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Policy Analysis

Grid-Scale Life Cycle Greenhouse Gas Implications of Renewable, Storage, and Carbon Pricing Options

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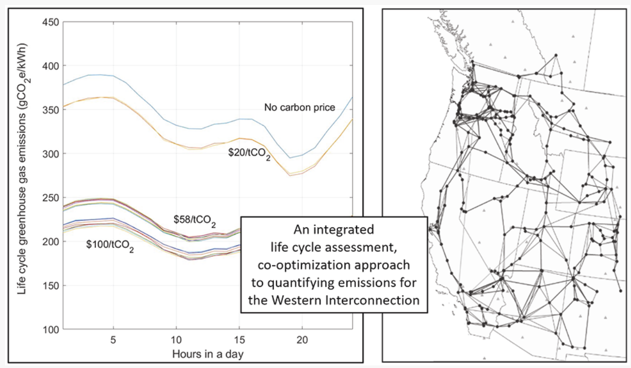
ABSTRACT: Models that characterize life cycle greenhouse gases from electricity generation are limited in their capability to estimate emissions changes at scales that capture the grid-scale benefits of technologies and policies that enhance renewable systems integration. National assumptions about generation mixes are often applied at annual time steps, neglecting spatiotemporal resolutions that provide insights on impacts from time-variable emissions. Our grid-scale model incorporates details of transmission and generation planning that allows a geographically and temporally textured and more realistic assessment of the life cycle greenhouse gas emissions outcomes, using a case study of the Western Interconnection of North America. Results from a co-optimized model of generation, transmission, and operations—the Johns Hopkins Stochastic Multistage Integrated Network Expansion Model—provide a detailed characterization of twenty-one scenarios with different configurations of storage additions, new renewable capacity, and carbon prices. Life cycle results suggest that optimization models that focus on generation alone may underestimate emissions by 18−29% because only emissions from power generation are quantified (i.e., supply chain emissions are omitted) but also that carbon pricing is the predominant driver of reducing emissions in the scenarios we examine. Life cycle assessment of electricity generation should move beyond individual technologies toward capturing the influence of policies at the system level to better understand technology-policy dynamics for the grid.



■ INTRODUCTION

Climate change is among the most pressing challenges for the electric sector, due to the prominence of fossil fuels in the present generation fleet. While the U.S. power sector has experienced substantial emissions reductions in recent years, fossil fuels were still the dominant source of electricity at 63.5% of generation in 2018, with 35.1% of generation fueled by natural gas and 27.4% fueled by coal.[1] The grid has been changing not only from coal to gas but also with a growing portion of intermittent renewables: wind and solar PV have grown from 55000 to 272000 Gigawatt-hours per year (GWh/year) and 76 to 60000 GWh/year, respectively, from 2008 to 2018.[2] Provided that the costs of renewable technologies continue to fall, energy storage is broadly considered one of the most attractive solutions with notable potential to balance the intermittency of variable renewable power (namely, wind and solar). The true environmental benefits of new storage capacity are challenging to discern due to the overall dynamic interactions between power plants and storage inherent to the operations of an electric grid, particularly in comparison to policy options such as carbon pricing. But generation is only one part of the life cycle of power systems: the life cycle includes additional processes, such as materials extraction to construct power plants, upstream fuel extraction (where applicable), operations, and transmission of the electricity to consumers. Our analysis addresses these challenges with an examination of grid-scale greenhouse gas emissions through an integrated analysis of optimized technology-policy scenarios that captures the full supply chain implications.

Life cycle assessment (LCA) provides a robust method for examining these upstream and downstream emissions as a cradle-to-grave approach to quantifying the environmental burdens of products or processes from materials extraction to waste disposal (cradle to grave).[3,4] Present emissions models, however, are limited in their capability to estimate life cycle emissions changes at subnational scales and hourly time steps.[5,6] When quantifying the life cycle emissions of an electricity grid, national assumptions about the generation mixes are typically applied, neglecting to account for the regionalized differences and temporal dynamics implicit to

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power systems that can result in variable emissions results.[7] Similar challenges have been noted for other air pollutants[8,9] and water consumption.[10−13] Data that characterize dynamic grid interactions can result in more realistic life cycle emissions and nuanced understanding of their spatial and temporal distributions, but that requires that LCAs leverage information at more refined spatiotemporal resolutions.[14−16]

To the authors' knowledge, there has yet to be a comprehensive evaluation of the life cycle emissions associated with different configurations of renewable capacity additions, storage capacity additions, and carbon pricing options at the scale of grids (i.e., rather than individual technologies). In order to perform such an evaluation, robust methods must model the life cycle environmental and economic impacts of such changes at the grid-scale. A review of models that estimate the emissions of grid operations uncovers two approaches: (1) use of historical data or (2) use of power systems and market models based on optimization methods.[6] In this paper, the latter approach is taken because a focus will be on the synergistic impact of low-carbon technologies (i.e., storage and renewables) and market mechanisms (in this case, carbon prices) for which there is a lack of relevant historical data.

