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# A data-driven framework for quantifying consumption-based monthly and hourly marginal emissions factors

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ABSTRACT

The fleet of power plants supplying electricity to a power grid varies diurnally and seasonally, creating large time-dependent differences in the emissions associated with consuming electricity, particularly in grids with high penetrations of renewable electricity generators. In addition, modern grids are incorporating more demand-side interventions that incentivize electricity end users to temporarily modify their electricity consuming behavior in efforts to change the shape and magnitude of electricity consumption over a period of time. Current methods for quantifying the emissions associated with marginal shifts in electricity consumption are not sufficient given the changing dynamics of supply-side generation resources. This study introduces a novel multiple linear regression model that utilizes historical demand, variable renewable generation, and $CO_2$ emissions data to quantify hourly marginal emissions factors for the years of 2019 and 2020. The developed consumption-based $CO_2$ accounting method includes the emissions embedded in net electricity imports in addition to emissions from in-region generators. The proposed framework is applied to the case study of California Independent System Operator (CAISO), revealing a wide range of hourly-level marginal emissions factors (89–503 $kgCO_2/MWh$) during the period of study. The proposed method improves upon the existing literature by proposing a consumption-based method that is well suited for estimating emissions avoided through demand-side changes in load, particularly in electric grids, like CAISO, with high renewable energy penetrations.

## 1. Introduction

Understanding the interactions between electricity demand and electricity supply is an important first step in quantifying the emissions impacts of load modifying interventions and leveraging demand-side resources for deep decarbonization. In an electric grid, power supply must be balanced with electricity demand at any given time of day. This means that each time there is an increase in electricity demand, there is a commensurate increase in the supply of electricity (and conversely, electricity supply must be reduced if electricity demand decreases). Marginal generators are the power generation units that respond to these changes in demand; altering their output to match the new level of demand. Tracking the operation of marginal generators in the context of the electric grid operation provides key information in greenhouse gas accounting and developing emissions mitigation measures.

Traditionally, quantifying emissions of the electric grid focuses on total grid emissions (i.e., the sum of all emissions associated with the electricity supply over a given period of time) or the average emissions factor (i.e., the total grid emissions for a period of time divided by the total demand over the same period). These quantities are often easy to calculate, pending adequate data availability, but estimating marginal emissions at a point in time is not as straightforward because it is typically difficult to accurately identify marginal generators and isolate their emissions. Theoretically, electricity generators are dispatched according to the lowest marginal cost of electricity generation given operational and transmission constraints (Jenn et al., 2020). When compared to renewable electricity generators, fossil fuel-based generators have relatively high operational costs, and therefore, are often dispatched after renewables. Several studies have used comprehensive electric grid simulation models for assessing long-term (implying that future capacity expansion changes the generation mix) marginal emissions associated with electricity generation systems (Gagnon and Cole, 2022) and short-term (implying that the generation capacity mix does not change significantly), and have applied their estimates to different cases such as electric vehicle charging (Huber et al., 2021; Kamiya et al., 2019; Raichur et al., 2016) renewable energy integration

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(Buonocore et al., 2016; Li et al., 2020), energy efficiency (Buonocore et al., 2016) and energy storage (Pimm et al., 2021). For instance, one study developed a reduced-order power plant dispatch model for the North American Electric Reliability Corporation regions for years 2014 to 2017 and showed that clusters of low- or high-emitting power plants of similar production cost could create large changes in marginal emissions factors (MEFs) as ascending the order of dispatching generators (Deetjen and Azevedo, 2019). Another study builds upon cost-based dispatch by incorporating ramping limitations and applies this methodology to Great Britain's power system, finding significant variations in MEFs within a day and over the course of a year (Zheng et al., 2015). One limitation of simulation modeling approaches is that actual grid operation is more complicated than most simulations can capture. For example, more than one resource or generation unit can contribute to supply the last unit of electricity, or cheaper generators with limited generation capacity, such as hydropower, may choose to produce more electricity during more profitable times of the day. Khan (2018) found that oil was the only consistent marginal resource in Bangladesh, but in New Zealand, a study found that peak demands were primarily met by hydropower (Khan et al., 2018). Li et al. (2017) found that for the Midcontinent Independent System Operator (MISO) in the years spanning 2015 through 2018, fossil-fuel burning generators were generally the marginal resource, but it also found that at high demand times, hydropower also contributed to marginal generation in the MISO Central subregional grid, while wind energy contributed to marginal generation in the MISO North subregional grid (which had about 27% of total electricity generation from wind). Electricity imports and exports dynamics are among other factors that further complicate electric grid operation beyond what models can capture.

Alternatively, regression models are used to track short-term marginal emissions (typically on the scale of hour-to-hour) and are generally more accurate than simulated values obtained from electricity system models (Deetjen and Azevedo, 2019). Regression-based models rely primarily on historical granular electricity generation, consumption, and greenhouse gas emissions data to estimate marginal emissions. One advantage of using observed historical data to estimate marginal emissions is that the data capture grid operation constraints as they occurred, in contrast to some simplifying assumptions in electric grid models that might ignore generator outages or transmission congestion constraints. Different imports and electricity purchase structures and load serving obligations can also be hard to accurately simulate in electric grid models. Other constraints, such as maintaining grid stability and reliability, might result in deviations from loading orders and/or lifting or enforcing certain environmental rules, which are hard to predict and capture in electric grid simulations that are suited to mostly capture the grid's normal operations (Mccall et al., 2016). Another advantage is the low complexity of regression models (as compared to electricity system models), which makes it easier to interpret and validate results. Different regression models have been previously used to analyze marginal emissions of Great Britain's electric grid by Hawkes (2010), India's electric grid by Sengupta et al. (2022), Ontario's electricity system in Canada by Gai et al. (2019), Pennsylvania, Jersey, Maryland Power Pool (PJM) in the US by Donti et al. (2019), MISO by Thind et al. (2017), and North Electric Reliability Council (NERC) regions in the US by Siler-Evans et al. (2012). These studies utilize various statistical models with a range of different independent variables. Some studies used a simple linear regression model with hourly changes in generation as the only independent variable (Hawkes, 2010; Huber et al., 2021; Siler-Evans et al., 2012). In one of the earliest MEF quantifying studies, Siler-Evans et al. (2012) assumed that changes in electricity demand are only balanced by changes in the output of fossil fuel-based generators, ignoring the role of changes in production from non-fossil fuel powered generators in meeting marginal demand. Seckinger and Radgen (2021) similarly assume that all marginal demand is met with fossil fuel technologies when calculating MEFs for the German grid, citing the prioritizing of renewables as justification for this structure. Although this might be an adequate assumption for grids with low penetrations of renewable energy, or with strict resource queuing rules, many regional grids incorporate significant levels of alternative sources, and emissions free generators are increasingly on the margin. In fact, specific loading orders can also facilitate the marginal operation of renewables, regardless of their low production cost advantages (e.g., California's 2003 Energy Action Plan that prioritizes renewables over fossil fuel generation Bender et al. (2005)). Some studies have included electricity generation from variable energy resources, as well as levels of electricity demand as predicting variables that marginal emissions depend on Gai et al. (2019), Pimm et al. (2021), Thomson et al. (2017). A number of these studies are summarized in the supplementary data Table A.1. Growing shares of battery storage deployments will also create new grid operation dynamics. It has yet to be explored how different charging and discharging patterns can impact marginal generators and emissions.

