Utility-specific projections of electricity sector greenhouse gas emissions: a committed emissions model-based case study of California through 2050

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Abstract

The environmental profile of electricity is changing rapidly, motivating a need for provider- and time-specific estimates for accurate environmental assessment. This work shows that defensible, provider- and time-specific emissions projections can be derived from two major factors: committed emissions from existing power plants and policy restrictions on future system characteristics. This letter introduces a bottom–up, power plant-based model that projects utility-specific annual average greenhouse gas (GHG) intensity of electricity in the U.S. state of California for 2018–2050, believed to be the first openly available GHG emissions model with utility-specific projections. California is a useful case study for testing in part because of its strict regulatory GHG targets and the complexity of its electricity system, including limited asset ownership by utilities and substantial reliance on imported electricity. This plant-based approach to emissions projections bounds uncertainty in a way that less infrastructurally grounded approaches cannot. For example, emissions from unspecified sources of power can be estimated based on available plants. Based on historical power plant lifetimes, existing policy, and default model assumptions, the CO$_2$ intensity of Californian electricity is projected to drop from 175 kg CO$_2$/MWh (sales + losses, 2020) to 95 kg CO$_2$/MWh by 2030, operationally decarbonizing by 2047. Upstream methane leakage increases GHG intensity of natural gas-fired power plants by about 30%, assuming a 100 year time horizon and national average estimates for leakage (which likely underestimate leakage for California). Although drivers like market conditions also affect future outcomes, California's current policy targets do not appear to require early retirement for utility generation assets, though up to about two gigawatts of extant in-state merchant capacity might be affected. Under current policy, new generating assets must either comply with the 100% clean electricity standard by 2045 or stop selling in California before the end of their expected useful life.

1. Introduction

Energy use has historically been one of the most significant predictors of environmental intensity (Huijbregts et al. 2010), largely because of the dominance of fossil fuels. As the energy sector with the most diverse fuel mix, the electricity sector has also exhibited highly variable environmental intensity (Mutel et al. 2012), with impacts like greenhouse gas (GHG) emissions, air emissions, water intensity,
waste production, and others depending heavily on fuel mix and other supplier specifics. Fuel mix and environmental intensity vary in time, from sub-hourly to decadal time frames (Cubi et al. 2015, de Chalendar et al. 2019, Kiss et al. 2020), and by provider, from sub-utility (e.g., green purchase programs) to national levels (Tamayo et al. 2015, Ang and Su 2016). Understanding electricity systems with temporal and provider-entity specificity, then, is important for accurate assessment.

Climate change is a major focus area for environmental assessment (Grubert 2017), contributing to particular policy and analytical interest in GHG emissions. The dynamism of GHG intensity of electricity by time and provider is likely to grow as decarbonization targets like renewable portfolio standards (RPS) and clean electricity standards (CES) become stricter. Such standards aim to increase the share of renewable and/or zero-carbon energy resources and are increasingly common at various jurisdictional levels, including countries, states, cities, and companies (RE100 2020, Kieffer and Couture 2015, Trumbull et al. 2019). Depending on local conditions, such standards foster changes to energy procurement via adjustments to purchasing contracts (Cullenward and Weiskopf 2013); investment in new, compliant assets; or other means, with variable influence on both entity-specific and global environmental impacts. Allocating these impacts appropriately is thus dependent on an increasingly high resolution understanding of electricity system characteristics.

Knowledge of specific decarbonization standards can guide estimates of current and future GHG intensity of electricity, as such targets effectively cap emissions by restricting the types of resources that can be procured in the future. Complementing this effective cap, an effective floor, or emissions minimum, can be derived from estimates of ‘committed emissions,’ or future emissions from existing power plants (Davis et al. 2010, Pfeiffer et al. 2016, Tong et al. 2019). This work adds to the GHG modeling literature by introducing a method for modeling entity- and temporally-specific future GHG intensity using a few simple assumptions, given information about existing power plants. Such projections are important not only for environmental assessment (de Chalendar et al. 2019), but also for evaluating policy feasibility and compliance risk. For example, a near-term zero-GHG policy target might be more feasible for a system with the majority of its assets close to retirement than one with mostly brand-new, carbon-intensive facilities.