While many LCAs focus on individual power generation technologies,[17−21] few (if any) LCAs have quantified the effects of carbon pricing on grid-scale emissions. Similar to power generation technologies, numerous LCAs have previously been published that study the environmental implications of energy storage technologies.[22,23] Such studies tend to focus on one or a combination of battery energy storage systems (BESS) such as lithium-ion technologies,[24−26] pumped hydro energy storage (PHES), and compressed air energy storage (CAES).[22,27] Elzein et al.[25] argue that studies have focused on life cycle effects of battery manufacturing, while the grid-scale implications associated with the operation of new storage capacity remain poorly characterized. They contributed an integrated optimization-LCA model of energy storage for the grid of France in 2017. Such advancements enable a more robust examination of the use phase of grid-scale energy storage because the dynamic interactions between storage capacity and the mix of generation operations and investment can be investigated at the scale of power plants.

Further, a combined LCA-optimization approach can enable an investigation of how new renewable and storage technologies interact on the grid under different carbon prices. In this work, we seek to couple LCA and optimization to explore the life cycle emissions implications of renewable systems integration at the scale of a grid, focusing specifically on the addition of storage, new renewable capacity, and carbon pricing policies.

The coupling of optimization and LCA to study environmental impacts of multicomponent systems has been proposed and implemented many times in the past two decades.[25,28−31] Despite the relative abundance of literature that focuses on combining LCA and optimization, we find that (1) literature that quantifies life cycle emissions at the scale of a regional grid for different configurations of energy storage, renewable capacity additions, and various carbon pricing options is largely absent, (2) with rare exceptions (e.g., Elzein et al.[25]), grid-scale interactions resulting from new capacity additions are generally overlooked, and (3) there has been limited examination of uncertainty within these coupled models. In our analysis, we address these three limitations. The market model that we couple with LCA is a co-optimized model of investment in generation, transmission, and storage, as well as grid operations, entitled the Johns Hopkins Stochastic Multistage Integrated Network Expansion (JHSMINE) model.[32−38] Leveraging of the JHSMINE model enabled detailed analyses of aggregate power plants in our study area—the Western Interconnection of North America—yielding estimates of their life cycle greenhouse gas emissions for full grid-scale characterization. The aggregated power plants that are modeled in JHSMINE are merged representations of all generation units that use the same technology. By aggregated power plants (hereafter, power plants), we refer to the merged generation units that use the same technology and are located at the same node in our optimization model. Our contribution is, in part, the perspective of the collective grid as the product system (or the collection of processes within the LCA system boundaries) rather than only an examination of individual technologies. Our combined LCA-optimization approach produces estimates that account for the interactions between storage capacity and individual generators under different future scenarios. Finally, we capture the uncertainty of the full life cycle emission using Monte Carlo Simulation at the scale of each power plant operating in the study area. While the approach has been developed specifically for a case study of electricity generation in the Western Interconnection, our approach is broadly applicable to different product systems operating at a regional scale.

■ MATERIALS AND METHODS

Study Area. The study area is the Western Interconnection comprising the western geographic area of North America, where the grid is synchronously operated (Figure 1).[39] Of the United States, all of Arizona, California, Colorado, Idaho, Nevada, Oregon, Utah, and Washington are part of this interconnection in addition to parts of Montana, Nebraska, New Mexico, South Dakota, Texas, and Wyoming. Parts of Northern Mexico are included in addition to the Canadian provinces of British Columbia and Alberta. While coal and natural gas remain strong contributors to the region's power supply, they combined represent only 40.5% of the 249 GW of the region's generating capacity.[40] Of the total capacity, hydroelectric power ranks first at 38.2%, followed by natural gas (27.4%), coal (13.3%), nuclear (8.5%), wind (6.6%), solar (3.1%), geothermal (1.9%), and other sources (1.2%). The Western Interconnection was selected as the study region due to its importance to Western North America: it serves 80 million people and spans more than 1.8 million square miles.[41] Further, a series of recent efforts have resulted in vetted optimization scenarios that examine the influence of different renewable-storage-policy configurations with the JHSMINE model, created in collaboration with the Western Electricity Coordinating Council (WECC). The WECC plays an important role for this interconnection as the nonprofit corporation in charge of maintaining reliable power in the interconnection, assuring open and nondiscriminatory access to transmission, and providing a forum to resolve disputes.[39]