Regardless of the statistical model and predicting variables used, all previous studies reported that MEF trends are distinct among seasons and hours of the day, and can also be significantly different from the concurrent average emissions factors (AEFs) due to factors such as electricity demand patterns, electricity generation fleet, the legacy of technology mix, fuel type, operational cost, dispatchability and grid interconnectedness (Buonocore et al., 2016; Hawkes, 2010; Jenn et al., 2020).

Geographic boundaries are critical for accurate emissions accounting (Ryan et al., 2016). Previous studies have typically taken a generation-based approach for calculating changes in emissions and generation by considering generators located within their region of focus (Hawkes, 2010; Siler-Evans et al., 2012). This approach assumes that changes in electricity demand are equal to changes in electricity supply in that same geographic area, ignoring the influence of electricity trades with external areas. Electricity trades were modeled by Tranberg et al. (2019), who assessed real-time grid-wide average emissions in European electricity markets, and by de Chalendar et al. (2019), who analyzed annual and median daily emissions (not marginal emissions) for 66 electricity balancing authorities across the US. The latter study showed that exchanges between regions play an especially large role in the Western Interconnection (where California Independent System Operator or CAISO is located), since, as an example, 2016 net imports accounted for 29% of annual consumption by net importing regions and 2016 net exports accounted for 37% of annual generation in net exporting regions (de Chalendar et al., 2019). While electricity trades have been modeled in a few average grid emissions studied, they are widely absent in regression-based MEF assessment studies.

The large variation in these factors among different electric grids highlight the need for evaluating regional specific MEFs. Moreover, rapid shifts in electricity supply mix make it essential to frequently re-assess MEF estimates. In this study, MEFs of CAISO, a grid that generated 20% of its annual electricity consumption from solar PV and wind turbines in 2019 (and 21% in 2020), are evaluated. The analysis is done independently in each year and examine changes that occur between the two years. This comparison provides insight as to the impact of supply factors, such as the use of hydropower, as well as the effect of changes in electricity demand patterns on MEFs.

## 2. Contributions of this study

Our framework refines three major aspects of the regression models previously used in MEF assessment literature through its approach in considering electricity trades and variable renewable energy generation. These improvements increase the ability to methodically quantify the efficacy of demand-side management (DSM) strategies for reducing emissions, since DSM affects the subset of generators at the margin as opposed to the whole set of generators across the grid.

1. This framework takes a consumption-based approach, rather than a generation-based approach (i.e., emissions associated with electricity consumption in CAISO are accounted for regardless of whether electricity is produced with in-region resources or imported from out-of-region). In addition, electricity generated with in-region resources and exported out-of-region is not considered for in-region electricity demand. The emissions associated with these exports are removed from the total emissions before emissions factor calculations.
2. The regression model used in this study mimics a net load curve to explicitly account for generation from emissions-free non-dispatchable solar PV and wind turbines, which is particularly important for analyzing grids with high levels of renewable energy penetration. Specifically, the model includes a designated term for variable renewable energy in the regression model, an inclusion lacking in previous US-based studies.
3. Lastly, this framework also makes methodological improvements that account for MEF-demand dependency and enables the analysis of more granular emissions dynamics and careful quantification of hourly and monthly MEFs.

## 3. Methods

This section describes the methodology developed to use historical data for estimating hourly average emissions factors and marginal emissions factors (defined in the next subsection) for CAISO independently for two years of 2019 and 2020.

### 3.1. Definitions

Here, the following definitions are used for quantifying emissions:

**Average Emissions Factor (AEF):** This metric quantifies the emissions associated with the average unit of electricity consumed by accounting for emissions from all electricity generating units in the CAISO region and net electricity imports. In this study, AEFs are calculated using periods of length one-hour.

**Marginal Emissions Factor (MEF):** This metric shows the change in emissions due to one unit change in electricity demand, as changes in demand impact marginal generators rather than all generators. In this study, MEFs are calculated using hour-to-hour changes in demand, variable renewable generation, and $CO_2$ emissions.

### 3.2. The system boundaries

This study is bounded around the CAISO region located within the Western Electricity Coordinating Council. Based on CAISO data (CAISO, 2021b), in 2019, about 76% of total annual electricity (219.5 TWh) was generated within the region (74% in 2020); the remainder was imported from multiple balancing authorities (BAs) in the Southwest and Northwest regions which are listed in Table 1. This electricity was generated from a mix of technologies that use natural gas, nuclear, hydro, and renewables, which included large fractions of solar PV and wind technologies (20%–21% of total supply).

### 3.3. Data sources and data processing steps

The utilized data sources and their corresponding main processing steps are as follows:

1. The list of power plants operating in each BA in each year were identified based on the US Energy Information Administration (EIA) Form EIA-860 reports (U.S. Energy Information Administration, 2020) by filtering power plant identification numbers for the two sectors of electric utility and independent power producers (IPP) for both CHP (combined heat and power) and non-CHP plants.

**Table 1**
Electricity supply sources in the CAISO region (total electricity supplied was 219.5 TWh in 2019 and 218.5 TWh in 2020). Electricity supply data from CAISO (2021b), and the breakdown of net imports from U.S. Energy Information Administration (2021).

| | 2019 | 2020 |
|---|---|---|
| **Total Supply (Sum to 100%)** | | |
| Fossil fuel (mostly natural gas) | 29% | 33% |
| Nuclear | 7% | 7% |
| Hydro | 12% | 6% |
| Solar PV and Wind turbines | 20% | 21% |
| Other Renewables | 7% | 7% |
| Net Imports | 24% | 26% |
| **Breakdown of Net Imports from BAs to CAISO (Sum to 100%)** | | |
| Los Angeles Dep. Water & Power (LDWP) | 35% | 31% |
| Bonneville Power Administration (BPAT) | 13% | 26% |
| Salt River Project (SRP) | 25% | 19% |
| Arizona Public Service Company (AZPS) | 19% | 11% |
| Balancing Authority of Northern California (BANC) | 6% | 6% |
| Nevada Power Company (NEVP) | −1% | 5% |
| Imperial Irrigation District (IID) | 5% | 4% |
| Western Area Power Administration - Desert Southwest Region (WALC) | 2% | 2% |
| PacifiCorp West (PACW) | <1% | <1% |
| Turlock Irrigation District (TIDC) | −2% | −3% |
| Centro Nacional de Control de Energia (CEN), and Comision Federal de Electricidad (CFE) (in Mexico) | −1% | −1% |

2. Hourly emissions data were extracted from the US Environmental Protection Agency's (EPA) Air Markets Program Data for each state, and were rearranged for each BA based on the list of power plants identified within each BA in the previous step (U.S. Environmental Protection Agency, 2021). (Note: EPA's Air Markets Program Data reports emissions associated for fossil-fueled power plants with capacities greater than 25 MW.)
3. Hourly data for electricity generation at BA level as well as electricity exchanges between BAs were collected from EIA's Electric System Operating Data (U.S. Energy Information Administration, 2021). Note that because these data are bidirectional between BAs, each electricity exchange is reported in two locations. Total electricity generation data were collected from each corresponding BA file (for example, total electricity generation of LDWP was extracted from LDWP file). The only exception was BPAT where historical data reported on the BPAT website (BPA, 2021) were used instead of EIA's data (U.S. Energy Information Administration, 2021) due to the large discrepancies in the reported EIA values.
4. Data for CAISO's electricity demand, total electricity generation and solar PV and wind turbine generation, as well as total imported electricity were sourced from the CAISO website (CAISO, 2021b). These data are reported in five-minute increments, but this study uses averaged values to represent each hour.