This research has developed a committed emissions/environmental target-based model, available as the supplementary file to this letter, using the specific case study of projecting utility-specific GHG intensity of electricity in the U.S. state of California between 2018 and 2050. To the authors’ knowledge, this model is the first openly accessible model to enable multi-decade, utility-specific emissions projections. The Excel-based model is designed to be self-contained, easy to use, and based on simple, transparent assumptions based on publicly available, frequently updated data. The relatively long projection period is enabled in part via an asset-specific, bottom-up approach that explicitly accounts for infrastructure lifetimes, which is valuable for highlighting asset specific risks. Default assumptions about infrastructure lifetime are technology-specific and based on historical U.S. data, so assumed lifetime is effectively an observed aggregate outcome variable based on inputs like financial viability and operations. Although other metrics of environmental intensity could be similarly assessed with the plant-specific approach used here, this research evaluates the GHG intensity of electricity in the form of annual average emissions factors, given as mass of CO₂ or CO₂-equivalent (CO₂e) emitted per megawatt-hour (MWh) of electricity sold or generated.

California is a useful case study in part because of the intersection of its complex electricity regulatory setting (Blumstein et al. 2002) with its strict decarbonization mandate, in the form of Senate Bill 100 (SB100) (60% renewable electricity by 2030 and 100% clean electricity by 2045) (California Senate 2018). Adding complexity, many of California’s utilities also have their own, more stringent targets; California’s utilities tend to have lower ownership control of generation assets than other U.S. utilities (figure 1, EIA 2019a); and California imports substantial amounts of electricity (about 32% in 2018) (California Energy Commission 2019c). These complexities pose challenges for allocating committed emissions to specific utilities—a task this type of model must be able to perform. Thus, modeling entity- and time-specific emissions by utility in California is both a proof of concept in a complex setting and a policy-relevant exercise in the context of strict statewide GHG standards.

2. Methods

This research develops utility-specific annual average electricity GHG emission factors for California’s five largest utilities, which collectively accounted for about 64% of 2018 retail electricity sales in California (EIA 2019a): Southern California Edison (SCE), Pacific Gas and Electric (PG&E), Los Angeles Department of Water and Power (LADWP), San Diego Gas and Electric (SDG&E), and Sacramento Municipal Utility District (SMUD). The remaining 72 entities categorized by EIA 861 (EIA 2019a) as utilities in California with 2018 retail sales are collectively assessed as ‘Other utilities.’ Utility-specific annual average emissions factors are the outputs of an Excel-based model available to users as the supplementary data File of this letter (available online at https://stacks.iop.org/ERL/15/1040a4/mmedia). The
model was designed with several key guiding principles: 1) to be flexible, enabling users to change assumptions where practical; 2) to use public data, preferably from centralized sources with frequent, predictable update cycles; and 3) to rely on a small number of clearly stated assumptions. The remainder of this section details implementation and implications of these principles, then describes the model.

2.1. Data
The model is primarily based on three US federal data products: eGRID (2018, v2, US EPA 2020); EIA 860 (2018, EIA 2019b); and EIA 861 (2018, EIA 2019a). These products are released as Excel workbooks with consistent formats annually (EIA 860 and 861) or every two years (eGRID), so new data can be copied into the model directly, simplifying updates by users. The base year of 2018 matches the most recently available eGRID data as of this writing, released in March 2020. eGRID and EIA 860 provide plant-specific core information (e.g. on emissions, generation, fuel, age, and operator), and EIA 861 provides utility-specific information (retail sales and losses). Only plants in eGRID’s CAMX (Western Electricity Coordinating Council, or WECC, California), NWPP (WECC Northwest), and AZNM (WECC Southwest) subregions are considered to be available to California utilities, an approximation that appears reasonable based on plant-specific checks, validation of 2018 model results with available emissions intensity data, and California Energy Commission references to Northwest and Southwest imports (California Energy Commission 2019c). These federal data products are augmented by additional data specific to California, primarily drawn from utility-specific planning documents or the California Energy Commission. See the supplementary data file for specific references.