Data Sources and Methods. The method we develop for the present analysis involves the integration of two modeling approaches and its implementation for a specific region (WECC): (a) the co-optimization of generation, transmission, storage expansion, and operations, and (b) Life Cycle Assessment for inclusion of supply chain emissions. The former enables us to simulate market adjustments in response

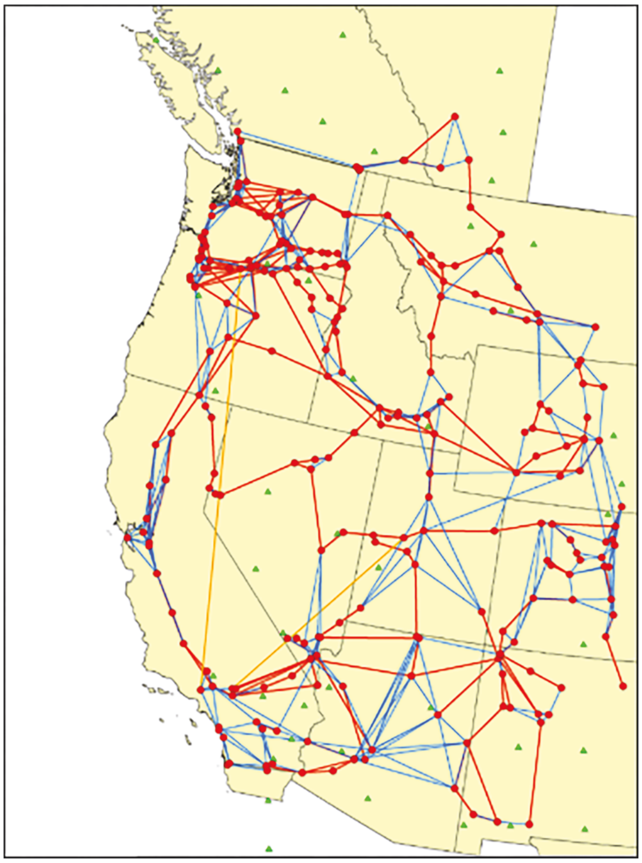

Figure 1. Map of JHSMINE reduced 300-bus network of Western Electricity Coordinating Council of North America. Dots represent nodes of the grid, and triangles represent the location where new renewable generation can be sited. Red/Orange lines are existing AC/DC lines, and blue lines are equivalent lines that are results of the network reduction.

to hypothesized storage and renewable introductions as well as the effects of changes in carbon pricing policies. In our model, a perfectly competitive market is simulated by minimizing annualized costs of operations, power system expansions, and associated decisions arising from carbon pricing. While we capture the impacts of fuel supply in LCA, upstream sectors are not operating under carbon dioxide equivalent pricing; instead, carbon is subject to pricing only when emitted at the power plant. As a result, we do not price emissions associated with fossil fuel combustion and leakage upstream (such as diesel fuel used in rail transport of fuel or gas compressor operations), which could result in distortions in economic decisions concerning which fuels are produced as well as how and where they are produced.[42] However, LCA will quantify those upstream emissions, in addition to those from power plant operations.

In the present work, we deploy JHSMINE, a co-optimization planning model that encompasses generation and transmission (and storage, if any) decisions over a multidecade time horizon, co-optimizing both grid operations but also power system expansions that allow the system to adapt to economic, policy, and technology development settings. The objective function of JHSMINE is to minimize the societal cost that includes (1) cost of power system expansions (e.g., building new generation), (2) cost of grid operations (e.g., fuel cost), and (3) carbon pricing (e.g., paying for emission allowance). The constraints of JHSMINE generally include (1) restrictions on siting of new generation, transmission, and storage facilities, (2) operating limits of generation, transmission, and storage facilities, (3) meeting electricity and ancillary service demands, and (4) policies requirement such as renewable portfolio standards.[33] Key model inputs include policies, capital and operating costs and performance characteristics of different technologies, and electricity demand and ancillary services demand. To speed up the model solving, we relax the binary variables of the transmission construction and assume a "pipes-and-bubbles" power flow (i.e., all lines are modeled as DC connections). However, our previous work[37] estimated that such modeling simplification would not strongly affect the transmission decisions in the WECC system.

With existing scenarios developed for the WECC region for 2034,[32,34,35,43−45] we employ a hybrid LCA-JHSMINE approach to evaluate the life cycle greenhouse gas implications of a variety of scenarios and examine how its results compare to LCA and optimization approaches singly. JHSMINE results provide a temporal resolution that is not typically captured within LCA, at 96 operating hours a year, enabling more accurate representation of grid component interactions and the temporal variation of emissions in LCA. This methodological advance in LCA overcomes the limited ability of existing models to compare the life cycle impacts of changes to the grid. The scope of the LCA encompasses not only the full grid as characterized by JHSMINE but includes the upstream and downstream emissions associated with each power plant (Figure 2).