Several considerations and adjustments were made when cleaning and processing data. First, the timestamps for the data associated with the three BAs located within the Arizona time zone (i.e., AZPS, SRP and WALC) were shifted for one hour for the affected data points between November and March of each year, so that the all timestamps are aligned with the Pacific Time zone. Second, electricity trades between CAISO and the two BAs located in Mexico (CEN and CFE) were ignored in this analysis due to lack of associated emissions data. Instead, the magnitude of these electricity trades were distributed among the other BAs within the US in proportion to their concurrent electricity trades with CAISO. (The electricity traded between CAISO and the two BAs in Mexico was only about 57 GWh, or 1%, of total net imports to CAISO in 2020, as shown in Table 1.) Third, CAISO's reported total net imports were cross-checked with the sum of electricity trades between all of the individual BAs and CAISO to ensure that the two values were equal. When the sum of hourly electricity trades between CAISO and other BAs did not match CAISO's reported total net electricity imports in a given hour, CAISO's total net import value was used to normalize the interchange electricity amounts with each BA (scaling the magnitude of the exchanges with each BA to ensure that the two totals matched). Fourth, for the bidirectional exchanges reported by the EIA, the values reported from CAISO's perspective were primarily used, and data from other BAs were only used to verify or fill in missing or misreported electricity interchanges. If hourly data were missing from both sources, five-day averaged values for the same hour were used. Fifth, it was ensured that total electricity demand for CAISO was balanced with the sum of total electricity generation and total net imports in each hour. Finally, before beginning the regression process, an outlier analysis was performed to identify data points that were likely the result of incorrectly reported emissions values by BAs, or exacerbated by limitations in the data processing methodology (e.g., a small error in emissions reporting could be magnified by the scaling process that matches BA-reported imports with CAISO-reported imports). More details on the analysis can be found in the supplementary data.

### 3.4. Consumption-based hourly $CO_2$ emissions estimates

Hourly emissions associated with CAISO's electricity demand were tracked using Eq. (1), which explicitly accounts for the emissions associated with electricity imports and exports. In this equation, $E^C_{i,j}$, $E^X_{i,j}$, and $E^I_{i,j}$ are emissions associated with in-CAISO power generation, exports (from CAISO, $C$, to other BAs, $M$) and imports (from other BAs, $M$, to CAISO, $C$), and $i$ and $j$ are indexes for the month and the hour of day, respectively. Additionally, in this equation, $\frac{X^{C\to M}}{G^C}$ calculates the fraction of emissions associated with the electricity produced in CAISO ($G^C$) but consumed in other BAs; while $\frac{I^{M\to C}}{G^M}$ calculates the fraction of emissions associated with the electricity produced outside CAISO ($G^M$) but consumed in the CAISO region. It is notable that this accounting method for $CO_2$ emissions is an improvement over the methodology used in reporting $CO_2$ emissions in five-minute increments on the CAISO Today's Outlook website (CAISO, 2021a) where emissions are approximated using resource-specific $CO_2$ emissions rate for in-CAISO generators and a fixed unspecified emissions rate (i.e., 0.428 $mTCO_2$/MWh as established by California Air Resources Board) for imported electricity (Hundiwale, 2016).

$$E_{i,j} = E^C_{i,j} - E^X_{i,j} + E^I_{i,j} = E^C{}_{i,j} - \left(\sum_M E^C \cdot \frac{X^{C\to M}}{G^C}\right)_{i,j} + \left(\sum_M E^M \cdot \frac{I^{M\to C}}{G^M}\right)_{i,j} \quad (1)$$

### 3.5. The averaging method for estimating AEFs

For AEF calculations, the emissions data were first grouped by month $i$ and hour $j$ of the day (e.g., "January, hour 1" has 31 data points), and then derived a regression model based on Eq. (2) to calculate an average $CO_2$ emissions factor ($AEF_{i,j}$) using electricity demand ($D_{i,j}$) as a predicting variable for each hour ($j$) and month ($i$) pairing. Twenty-four hourly AEFs were calculated in kg $CO_2$/MWh for each month (e.g., 24 AEFs in January and 288 AEFs in 2019), which represent an average day in that month.

$$E_{i,j} = AEF_{i,j} \cdot D_{i,j} \quad (2)$$

### 3.6. The regression model for estimating MEFs

Following the steps illustrated in Fig. 1, the CAISO data were first re-ordered from lowest to highest hourly electricity demand to form the load duration curve for each year for both years of analysis. Then, electricity demand was partitioned into 10 equal bins, where each bin represented 10% of the range between the lowest and the highest demand (shown in the load duration subplot in Fig. 1). This binning method allowed quantifying MEFs for hours with similar demand level (in contrast to AEFs, where binning was done by time of day, so similar hours of different days in a month were grouped together). This binning method results in a variable number of data points in each of these 10 bins. For instance, Bins 7–10 contained a smaller number of hours compared to Bin 2–4, as these bins covered the highest demand hours that occur infrequently throughout the year (see the steep slope area in the load duration curve in Fig. 1), but they might have more significance to the regression slope due to larger supply needs during these hours. Considering the very small number of hours in Bin 10, (e.g., only 33 h in year 2020), Bins 9 and 10 were combined prior to the regression step of the analysis. Further combination of bins was performed ad hoc during the regression process to ensure a minimum number of data points for each regression (described in more details later in this section). It is notable that because the bins are defined at the annual level, some months might not have certain demand levels; for example, demand levels that fall in Bin 9 and Bin 10 only occur during summer months.

Secondly, after assigning bins to each hour, the differences between consecutive hours were calculated for emissions ($\Delta E_{k,i}$) in kg, electricity demand ($\Delta D_{k,i}$) in MWh, and the sum of solar PV and wind generation values ($\Delta R_{k,i}$) in MWh. These variables describe the changes between the hour $j$ and $j-1$ and have a label of $k$ that specifies the bin their demand level falls in. This step is illustrated in the table presented in the center of Fig. 1.

Thirdly, the multiple linear regression model shown in Eq. (3) was applied for each demand level and month combination to estimate MEF values. In the event that a demand level and month combination only occurred in a small number of hours, demand level bins were combined with an adjacent bin until a minimum threshold of 25 datapoints was reached. In this regression model, $a_{k,i}$ estimates MEF and $b_{k,i}$ estimates the impact of solar PV and wind generation (both in $kgCO_2$/MWh) for each bin $k$ and month $i$.

$$\Delta E_{k,i} = a_{k,i} \cdot \Delta D_{k,i} + b_{k,i} \cdot \Delta R_{k,i} + c_{k,i} \quad (3)$$

Detailed regression results for each month and demand level combination can be found in the data repository also mentioned at the end of this document (https://data.mendeley.com/datasets/7w87xy5pwj/2).