2.2. Assumptions
The model is based on two fundamental assumptions expected to lead to conservatively high estimates of GHG intensity, which are preferred to underestimates due to the relevance of this work for evaluating policy risk. First, existing power plants operate through the end of their useful lives with constant eGRID-derived emissions, generation, and operators. EIA data from 2001–2018 for the GHG emitting power plants in our sample show that at the plant level, both capacity factor and heat rate have tended to decline over time (EIA 2019b, 2020), meaning these plants have tended to run less but more efficiently as they age (Grubert 2020). Both trends suggest the assumption of constant output will lead to a GHG overestimate. Second, utilities do not overcomply with the stricter of state-level or internal renewable or clean electricity targets (or linear interpolations between stated targets) in a given year. This assumption appears reasonable based on performance to date (supplementary data file), and it will also tend to overestimate GHG intensity (overcompliance is still compliance, but undercompliance is not). Together, these assumptions provide both a minimum emissions estimate (i.e. estimated committed emissions from existing plants) and an emissions cap (because the renewable or clean electricity standard limits future emissions).

Emissions are allocated to specific utilities by assigning sufficient generation to meet demand in a given year, then re-associating generation to emissions using eGRID data on emissions and generation for each power plant. Each utility’s annual demand is met by, in order, 1) generation from assets the utility owns or publicly contracts that are still operating in that year; 2) generation from unspecified renewable or clean electricity standard compliant resources up to the amount required to meet the
active standard in a given year; 3) generation from imported hydroelectricity, allocated to utilities based on state data on fuel mix and imports (California Energy Commission 2019a, 2019c) and assumed to remain constant over the projection period due to the long life of hydroelectricity assets (EIA 2019b); 4) generation from other non-owned or contracted imports still operating that year [calculated based on the 2018 fuel mix for Northwest and Southwest imports (California Energy Commission 2019c), then assuming fuel-specific declining availability based on modeled retirements of merchant generators in CAMX, NWPP, and AZNM outside of California], which is allocated proportionally to unmet demand for a given utility; 5) generation from merchant plants in California still operating that year, which is also allocated proportional to unmet demand for the utility; and finally 6) generation from ‘new build’ power plants with emissions profiles determined by the user, which is assumed to fulfill any unmet demand after the other resources have been allocated. One effect of this allocation sequence is that utilities may under-comply with state decarbonization requirements if an asset they own or have a reported contract with would otherwise need to close before its modeled retirement date. Imports and merchant generation, however, are allocated only after compliance requirements are met.

Other assumptions embedded in the model that users cannot easily change include static utility-specific loss rates based on 2018 data from EIA 861 (EIA 2019a); linear growth for electricity demand based on IEPR 2019 (California Energy Commission 2020); the definition of RPS-qualifying resources in California (wind, solar, geothermal, and biomass, using the WND, SUN, GEO, AB, LFG, MSW, OBG, and WDS fuel codes from eGRID, in addition to any hydroelectric facilities under 30 megawatts); and the use of single estimates of upstream methane intensity for natural gas or coal, regardless of originating basin or extraction technique.

2.3. Model design and user controls

Users primarily interact with the model via toggles and inputs on the worksheet ‘User Inputs.’ Results are summarized on the ‘Results Summary’ sheet, with values updating automatically to reflect user choices. Major user controls include whether renewable or clean electricity standards cover sales only versus sales and losses (e.g. from transmission and distribution); consideration of plant CO₂ only versus GHG emissions including plant-level CO₂, CH₄, and N₂O, plus upstream CH₄ for natural gas and coal (e.g. well, transmission system, and mine methane leaks); and the GHG intensity of new-build generation. Emissions embodied in infrastructure are not included in this operational factor but are discussed elsewhere (Smoucha et al 2016, Pehl et al 2017, Wu et al 2018). Users can also directly enter the year that California adopts a clean electricity standard in addition to its renewable portfolio standard; the year when the 100% clean electricity requirement takes effect; the assumed retirement date for plants that the model would otherwise predict closed before 2018; the assumed lifespan of steam turbine, hydroelectric, and other generation facilities; low, medium, and high electricity sales growth rates by utility; a user-determined assumption about GHG intensity for newly built generation assets in each year; and year-by-year renewable or clean electricity standards for the state overall and for individual utilities.