At the time of this analysis, databases had yet to be developed that track the date and location of every piece of equipment for each power plant included in our study. Further, our scenarios include candidate generators, which have yet to be in operation, and a future fuel supply where the exact sources and infrastructure locations are unknown. The LCA component of this research is thus inherently uncertain, necessitating the use of uncertainty analysis. To address these uncertainties, our approach encompasses Monte Carlo Simulation to characterize the probability distribution of greenhouse gas emissions outcomes for each scenario, reflecting uncertainties upstream emissions. As examples, upstream uncertainties for coal might include the quality of the fuel and technology vintage (full details for each technology type available via NREL's harmonization studies[17,46−51]). Monte Carlo Simulation is a widely accepted, commonly utilized tool to characterize uncertainty in LCA.[52−55] We integrate both inputs and outputs from JHSMINE combined with published distributions of existing LCAs of electricity generation that have been published by the National Renewable Energy Laboratory (NREL). The US Department of Energy has funded the NREL to complete a rigorous review of published LCAs of electricity generation through the Life Cycle Assessment Harmonization project.[17,46−51] That project had three goals: (i) to gain insights into the range of published results across electricity generation technologies, (ii) to decrease the variability by correcting inconsistencies in assumptions and methods across studies, and (iii) to publish a more robust central tendency of LCA results by technology. Similar to Surana and Jordaan,[56] we rely on NREL's data for the consistency and comprehensiveness of their methodological approach and transparency in reporting individual studies despite the availability of other harmonization studies.[57]

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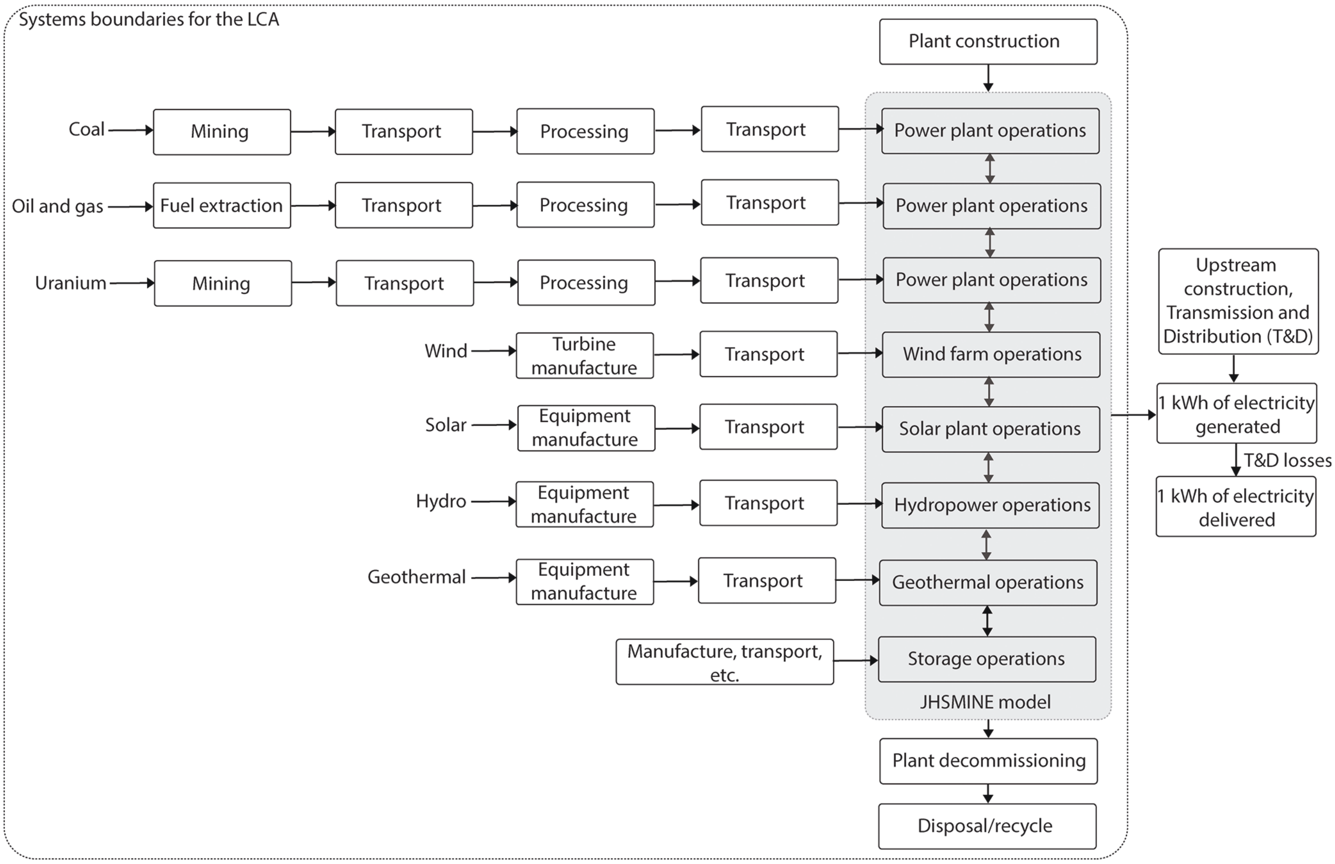