Finally, MEF values were converted from a specific month/bin pairing to month/hour pairing by multiplying the month and bin-specific MEF values by weight factors $w_{j,k}$ that are associated with the histogram of bins in each hour of each month (see Eq. (4)). In other words, hourly MEFs are found with a weighted sum, where the weight is dependent on the bin distribution for a specific hour in a specific month, and these weights are multiplied by the MEFs for those month/bin pairings. The resulting hourly MEFs are obtained in the format of "month-hour" in which 24 MEFs represent an average day in each month. For illustration, weight factors that had hourly electricity demand in Bins 2–4 are displayed at the bottom-right of Fig. 1 for January 2020. As the plot suggests, the majority of hours had demand levels concentrated within a single demand bin (e.g., 48% of electricity demand in hour 5 of January 2020 was within the demand range of Bin 2 and 52% within Bin 3; whereas, electricity demands in hours 2–4 were entirely within the demand range of Bin 2).

$$MEF_{i,j} = \sum_k (w_{j,k} \cdot a_{k,i}) \quad (4)$$

## 4. Results

In this section, the regression results for MEF values are presented for each month and demand level in 2019 and 2020, as well as the estimated month and hour level MEF and AEF values. Additional evidence from the operation of the electric grid are provided to support the responsiveness of different grid resources to changes in electricity demand which help validating the estimated MEF trends.

In general, the results are consistent with the range of AEFs and MEFs estimated in other studies for CAISO. The coefficient of determination ($R^2$) for the regression results lies between 0.40 and 0.98 for the distinct regressions, with better predictability in higher demand levels. From a practical standpoint, having higher accuracy of MEF estimation

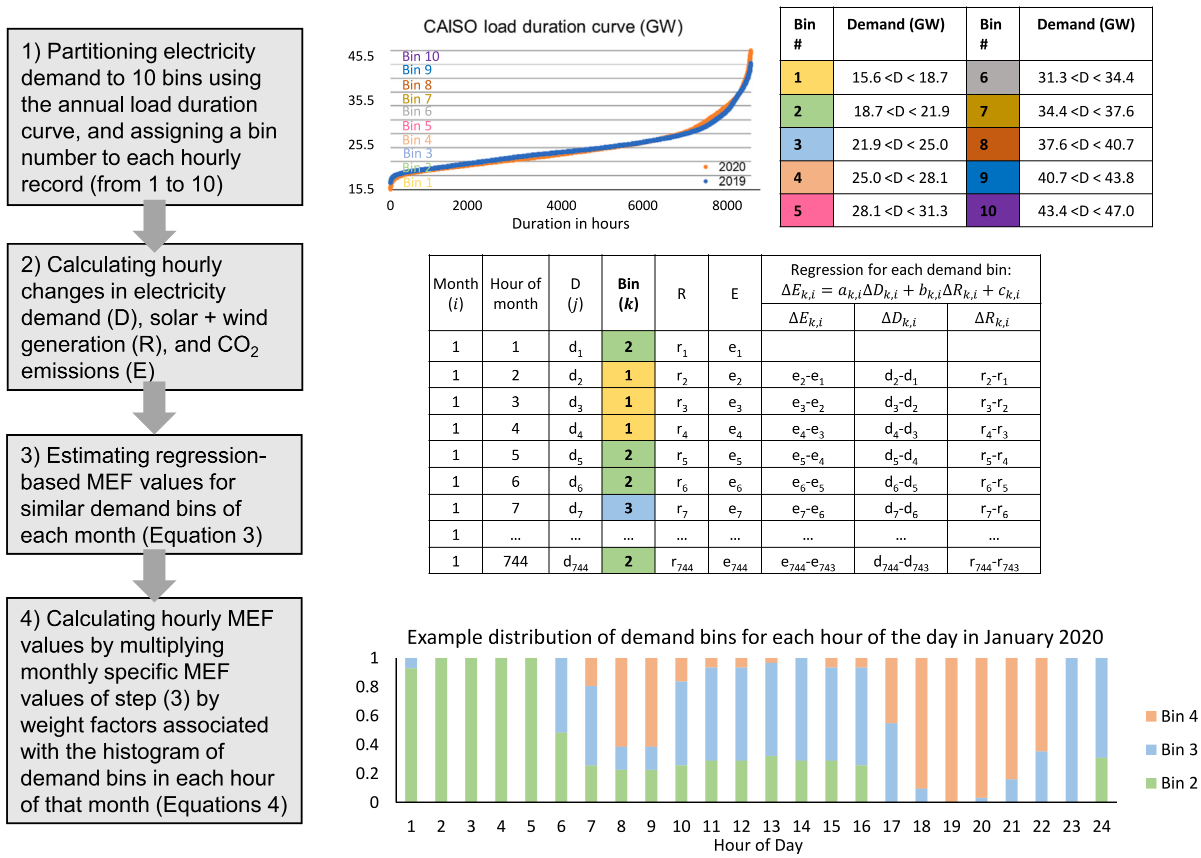


**Fig. 1.** Visual representation of the proposed framework to evaluate MEF values.

in higher demand levels is most important since periods with high MEFs (normally coincident with high demands) have the greatest implications for emissions reductions and increases due to changes in demand (see the supplementary data for more details). It is worth noting that the model shows a better performance in 2019 as compared to 2020, likely due to data quality issues and the larger spread of the data that occurred in 2020. As other studies reported, electricity demand patterns were impacted by COVID-19 pandemic-related lockdowns, such as lower consumption levels than previous years especially in March and April months (Krarti and Aldubyan, 2021), and sector-specific changes in loads, such as increased residential sector consumption in the middle of the day (Kawka and Cetin, 2021).

### 4.1. Correlation between emissions and demand

The hourly data distribution in both 2019 and 2020 suggests a strong linear correlation between hourly demand and hourly $CO_2$ emissions, as shown in Fig. 2 subplots A and B. As demand goes up, less spread is seen in the magnitude of hourly emissions and data points than for lower demand, implying a tighter correlation between emissions and demand for higher demand values. At higher levels of demand, the emissions produced also tend to lie above the line of best fit, which suggests that as demand increases, the emissions per unit of demand also increase. This is consistent with the common operational practice of bringing fast-reacting and dirty electricity natural gas combustion units online to meet the highest levels of demand when the range of the typical resources used to meet demand is exceeded. In 2019, there was an average of 266 $kgCO_2$ generated per MWh, and in 2020 this number rose to 310 $kgCO_2$ per MWh, with these values equal to the slopes of the lines of best fit for the top two graphs of Fig. 2.

