). If the data are downloaded through the viewer, there are other geographic resolutions: states, national, and 134 "balancing areas" covering the contiguous United States.
Temporal coverage	N/A	N/A	2022–2050, even years
Temporal resolution	N/A	N/A	Hourly. If downloaded through the viewer, month-hour, time-of-day, and annual aggregations are also available.
Data release lag	N/A	N/A	N/A

CARBONARA

Data Provider: Singularity Energy
Data Product: Carbonara
Website
Link to access data

Factor type	Operating (Singularity plans to add margin factors in Q2 2022.)
Methodological approach	Currently implements two models: Operator-provided for regions where the ISO publishes marginal fuel data and a derivative-based statistical model for other regions. Carbonara is model-agnostic and hosts multiple marginal models for many regions and expects to add more in the future.
Pollutant types included	CO2
Input data used in calculations	EIA Hourly Electric Grid Monitor ISO-provided data EPA eGRID database
Link to documentation about methodology	**API Documentation**
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	The dispatch-based model depends on specific ISOs' treatment of imports/exports. The statistical model currently does not include import and export but can be easily extended using a "multi-region input output model."
Assumptions about what resources can be marginal	For a dispatch-based model, it's based on whatever resources the grid operator identifies as being marginal in real-time energy markets. For a statistical model, we assume certain baseload fuels (depending on the region) cannot be marginal.

CARBONARA: CONTINUED

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Up to 500 API requests per month free, otherwise need to pay software-as-a-service (SaaS) monthly fee	Up to 500 API requests per month free, otherwise need to pay SaaS monthly fee	Up to 500 API requests per month free, otherwise need to pay SaaS monthly fee
Data format	API	API	API
Geographic coverage	~80 balancing authorities covering all of the continental United States and parts of Canada	9 major ISOs in the U.S. and Canada	8 major ISOs in the U.S. and Canada
Geographic resolution	Balancing areas, subregions available for some areas	Balancing areas, subregions available for some areas	Balancing areas, subregions available for some areas
Temporal coverage	Back to 2018, older data available upon request	Current 5-minute real-time operating period	2 hours ahead for 5 minute forecasts, 24 hours ahead for hourly forecasts
Temporal resolution	5 minutes or 1 hour, depending on the region	5 minutes or 1 hour, depending on the region	5 minutes or 1 hour
Data release lag	Same as real-time for major ISOs, ~24 hours for other regions	Varies by region, generally under 5 minutes	Same as real-time

EGRID

Data Provider: U.S. Environmental Protection Agency (EPA)
Data Product: eGRID non-baseload emission factor
Website
Link to access data

Factor type	Short-run
Methodological approach	Non-baseload
Pollutant types included	CO2, CH4, N2O, NOx, SO2, CO2e
Input data used in calculations	EPA Continuous Emissions Monitoring System (CEMS) U.S. EIA Form 860
Link to documentation about methodology	https://www.epa.gov/egrid/egrid-technical-guide
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	Estimates available for different regional aggregations which may capture the effects of interchange across borders
Assumptions about what resources can be marginal	Only fossil or biomass power plants can be marginal

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Free/public	N/A	N/A
Data format	Excel file	N/A	N/A
Geographic coverage	United States	N/A	N/A
Geographic resolution	Balancing Area, State, NERC Region, and eGRID subregion	N/A	N/A
Temporal coverage	2004–2020, published for even years 2004–2018, since 2018 has been published annually	N/A	N/A
Temporal resolution	Annual	N/A	N/A
Data release lag	1–2 years	N/A	N/A

ELECTRICITY MAPS

Data Provider: Electricity Maps
Data Product: Electricity Maps
Website
Link to access data

Type of marginal emission rate	Short-run (estimates dispatch changes in the day-ahead market)
Methodological approach	Statistical dispatch
Pollutant types	CO2e
Input data used for calculations	Generation, import, and load data Electricity market data Weather data
Link to documentation of methodology	**https://www.tmrow.com/blog/marginal-carbon-intensity-of-electricity-with-machine-learning/**
Link to external peer review or validation of estimates	None publicly available
How is power flow accounted for	Uses "**flow tracing**" method described in **peer-reviewed academic literature** to account for imports and exports
Assumptions about what resources can be marginal	Assumes wind and solar can never be on the margin

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Behind paywall (1 month free trial available)	Behind paywall (1 month free trial available)	Behind paywall
Data format	CSV or Excel	API	API
Geographic coverage	Global but on-demand for marginal	Global but on-demand for marginal	Global but on-demand for marginal
Geographic resolution	Grid balancing area	Grid balancing area	Grid balancing area
Temporal coverage	Up to 6 years in the past depending on the region	N/A	Up to 24 hours in the future
Temporal resolution	Hourly	Hourly or less	Hourly
Data release lag	Unknown	< 2 hours	Updated every 15 minutes

PJM

Data Provider: PJM Interconnection
Data Product: Marginal Emission Rate
Website
Link to access data