3. Results

3.1. Emissions intensity for California’s utilities

Figure 2 shows model results based on default assumptions. Figure 2(a) shows projected utility-specific annual average plant CO₂ emissions intensity per retail MWh sold, with an annual timestep through 2050, assuming the mid-demand scenario growth rates defined by IEPR 2019 for the planning areas containing each utility (California Energy Commission 2020). Results for CO₂ equivalents, including upstream methane leakage from coal and natural gas systems, can be viewed in the model. Figure 2(b) shows annual plant retirements within the CAMX region by year and fuel. The spike in 2023 is a model artifact, reflecting that some plants still operating in California have already exceeded their expected lifetime. This forced retirement year is an explicit user control in the model.

Although published values for the GHG intensity of electricity by utility are rare, results shown in figure 2(a) are consistent with available estimates. For example, the model estimates PG&E’s 2018 GHG intensity at 94 kg (206 lb) CO₂/MWh retail sales + losses, compared with a third party 2018 PG&E system-average estimate of 94 kg (reported as 206 lb) CO₂/MWh (scope of ‘MWh,’ e.g. retail sales, sales + losses, etc not specified) (The Climate Registry 2019). As about 40% of PG&E’s electricity generation for 2018 was not linked to known power plant ownership or contracts in the model, the model appears to perform well, particularly given that GHG intensity varies widely so would not be expected to coincidentally match. Verified values for SMUD of 211 kg (reported as 465 lb) CO₂/MWh for retail markets or 268 kg (reported as 591 lb) CO₂/MWh for wholesale markets (scope of ‘MWh’ not specified) similarly compare favorably with the model estimate of 239 kg (526 lb) CO₂/MWh retail sales + losses. Verified system average values for 2018 GHG intensity were not identified for other utilities modeled for this work, but directional findings (e.g. that LADWP’s near-future emissions intensity is the highest and that interannual variability can be substantial) are consistent with older estimates.
Figure 2. Default utility-level greenhouse gas intensity and plant retirement profile for California’s electricity, mid-demand scenario (2018–2050).

(SEEC ClearPath California 2013, BREEZE Software 2017). Similarly, model values are consistent with other published model values. For example, de Chalendar et al estimate a 2016 average GHG intensity of 384 kg MWh$^{-1}$ for LADWP using hourly carbon accounting (de Chalendar et al 2019), compared with this model’s estimate of 377 kg MWh$^{-1}$ retail sales + losses for 2018.

3.2. California’s power plants

Figure 3 shows estimated committed generation and emissions through 2050 associated with power plants that were operating in California as of 2018, assuming retirement either on announced timelines per EIA 860 (EIA 2019b) or default plant lifetimes (50 years, steam turbine-based plants; 150 years, hydroelectric plants; 30 years, all others; see supplementary data file, ‘Assumptions and Validation,’ for source data informing these defaults).

Substantial generation and emissions from in-state natural gas-fired power plants are expected to persist for about a decade, with continued contributions from newer plants through the 2040s. Under default model assumptions for retirement dates (figure 2(b)), nearly 2 GW of merchant capacity associated with direct operational CO$_2$ emissions remains in service through at least 2045 (1.3 GW past 2045), suggesting that existing state policy will lead to early retirements (though note that none of this existing capacity remains in service beyond 2048 under default model assumptions).

Model results are sensitive to plant lifetime, as operating plants are the main driver of modeled emissions. Figure 4 replicates figure 2, but assuming that plants without announced retirement dates retire either 10 years earlier (figure 4(a)) or 10 years later (figure 4(b)) than default assumptions. Sensitivity to retirement dates, including for specific plants, can
be explored in more detail using the model (supplementary data file).

### 3.3. Model validation

Figure 5 shows that the modeled fuel mix matches reported aggregated fuel mixes (California Energy Commission 2019a) fairly closely in most cases.