Fig. 2 also examines the correlation between *changes* in emissions and *changes* in demand calculated as the difference between two consecutive hours for each variable (subplots C and D). In 2019 there was an average emission of 322 $kgCO_2$ per MWh of marginal electricity generated and in 2020 this number fell to 308 $kgCO_2$, with these values equal to the slopes of the lines of best fit for subplots C and D. The magnitude of changes in demand in 2019 cover a wider range compared to 2020, highlighting higher hour to hour variations in load, while changes in emissions remained approximately in the same range in both years. Overall, there is a wider variation in the range of changes in emissions when the magnitude of demand changes are positive and large (Q1) than when the magnitude of demand changes are large but negative (Q3) for subplots C and D. Additionally, a significant number of hours in Q4 of subplots C and D have an increase in demand on the scale of GWh and decrease in emissions on the scale of thousands of metric tons. These events, and more generally, the large deviations from the lines of best fit, emphasize that changes in demand alone cannot accurately predict changes in emissions and that a multiple linear regression model capable of capturing the influence of the varying supply of renewable energy is necessary.

### 4.2. MEFs by demand level in each month

Our data binning and regression model resulted in a total of 67, for 2019, and 61, for 2020, independent MEF values (one for each distinct demand bin and month pairing in that year). These values are shown in Fig. 3, and the plotted trend lines show a positive correlation between MEF and demand level. The higher MEFs for high demand levels are caused by emissions-intensive marginal generators. The relationship between demand level and marginal generation also results in seasonal variations in MEFs. Summer months, which typically have higher demand levels due to increased electricity usage for air conditioning show relatively high MEFs when compared with cooler months. While high demand levels are centralized around summer months, lower demand levels occur across many months and have a

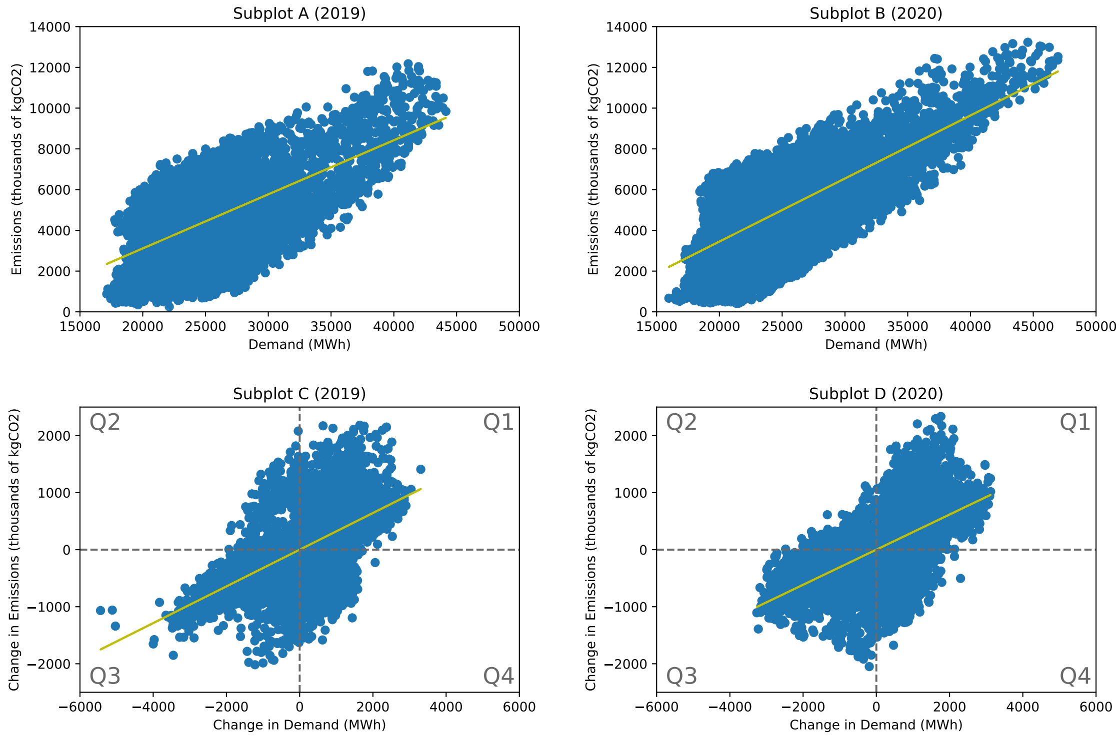


**Fig. 2.** Scatter plots of hourly $CO_2$ emissions and hourly demand for electricity in 2019 (Subplot A) and 2020 (Subplot B), as well scatter plots of changes between consecutive hours in hourly emissions and hourly demand between in 2019 (Subplot C) and 2020 (Subplot D). The line for best fit is shown in yellow, with $R^2 = 0.35$ (Subplot A) and 0.50 (Subplot B) for hourly emissions and demand, and $R^2 = 0.40$ (Subplot C) and 0.39 (Subplot D) for hourly changes in emissions and demand.

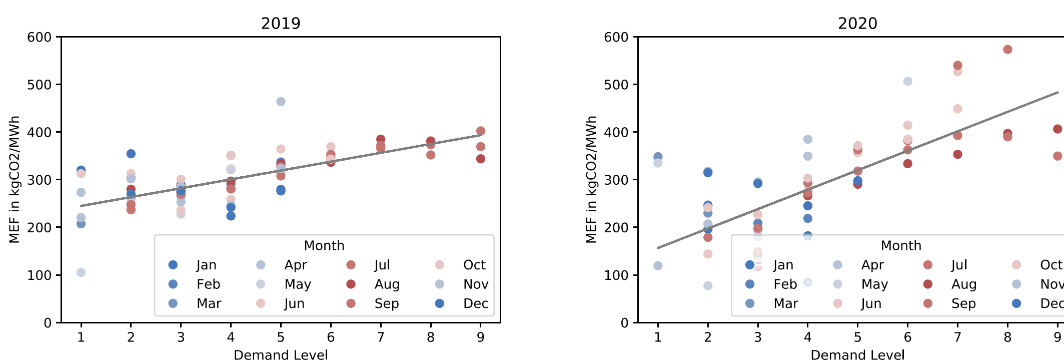


**Fig. 3.** MEFs for each demand level and month combination in 2019 and 2020 with line of best fit.

wider range of corresponding MEFs than higher demand levels. The slope of the line of best fit was steeper in 2020 than in 2019, meaning that MEFs were more responsive to demand level in 2020. The causes of this shift are explored further in the discussion section. Figures displaying MEFs organized by month instead of demand level can be found in the supplementary data.