Figure 2. Simplified scope of the grid-scale LCA, with systems boundaries for each technology based on NREL's harmonization studies.[17,46−51] Life cycle emissions are estimated using NREL harmonization data for each type of generation modeled in JHSMINE, adjusted for each power plant's operational efficiency using their heat rates. Results from the JHSMINE model determine the optimized interactions between energy types and storage on the grid, under 21 scenarios of renewable energy, storage, and carbon pricing options. Our analysis and discussion focus primarily on upstream emissions as NREL's harmonization studies found that emissions impacts are weighted toward the upstream.

We chose probability distributions to characterize the life cycle emissions of each technology type based on a Chi-square test of fit to the empirical data from the harmonization study. Fourteen candidate distributions were tested (list of continuous distributions available in Oracle Crystal Ball[58]). For each technology, we truncated distributions by the highest and the lowest data points available in the empirical data. Geothermal was the only instance of scarce data, with only 7 data points available. In that case, we assumed a normal distribution.

In total, 21 different scenarios were examined representing different configurations of new capacity of pumped hydroelectric storage, compressed air energy storage, and wind power, and battery energy storage systems under different carbon pricing options in USD per metric ton of carbon dioxide($/t$CO_2$) (Table 1). The scenarios involved the addition of 1200 MW of Pumped Hydro (PH) in Columbia Gorge, Oregon; the addition of 1200 MW of Compressed Air Energy Storage (CAES) in Utah; and 3000 MW wind and new transmission capacity in Wyoming ("Pathfinder"). For Battery Energy Storage Systems (BESS), we modeled an existing capacity of 2456 MW as the base case where there are no new additions. Besides the PH, CAES, and Pathfinder wind power capacity, JHSMINE can add new transmission, generation, and storage capacity (if allowed) through optimization to minimize the societal cost. For example, BESS scenarios included 1519 MW and 3919 MW capacity additions of Lithium-Ion (LIB) batteries that are deployed, respectively, for two of the $58 and $100 USD carbon price scenarios.

We quantify the cost outcomes with the metric of "resource cost," which is calculated as the total cost in the electricity sector (including the capital cost and the fixed operations and maintenance of PH, CAES, and Pathfinder Wind project), excluding payments for carbon emissions. Since the total energy demands of all scenarios are nearly the same at 1095 TWh in the year 2034, we can further evaluate the resource cost at the per MWh level.

For each scenario, we modified a previous approach for estimating national scale life cycle emissions[37] for application at the scale of individual power plants (rather than countries). Each power plant's heat rate was used to scale the upstream emissions from what the NREL study termed "generalized harmonization results" (in contrast, a representative power plant efficiency was assumed for the NREL study), with upstream emissions being characterized by the distribution of published harmonization results. Results for each of the twenty-one JHSMINE scenarios were then estimated with an aggregated grid-scale annual result (eq 1).

$$EF_{grid} = \sum_{i=1}^{n} \frac{Gen_i}{Gen_t} * EF_i \tag{1}$$

$$EF_i = EF_h * \frac{\varepsilon_i}{\varepsilon_h} \tag{2}$$

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Table 1. JHSMINE Scenarios Examined in the Analysis[a]

Scenario Name	Ph	Caes	Wind	Bess	$/tCO_2$
Base Case	No	No	No	No	0
$20/tCO_2$	No	No	No	No	20
Ph, Caes, Wind, $20/tCO_2$	Yes	Yes	Yes	No	20
$58/tCO_2$	No	No	No	No	58
Ph, Caes, Wind, $58/tCO_2$	Yes	Yes	Yes	No	58
Caes, $58/tCO_2$	No	Yes	No	No	58
Ph, Caes, $58/tCO_2$	Yes	Yes	No	No	58
Wind, $58/tCO_2$	No	No	Yes	No	58
Ph, $58/tCO_2$	Yes	No	No	No	58
Ph, Wind, $58/tCO_2$	Yes	No	Yes	No	58
Caes, Wind, $58/tCO_2$	No	Yes	Yes	No	58
Bess, $58/tCO_2$	No	No	No	Yes	58
$100/tCO_2$	No	No	No	No	100
Ph, Caes, Wind, $100/tCO_2$	Yes	Yes	Yes	No	100
Caes, $100/tCO_2$	No	Yes	No	No	100
Ph, Caes, $100/tCO_2$	Yes	Yes	No	No	100
Wind, $100/tCO_2$	No	No	Yes	No	100
Ph, $100/tCO_2$	Yes	No	No	No	100
Ph, Wind, $100/tCO_2$	Yes	No	Yes	No	100
Caes, Wind, $100/tCO_2$	No	Yes	Yes	No	100
Bess, $100/tCO_2$	No	No	No	Yes	100