LADWP and SMUD each either own or report contracts for relatively high shares of their electricity (82% and 75%, respectively, versus 14% for SCE, 62% for PG&E, 25% for SDG&E, and 25% for the collective other utilities; see supplementary data file for specific plant ownership or contract relationships), which contributes to the close match between published and modeled fuel mix for those utilities. Several of the utilities included in this study—particularly SCE and SDG&E—report substantial ‘unspecified sources of power,’ or ‘electricity that is not traceable to a specific generating facility, such as electricity traded through open market transactions’ (California Energy Commission 2019b). Using an asset-based approach enables the model to produce a nonverifiable estimate of what these unspecified sources of power might be. Figure 5 suggests that, as expected based on the merchant resource mix in California and neighboring regions, much of the power that is not easily assigned to a specific utility is generated using natural gas but that in aggregate, the large utilities disproportionately purchase renewable wholesale power relative to available merchant generation. The disparity between reported and model values with respect to renewable electricity is likely due to the fact that the model does not reflect contracts and purchase agreements not readily available from public planning and reporting documents (e.g. IRPs, 10Ks).

Figure 6 shows annual average CO$_2$ intensity for electricity in California projected by the model.
presented here, using default assumptions; by the National Energy Modeling System (NEMS), using the 2020 Annual Energy Outlook reference case for the combined WECC: California South and North electricity sector (Energy Information Administration 2020); and by E3’s PATHWAYS model, using the ‘CEC 2050’ case (Mahone et al 2018). NEMS is a modular model of regionalized U.S. energy markets, including market dynamics, industry detail, and policy/regulatory effects (Nalley et al 2019). Similarly, the California PATHWAYS model is a techno-economic model that models electricity system dynamics with an hourly timestep and accounts for cost and climate conditions (Mahone et al 2018). Both project annual emissions through 2050, though not with utility specificity.

Figure 6 shows that this model’s results are within 20% of NEMS results through 2030 and within 20% of PATHWAYS results through 2040, after which this model’s default scenario projects lower emissions intensity for California. Note that GHG emissions factors for electricity vary by an order of magnitude depending on fuel mix (de Chalendar et al 2019). Near term discrepancies are believed to result from this model’s more specific representation of Californian utility ownership of out-of-state power plants, specifically Intermountain (a coal-fired power plant in Utah, with announced retirement in 2027) and Palo Verde (a nuclear power plant in Arizona, with modeled retirement in 2036): each contributes about 8 TWh/year to the California grid via ownership contracts, adding about 25 kg CO₂/MWh for the entire state (if the generation is coal) or displacing up to that much (if the generation is zero-carbon, like nuclear), depending on assumptions about alternative sources of generation. Longer term differences are potentially a result of NEMS’ very low expectation of power plant retirements (11 GW of capacity in CAMX total through 2050, versus this model’s lifetime-based assumption of 92 GW of capacity).
and PATHWAYS’ much larger electricity demand, based on an assumption of significant electrification. Although both NEMS and PATHWAYS account for existing policy, they do not incorporate utility targets, and neither model output achieves zero GHG electricity on an annual average basis by California’s 2045 deadline (note that PATHWAYS results assume that because California’s policy has been interpreted to apply to retail sales only, a system can still be compliant with a zero-carbon target if carbon-based electricity generation does not exceed system losses).

4. Discussion

The results described above show that projecting the utility-specific annual average GHG intensity of electricity is possible with a plant-specific committed emissions approach and relatively few assumptions.
Combining a committed emissions approach with state- and utility-specific policy standards (in this case, renewable and clean electricity standard targets by year) enables a much more detailed and context-aware model of future emissions than is typically available. Model performance compares favorably with known information and other models on both utility (figure 5) and temporal (figure 6) specificity, particularly given that the model is a self-contained Excel workbook based on publicly available datasets and a small number of simple assumptions. Although the use of plant lifetime as a proxy variable for various market pressures, operational considerations, etc. appears to be a reasonable approximation, this model contains no explicit representation of markets and grid requirements. Similarly, ‘new build’ capital is modeled merely as an emissions factor, not as specific plants with explicit grid characteristics. Thus, although it is well suited to evaluating compliance risks associated with specific capital assets and testing the effect of asset retirements and policy on emissions profiles, the model is not a grid planning tool.