### 4.3. Month-hour MEFs

Demand-level based MEFs, like those shown in Fig. 3, can be directly applied in situations in which demand level can be estimated; however, they do not provide information about diurnal MEF patterns, which are important for predicting the changes in emissions associated with changes in electricity consumption that occur at specific times of the day. To address this need, month-hourly MEFs were derived using the relationship between time-of-day and demand. The results are shown in the form of heat maps in Fig. 4. The MEF values in 2019 and 2020 are consistent and similar in terms of hours when the highest and lowest MEF values are concentrated (i.e., highest in the evening of summer months and lowest in the morning of spring months). However, there are two significant differences between the MEFs in 2019 and 2020 that are worth highlighting. First, the highest MEF values reached in 2020 are substantially higher than those in 2019; i.e., nearly 500 kg $CO_2$/MWh in evening hours in July 2020 compared to roughly 370 kg$CO_2$/MWh in August 2019. Second, lower MEFs during the evening hours of spring months in 2020 (dropping as low as 100 kg$CO_2$/MWh in the evening in March) show a contrast to 2019, where MEFs are around 330 kg$CO_2$/MWh at similar periods. In fact, the MEFs calculated for the evening of March 2020 are significantly lower than the lowest MEFs at any point in 2019. These differences in MEFs

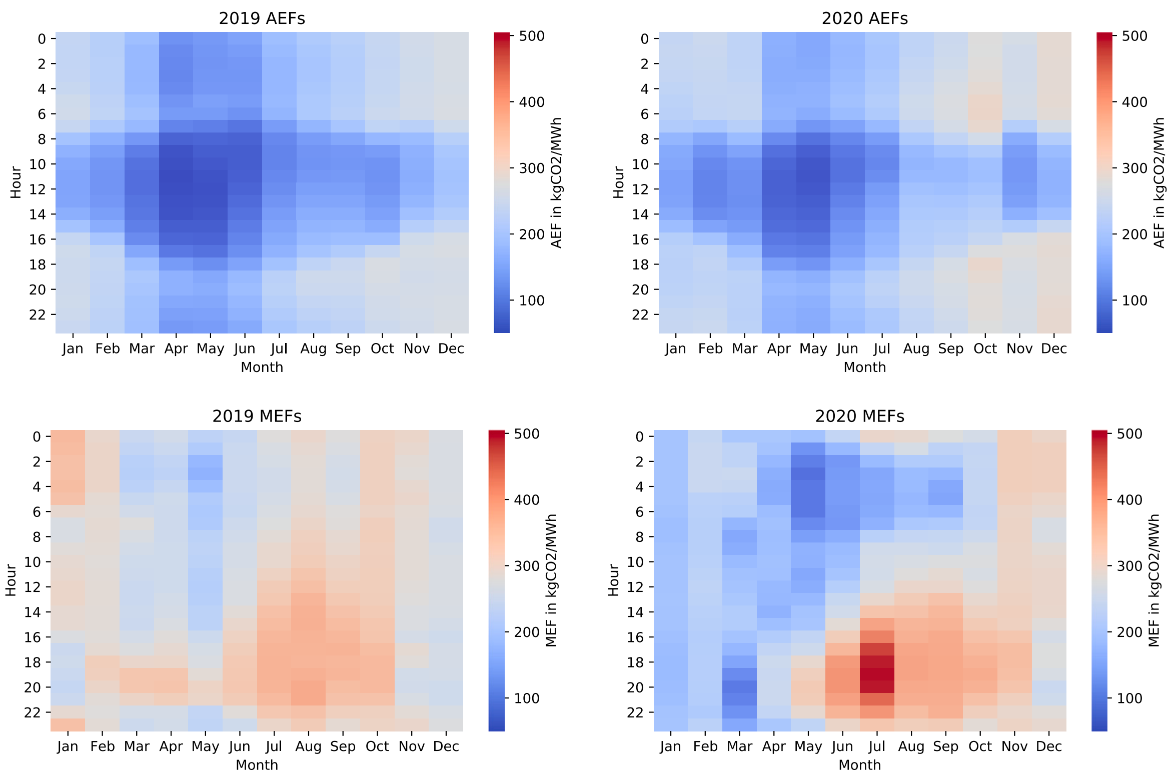


**Fig. 4.** Month-hour distribution of AEFs (top) and MEFs (bottom) in 2019 and 2020. Colors represent the magnitude of emissions factor in $kgCO_2/MWh$.

imply that different resources were operating at the margin in the two studied years. These differences were investigated in further detail in the discussion section by examining the electricity generation fleet in March and July of each respective year. (See Fig. 5.)

### 4.4. Month-hour AEFs

The temporally based AEFs show strong diurnal and seasonal trends in Fig. 4. From a seasonal perspective, the AEFs, which are representative of the average grid mix, reach their lowest values in the spring when there is a high availability of clean power sources like solar, wind, and hydropower, as well as moderate demand levels across CAISO. The AEFs are significantly higher in the late summer/fall months when electricity consumption is much higher, as well as in winter months when supplies from solar resources are limited. AEFs tend to be lower in the middle of the day due to the availability of solar power and the relatively low level of demand. In most months, AEFs increase in evening hours as demand increases and solar PV comes offline causing a larger fraction of the load to be met with natural gas generators and imports.

## 5. Discussion

In this section, some important aspects of the observed trends in MEFs and AEFs are discussed.

### 5.1. Consumption-based versus generation-based MEFs

Regression-based hourly-level MEF estimates are rare in literature; however, hourly MEF values have been periodically reported by the Center for Climate, Energy, and Environmental Decision Making (Azevedo et al., 2020) for various regional aggregations using a generation-based method. The consumption-based month-hour MEFs in 2019 were compared to MEF estimates reported by CEDM for CAISO in year 2018, the most recent year that MEFs were reported (Azevedo et al., 2020). (Note that CEDM used a methodology similar to Siler-Evans et al. (2012) for estimating MEFs that, as discussed earlier, relied on hourly changes in fossil fuel generation as the single variable for predicting changes in emissions.) The comparison shows that differences between the estimated MEFs and CEDM's estimated MEFs in the same month and hour ranged from −15% to 126% (42% average difference and 39% median difference), and the estimates were lower in value in 99% of hours. While some year-to-year variation could explain these differences, lower MEF estimates across the majority of hours in the study are expected given the differences in methodology. As shown in Fig. 6, the hourly changes in demand were typically larger than the hourly changes in natural gas generation, requiring other supply resources such as hydropower, imports, and, in some cases, renewables to respond to changes in demand (CEDM's MEF methodology assumes all marginal generation is met by in-region fossil fuel plants). While many renewable sources are first-to-take, Fig. 5 shows that emissions-free hydropower generation can exhibit strong load-following behavior in evening hours. Additional demand in the evening is met by a mix of imports, natural gas, and hydropower, resulting in MEFs that can be significantly different and often lower than those calculated using in-region fossil fuel generation changes alone.

Additionally, in terms of applications, the use of demand change as a marginal emissions estimator is advantageous over fossil-fuel generation change for a couple of reasons. First, having knowledge of the changes at a specific time in the electric grid's fossil fuel generation is much more data-intensive and complicated than knowing about the changes in electricity demand for a region or balancing authority. Secondly, the MEF values that simply represent $CO_2$ emissions change per unit of *demand* change are more ideal to quantify marginal emissions changes associated with end-use demand changes than MEFs derived from fossil fuel generation change. (Fossil fuel generation change would be indirectly correlated with end-use demand changes, which may be highly uncertain in many hours of the year.) Practically, MEFs developed in this analysis can directly be multiplied by measured changes in electricity consumption for any end-use, allowing for more