[a]The 21 scenarios involved different configurations of new capacity of pumped hydroelectric storage (PH), compressed air energy storage (CAES), pathfinder wind power (wind), and battery energy storage systems (BESS) under different carbon pricing options in USD per metric ton of carbon dioxide($/tCO_2$). Carbon prices were selected to be reflective of the absence of carbon pricing ($0/tCO_2$), California's present carbon price ($20/tCO_2$),[59] the anticipated carbon price in California in 2034 ($58/tCO_2$),[44] and an ambitious scenario where policy-makers select a high price ($100/tCO_2$). Besides the PH, CAES, and pathfinder wind power capacity, JHSMINE is allowed to add new transmission, generation, and storage capacity (if allowed) through optimization to minimize the societal cost.

where E_{Grid} is the grid emissions, Gen_i is the optimized generation from each individual power plant i (total of n), Gen_t is the optimized generation from all power plants, and EF_i is emissions factor adjusted to represent the heat rate of each representative powerplant (eq 2). The emissions factor for each power plant (EF_i) was calculated by adjusting the emissions factor from the harmonization studies (EF_h) to reflect the operational efficiency of the power plants (ε_i) (calculated with the heat rates) instead of the efficiency employed in the harmonization study (ε_h). Using methods from Surana and Jordaan[60] replicated at the scale of power plants, a Monte Carlo Simulation was run in Oracle Crystal Ball with 10000 repetitions sampling from applied emissions distributions (i.e., NREL harmonization results) for each power plant.

Grid interactions for generation scenarios are modeled for hourly timesteps in JHSMINE for four representative days (96 h) for the future year (in this case, 2034), enabling an examination of hourly life cycle emissions. The transmission-generation-storage co-optimization core of JHSMINE limits the temporal resolution to 4 days. However, to reduce the bias introduced by the limited temporal resolution and to capture the interday variability (e.g., seasonal variability), we selected each of the days from four time periods of days that were clustered from the year 2034 (365 days) based on time-series from the WECC common case of 2026 and 2034 load data.[34] One day from each time period is modeled, selected so that the total deviation of means and standard deviations between sampled days and the original data are minimized. The 4 days include: (1) November 20 corresponding to 108 days of the late summer through the end of winter (October to the end of January); (2) February 8 representing 73 days of spring (February through early April); (3) June 13 representing 70 days of late spring and early summer (early April through the end of June); (4) September 10 representing 114 days of summer and autumn (the end of June through October). For each of the 21 scenarios, hourly life cycle emissions were then determined using the generation-weighted average emissions of all power plants for each of the 96 h modeled in JHSMINE (four representative days in the year 2034).

The life cycle emissions up to the use phase for each energy storage option were characterized using estimates published in the literature. Capacity for energy storage is reported either in terms of rated power in megawatts (MW) (i.e., the maximum charge and discharge power) or storage capacity in megawatt-hours (MWh) (i.e., the amount of energy capable of being stored). Distinguishing the two is a critical component of estimating the relative magnitude of the upstream emissions for new storage capacity. Cradle-to-gate emissions for Pumped Hydro (PH) and for the Compressed Air Energy Storage (CAES) were sourced from Denholm.[61] The scenarios with new Battery Energy Storage Systems (BESS), respectively, represent 6.4 and 16.5 GWh of new storage capacity for the $58/tCO_2$ and $100/tCO_2$ cases, respectively, located in California for the former but also in New Mexico, British Columbia, and Mexico for the latter. Lithium nickel manganese cobalt oxide (NMC) is the most typical chemistry in grid-scale BESS. This chemistry demonstrates the highest efficiencies and the most balanced performance characteristics in terms of energy, power, cost, and cycle life.[62] As a result, the additional emissions for the new capacity were estimated from a review of studies published between 2000 and 2016 that characterize NMC batteries; five results were obtained and characterized, and the average was assumed to be representative (see SI).[63]

RESULTS AND DISCUSSION

Our results provide four sets of insights for grid-scale emissions under different technology-policy scenarios for the Western Interconnection. First, grid-scale life cycle emissions are relatively low in comparison to individual fossil-fuel technologies, with the average base case with no new technologies and pricing being only 38% of coal-fired power (375 gCO_2e/kWh for the former and 975 gCO_2e/kWh for the latter, Figure 3a).