Factor type	Operating
Methodological approach	Operator-reported
Pollutant types included	CO2, SO2, NOx
Input data used in calculations	PJM Network Model Bids and offers
Link to documentation about methodology	**https://www.pjm.com/-/media/etools/data-miner-2/marginal-emissions-primer.ashx**
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	Imports are modeled but assumed to have a marginal emission rate of 0
Assumptions about what resources can be marginal	Any resource can be marginal

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Public/Free	Public/Free	N/A
Data format	API or CSV file download	API or CSV file download	N/A
Geographic coverage	PJM	PJM	N/A
Geographic resolution	LMP Load Nodes	LMP Load Node	N/A
Temporal coverage	2 years	Real-time operating interval	N/A
Temporal resolution	5 minutes	5 minutes	N/A
Data release lag	5 minutes	5 minutes	N/A

RESURETY

Data Provider: REsurety
Data Product: Locational Marginal Emissions (LME)
Website
Link to access data

Factor type	Operating
Methodological approach	Statistical dispatch
Pollutant types included	CO_2
Input data used in calculations	Transmission network data (shift factors and constraints) Offers and LMP data Resource node mappings Fossil emission rates
Link to documentation about methodology	https://resurety.com/solutions/locational-marginal-emissions/
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	Transmission network is modeled between nodes using shift factors as published by market operators or derived from market operator-published data
Assumptions about what resources can be marginal	Our methodology assumes that resources whose offer prices are equal to or very close to nodal LMP are able to be marginal. This includes fossil resources and curtailed renewable resources.

RESURETY: CONTINUED

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Subscription service	N/A	N/A
Data format	API, Excel reports. Data will be included in REmap and interactive dashboards in coming months.	N/A	N/A
Geographic coverage	ERCOT and PJM (CAISO, MISO, and other markets coming soon)	N/A	N/A
Geographic resolution	Wholesale pricing node	N/A	N/A
Temporal coverage	January 2018–present	N/A	N/A
Temporal resolution	Hourly	N/A	N/A
Data release lag	60–90 days	N/A	N/A

SGIP SIGNAL

Data Provider: WattTime/California Public Utilities Commission
Data Product: Self-Generation Incentive Program (SGIP) Signal
Website
Link to access data

Factor type	Operating
Methodological approach	LMP-Based
Pollutant types included	CO_2
Input data used in calculations	LMP, Gas Price, CO_2 Price Data
Link to documentation about methodology	**https://www.ethree.com/wp-content/uploads/2017/01/20160801_E3_-Avoided_Cost-2016-Interim_Update.pdf**
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	Interchange not considered
Assumptions about what resources can be marginal	Either natural gas plants or renewable plants

SGIP SIGNAL: CONTINUED

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Public/Free	Public/Free	Public/Free
Data format	CSV files or API	API	API
Geographic coverage	California and parts of bordering states (PacifiCorp West, NV Energy, WAPA Lower Colorado)	California and parts of bordering states (PacifiCorp West, NV Energy, WAPA Lower Colorado)	California and parts of bordering states (PacifiCorp West, NV Energy, WAPA Lower Colorado)
Geographic resolution	Balancing areas and subregions	Balancing areas and subregions	Balancing areas and subregions
Temporal coverage	2017–Present	Real-time 5 minute period	72 hours ahead for 5-minute data; also long-term forecasts available up to a year ahead for monthly time of day percentiles
Temporal resolution	5 minutes	5 minutes	5 minutes
Data release lag	None	Available 2–3 minutes ahead	N/A

WATTTIME

Data Provider: WattTime
Data Product: Marginal Operating Emission Rate (MOER)
Website
Link to access data

Factor type	Short-run
Methodological approach	Statistical
Pollutant types included	CO2
Input data used in calculations	Real-time data from individual grid operators EIA Hourly Electric Grid Monitor EPA Continuous Emissions Monitoring System Renewable Energy Curtailment datasets
Link to documentation about methodology	https://www.watttime.org/marginal-emissions-methodology/
Link to external peer review or validation of estimates	None publicly available
Approach to considering power flow between and within regions	Model considers power flows between regions
Assumptions about what resources can be marginal	Any resource can be marginal

WATTTIME: CONTINUED

DATA CHARACTERISTICS	HISTORICAL DATA	REAL-TIME DATA	FORECASTED DATA
Data access/cost	Behind paywall (free access for single grid subregion CAISO_NORTH)	Behind paywall (free access for single grid subregion CAISO_NORTH)	Behind paywall (free access for single grid subregion CAISO_NORTH)
Data format	API	API	API
Geographic coverage	Continental U.S., Canada (partial), Western Europe (partial), Australia	Continental U.S., Canada (partial), Western Europe (partial), Australia	Continental U.S., Canada (partial), Western Europe (partial), Australia
Geographic resolution	Balancing Authority (or BA subregions for certain BAs)	Balancing Authority (or BA subregions for certain BAs)	Balancing Authority (or BA subregions for certain BAs)
Temporal coverage	2 years of history from current month	Current 5-minute real-time operating period	72 hours ahead
Temporal resolution	5 minute	5 minute	5 minute
Data release lag	1 month (updated on 2nd day of each month at midnight UTC for the previous month)	None (updated every 5 minutes)	N/A (released every 5 minutes)

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Thank You!

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