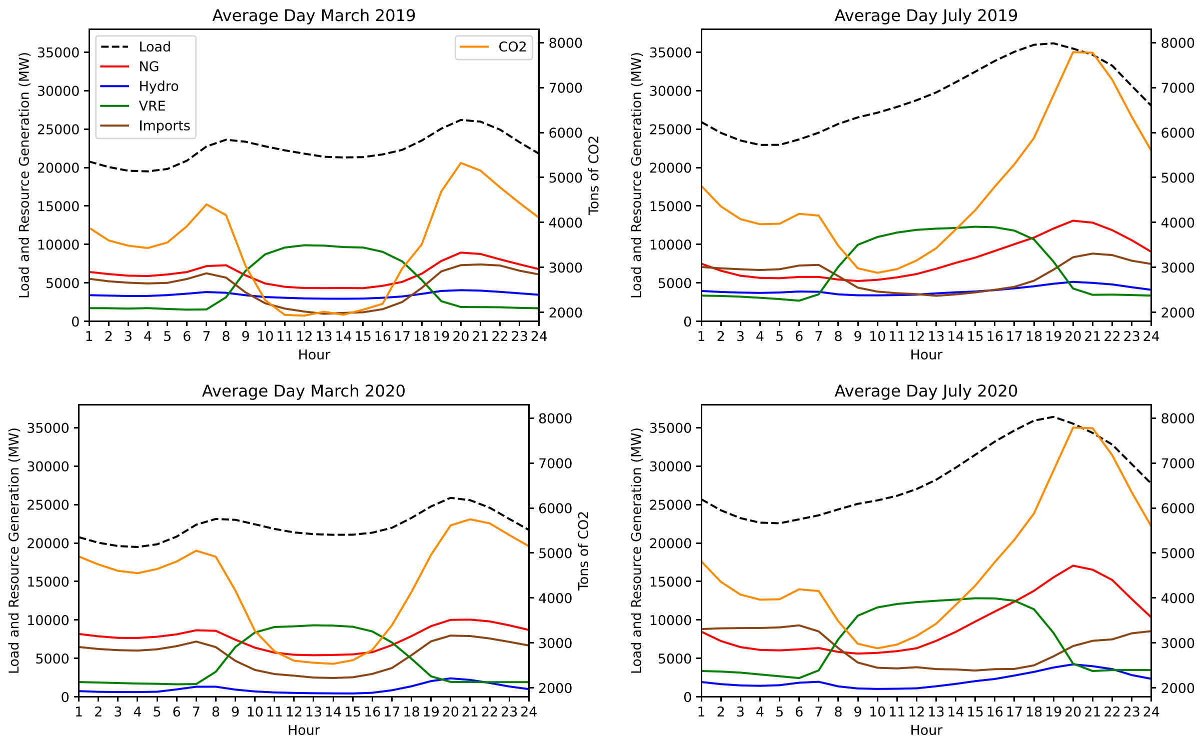


**Fig. 5.** Average hourly generation for each resource serving CAISO's electricity demand in March and July of 2019 and 2020.

precise and simple monitoring of emissions displacement by demand-side management measures such as load shifting or load shedding. While the MEF estimation exercise relied on historical annual data, applying this methodology with real-time emissions and demand data would enable a close-to-real-time MEF estimation that could be a useful tool to quantify the emissions associated with end-use electricity consumption patterns.

### 5.2. Year-to-year variation in MEFs

Since regression-derived MEFs rely on historical data, the predictability of MEFs for future years may be limited by how sensitive MEF values are to resource dispatch and fuel mix changes that occur from year to year. Comparing MEF values in 2019 and 2020 helps us answer this question. In fact, a wide range of differences were found in hourly MEFs between 2019 and 2020. (Note: The relative differences between month-hour MEFs in 2019 and 2020 are plotted in Fig. A.5 of the supplementary data.) While summer and winter months in 2020 typically show smaller differences in MEF values between the two years for the same month-hour combination, greater differences are observed in spring months. Despite the fact that both years had similar fossil-fuel and renewable generation shares (shown in Table 1), the role of hydropower seems to be significant in explaining these differences, as hydropower's share of generation decreased from 12% of total supplies in 2019 to only 6% in 2020 (more discussion of this change is provided in Section 5.3. The wide range of differences in hourly MEF values suggests that hourly-level MEF values should be evaluated often and that historical-based MEFs require a great caution if used for future years.

It is important to understand whether a less granular temporal MEF value would sufficiently represent changes in marginal emissions. To test this, the regression equation was applied to all hour-to-hour changes, regardless of demand level, to calculate a single annual MEF. The result was an annual MEF of 302 $kgCO_2/MWh$ in 2019 and 285 kg $CO_2/MWh$ in 2020. However, the month-hour MEFs calculated in this study ranged from 169 to 372 $kgCO_2/MWh$ in 2019 and from 89 to 503 $kgCO_2/MWh$ in 2020. The large range of MEFs that occurred in both years indicate that analyses that use an annual MEF (for example in Holland et al., 2022) for emissions calculations could significantly misrepresent emissions for activities with dynamic temporal patterns, and that being able to capture the diurnal and seasonal trends in MEF values is essential. Regarding average emissions, month-hour AEFs fall in a narrower range of values closer to the annual AEF. For an application in which AEFs are appropriate, using an annual AEF in place of month-hour AEFs for emissions calculations would be less erroneous than making the same simplification for MEFs.

### 5.3. The influence of hydropower and imports on AEFs and MEFs

In Fig. 6, the changes in generation were compared between consecutive hours for each fuel serving the electricity demand in the months of March and July of 2019 and 2020. This figure identifies which fuels respond more to changes in electricity load as well as diurnal trends in solar and wind availability. It appears that hydropower was more responsive to increases in demand in evening hours of March 2020 than in March 2019 (MEFs of 300–400 $kgCO_2/MWh$ in evening hours of 2019 compared to 100–200 $kgCO_2/MWh$ in 2020) and was able to reduce CAISO's reliance on imports and natural gas for marginal generation, despite demand changes being similar on an average day across the two years. As a result, hydropower effectively reduced marginal emissions and MEFs during the evening hours of 2020 when compared to 2019 (Fig. 4). Despite the limitation of hydropower generation in the year 2020 compared to 2019 (see Table 1), the hydropower dispatch ramp-up in 2020 was complimentary with renewable energy availability and successfully replaced fossil-fuel based marginal generation. This example provides further evidence that energy-limited resources like hydro, if dispatched strategically to offset the need for the dirtiest marginal generators, can help reduce emissions, even in a dry year.

Comparing the hourly generation changes between July 2019 and July 2020, it appears that the increased reliance on natural gas generation (in place of imports) in the early evening hours of 2020 compared to 2019 could have driven higher MEF values in 2020. When high temperatures in July spur increases in electricity consumption, it is often the case that neighboring BAs' electric energy consumption values