Second, the low emissions relative to electricity generated from fossil fuels are because hydropower is the dominant source of electricity in the region. Even in the present generation mix, coal and natural gas represented only 49.3% of total generation of 863000 GWh in 2017.[40] Of the total 2017 generation of 863000 GWh, hydroelectric power ranks first at 30.0%, followed by natural gas (25.6%), coal (23.6%), nuclear (6.7%), wind (6.4%), solar (4.4%), geothermal (1.8%), and other sources (1.2%). In our scenarios (each resulting in just over 1000000 GWh of annual generation), hydro continues to generate a large share of electricity at approximately 20% of generation across scenarios. For the base case (no carbon price and without any of the selected additions of storage and wind), coal and natural gas generate 18% and 34% of the total electricity with wind and solar at 14% and 1%, respectively. For

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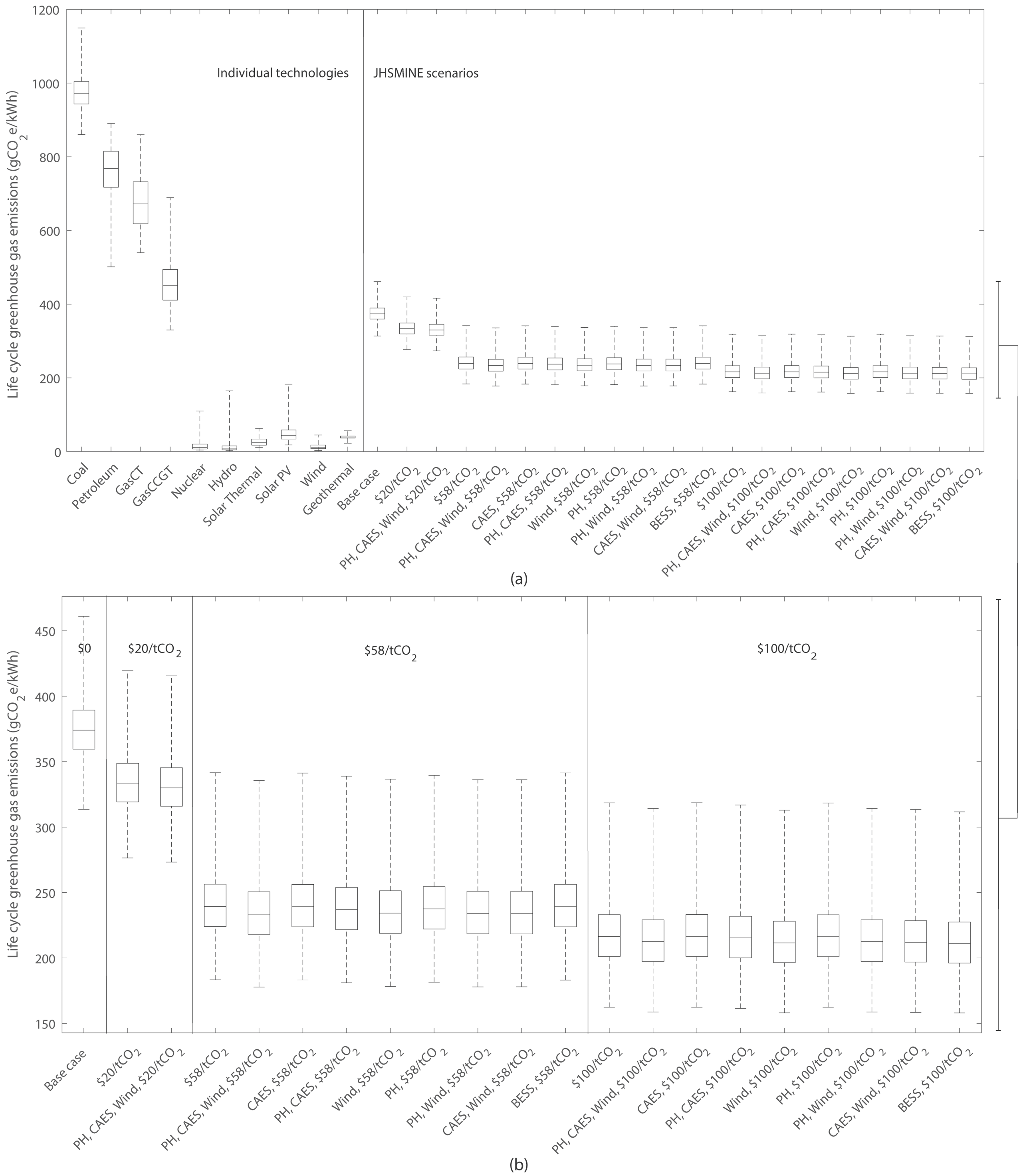