As figure 2 shows, substantial differences in utility-specific GHG intensity are projected to converge as state requirements for zero-carbon generation become stricter. Year-to-year variability in GHG intensity can be large, often due to specific asset retirements or renewable or clean electricity compliance targets. One reason that the large share of wholesale power in Californian utility generation portfolios (figure 1) is important is that utilities can theoretically adjust their portfolios relatively quickly, e.g. to comply with their own internal targets. SCE, PG&E, LADWP, and SDG&E have internal standards that exceed state requirements, and figure 5 suggests that they purchase disproportionately more RPS-eligible power relative to available wholesale generation than other utilities. Whether this represents market segmentation (whereby utilities with stricter targets are buying more existing RPS-eligible generation and leaving existing, noncompliant generation to utilities with looser standards) or utility-driven development of more RPS-eligible generation is unclear. Overall, though, the potential for such segmentation means that statewide requirements are particularly important for ensuring that potentially stranded, carbon-based assets do not simply sell to utilities without strict GHG goals.

Under default assumptions, model results suggest that committed generation and emissions will not prevent California’s utilities from complying with the renewable or clean electricity standards. The few instances of noncompliance within the model (see validation cells on the ‘User Inputs’ tab of the supplementary data file) are artifacts associated with the treatment of very old plants and plants using multiple fuels. LADWP is out of compliance with interpolated targets in 2022 and 2023, after which the model retires Haynes Generating Station, a natural gas-fired power plant that has already exceeded its predicted lifespan. SMUD is out of compliance with state targets in 2026 and 2027, and out of compliance with interpolated targets in 2025 and 2033–2036, but the model gives no credit for RPS-eligible biogas use at Cosumnes Power Plant because the plant fuel is listed as ‘OG’ (other gas) rather than natural gas plus biogas. Assuming 1.5% biogas in 2026 or 5.9% biogas in 2027, versus current biogas use of less than 5% (California Energy Commission 2018), returns SMUD to compliance with binding targets. ‘Other utilities’ have 90 MWh of battery storage online between 2045–2047 that are not modeled as eligible under a CES, but presumably would be storing CES-eligible power at that point.

The finding that California’s utilities can essentially comply with current targets without retiring any of their own assets before the end of their typical lifespans suggests both a rationale for the current timeline and a potential challenge for accelerating targets. For example, modeling a 2030: 100% clean electricity deadline suggests that none of California’s five largest utilities (nor the aggregate other utilities) could comply without early retirement of their own assets. As noted above, however, some merchant assets are likely to be partly or completely stranded by current policy. Further, based on historical precedent that asset lifetimes are rarely less than about 30 years, any new assets built from now on will be stranded under the current 2045: 100% clean electricity requirement if they are not compliant with that future requirement.

Figure 3(b) shows the large influence of methane leakage on GHG emissions from California’s natural gas-heavy grid. Upstream methane increases the CO₂ intensity of natural-gas fired plants by about 30% based on national average methane leakage rates (Alvarez et al 2018) and AR5 GWP-100, both of which carry substantial uncertainty (Grubert and Brandt 2019). Methane leakage varies by extraction basin: ongoing work suggests that California’s natural gas has a much higher than average leakage burden (Burns and Grubert 2020), which means California’s grid is likely more GHG intensive than presented in this work. Assumptions about methane leakage, GWP, etc. can be changed on the ‘Assumptions and Validation’ sheet in the model.

5. Conclusions

Understanding how existing, long-lived power plants contribute to future emissions can inform policy design and highlight where specific plants might pose compliance risks. As demonstrated by this California case study, this plant-based approach to emissions projections can also bound uncertainty in a way that more generalized approaches cannot: for example, ‘unspecified sources of power’ can be estimated based
on available plants, and treating power plants individually means that specific conditions about retirements or other characteristics can be included. This work demonstrates that annual average emissions intensity for a given entity, like a utility, can be projected using limited information about policy, specific power plants, and relatively simple allocation rules. Environmental impact analyses often seek specific emissions intensity information because of their variability and frequently large influence on results. This work shows that beyond regional or other geographic specificity, bottom-up estimates using a committed emissions framework can generate defensible emissions factors that are both entity- and time-specific. This inclusion of both entity and time is relevant for evaluating the likelihood of policy compliance; improving the accuracy of life cycle emissions estimates in a dynamic energy context; and informing strategic investment in climate mitigation efforts. Future work will extend this modeling approach to jurisdictions beyond California and environmental intensity metrics beyond GHGs.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

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