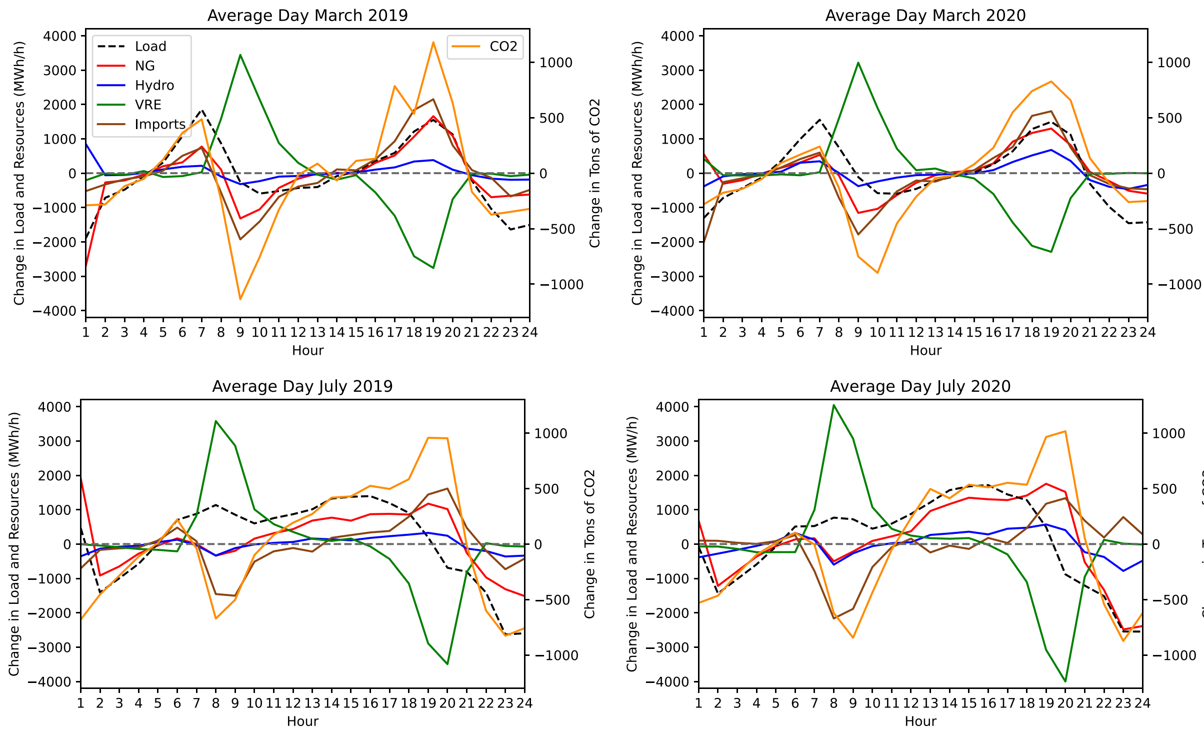


**Fig. 6.** Average changes in hourly generation between two consecutive hours for each resource serving CAISO's electricity demand in March and July of 2019 and 2020.

are high as well. As a result, imports from neighboring BAs might often be limited when CAISO's demand reaches its highest levels. While the breakdown of hourly electricity generated by technology (namely, natural gas combined cycles, gas turbines, steam turbines, and internal combustion engines) is not available for generation within CAISO or imports, the observed MEF values of roughly 500 $kgCO_2/MWh$ in the early evening hours of July 2020 suggest that generators at the margin could have been natural gas combustion turbines (known as "peaker" plants), which on average emit about 550 $kgCO_2/MWh$ (Steen, 2000). Considering the additional natural gas generation in July 2020 as compared to 2019 and the higher MEFs in 2020, it is likely that natural gas combustion units were more active during the peak hours of July 2020. In terms of the magnitude of the demand changes, electricity consumption increased more aggressively during the afternoon hours in 2020 (an increase of about 1800 MW in 2020 versus 1400 MW in 2019 between 3 and 4 p.m.).

### *5.4. Comparing MEFs versus AEFs*

Consistent with other studies, the results show that MEFs are significantly different from AEFs in most hours of the year (see Figs. 4 and A.6). In fact, in late spring and early summer months, the MEF can be nearly three times the magnitude of the AEF. This occurs when there is a high fraction of renewable energy on the grid, which results in lower AEFs, while the last unit of demand is still often met by fossil-fuel generation. While the MEF for a given hour in CAISO is typically higher than the AEF, this is not always the case given the complex dynamics of hourly changes in the fleet mix, which can be met in part by clean resources such as hydropower and or clean imports. For example, as it was explained in the previous section, operational changes such as hydropower generation timing could result in lower MEFs (100–200 $kgCO_2/MWh$) compared to AEFs (200–300 $kgCO_2/MWh$) during evening hours of March in 2020. However, hourly AEFs in general were lower in March 2019, in part due to the abundance of hydropower resources thanks to the wet conditions in the state in that year (CDWR, 2020).

### *5.5. The influence of other interactions*

Relying on historical data provides holistic context and evidence to understand various trends and driving factors in marginal emissions. However, some interactions can still be refined to provide better representation of regional complexities and dynamics. Although the presented method captures the electricity trades and emissions associated with imports and exports, it is limited in answering questions related to inter-regional influences on MEFs values (e.g., how long-distance renewable exports from CAISO to other regions can effectively reduce $CO_2$ emissions elsewhere. A larger scale regional regression model (for example, WECC-wide) with sub-regional representation is needed to be able to answer these types of questions. Additionally, with rising penetration of grid-scale battery storage technologies, the role of storage for displacing fossil-fuel-based marginal generators should be investigated in future studies.

It is worth noting that although the proposed method is well suited to capture historical dynamics of the electric grid, it is less insightful to provide information about future dynamics. Given the fast pace of structural and operational changes in electric grids due to renewable energy adoption, electric power grid modeling may be a more effective option if long-term MEFs are of interest (such as in Gagnon and Cole, 2022). However, historical data and regression-based MEFs are useful to validate the MEFs calculated through modeling exercises. Over the short-term analysis, although the use of AEFs for DSM emissions quantification is still widespread (Mayes and Sanders, 2022; Onat et al., 2015; Samaras and Meisterling, 2008), developing regression-based MEFs is much insightful and necessary, especially for grids with growing penetration of renewables.

## 6. Conclusion

In this paper, a proposed multiple linear regression model is used to quantify MEFs at the hourly level, relying on historical hourly emissions, electricity generation and consumption data. This model was applied for CAISO using historical data for 2019 and 2020. This paper's methodology improves previous MEF estimates by taking a consumption-based approach that accounts for electricity trades with neighboring regions, as well as including a specific term to account for generation from variable renewable sources (i.e., solar PV and wind). This study shows that capturing these factors is important in grids like CAISO that have high levels of renewable energy penetration and meet considerable fractions of their demand with imports.

The proposed method will become increasingly applicable as electric grids across the country incorporate more renewable technologies and aim for around the clock net-zero emissions targets. These methodological changes allow for better isolation of the impact of electricity demand on $CO_2$ emissions and explore the temporal variations in the emissions intensity of marginal demand. The MEFs calculated through the proposed methodology can also be used for evaluating the effectiveness of energy management measures and different grid-connected technologies for reducing emissions. For example, policymakers could use these granular MEFs to facilitate programs that can strategically utilize flexible loads (e.g., electric vehicle charging, heating and cooling, etc.) to reduce demand during the most emissions-intensive hours of the day. Accurate, up-to-date MEFs are an essential step in monitoring emissions and leveraging the timing of electricity consumption to effectively manage and reduce emissions.

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## CRediT authorship contribution statement

**Angineh Zohrabian:** Project administration, Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft. **Stepp Mayes:** Data interpretation, Formal analysis, Visualization, Writing – review & editing. **Kelly T. Sanders:** Supervision, Conceptualization, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data produced in this analysis are made available via a Mendeley data repository (http://data.mendeley.com/datasets/7w87xy5pwj/2).

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136296.

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