Figure 3. (a, b) Life cycle results for individual technologies compared to grid-scale scenarios. Individual technologies for comparison include coal, petroleum, natural gas combustion turbine (GasCT), combined cycle natural gas (CCGT), concentrating solar power (SolarThermal), solar photovoltaic (solarPV), wind and geothermal (Geo). Scenarios include different configurations of storage additions (Pumped Hydro (PH), Compressed Air Energy Storage (CAES), and Battery Energy Storage Systems (BESS)), new wind capacity, and different prices on carbon dioxide (none, \$20/tCO_2, \$58/tCO_2, \$100/tCO_2) (see Table 1). Part a compares the grid-scale LCA results to life cycle results for individual technologies. Part b shows more clearly the results for the grid-scale scenarios. Note that these results are based on the aggregate power plants using annual estimates.

the more aggressive scenarios, such as under only a \$100 price per ton CO_2, coal declines to near zero, and the share of natural gas and wind generation increases (to 40% and 19%, respectively). In the absence of coal, oil generation comprises a marginal amount of the supply (less than 1%), which decreases with scenarios that include new storage and wind.

Third, results suggest that grid-level estimates experience subtle-to-no difference based on configurations of new storage and wind capacity across the scenarios we examined (Figure

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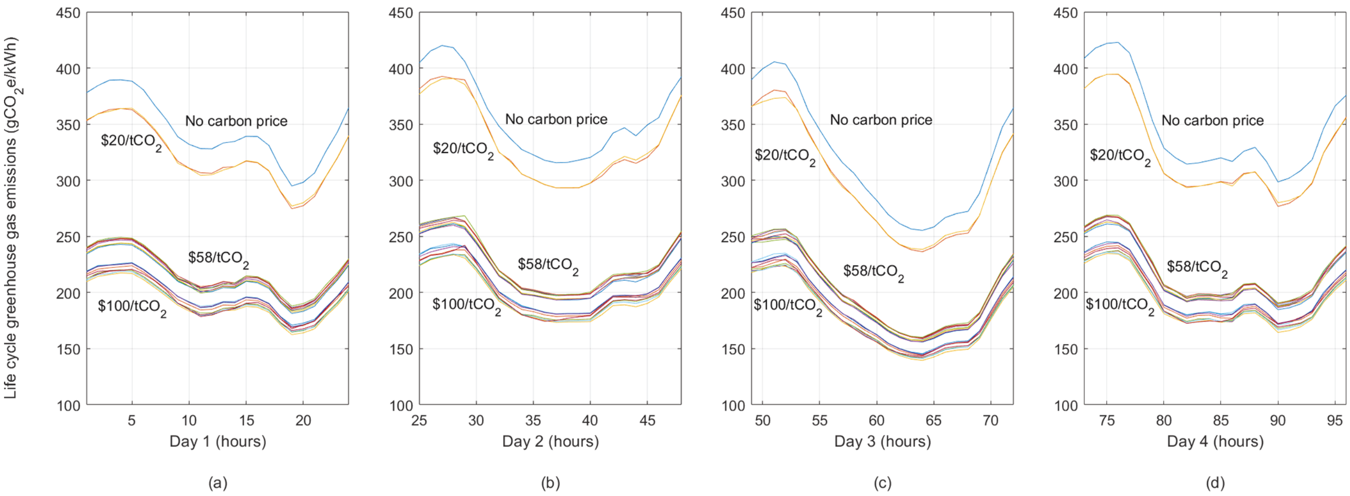

Figure 4. (a−d) Mean life cycle grid emissions for each scenario, estimated at hourly time steps for each of the four representative days modeled in JHSMINE.

3b). The low levels of variation are rooted in the relatively small magnitude of capacity additions in comparison to the grid's existing generation fleet: each scenario of new capacity of PH/CAES/Pathfinder wind was below 4 GW relative to a 249 GW grid. Changes in emissions due to new technology additions and their interactions with the grid were on the order of 1−3% in comparison to carbon pricing alone. Emissions associated with the manufacture of storage were also negligible (less than 1%, see SI). The emissions reductions from adding and/or increasing carbon pricing alone were substantial, however, through lower operations of fuel-burning plants. In comparison to the base case with no carbon price, carbon price scenarios for $20/tCO_2$, $58/tCO_2$, $100/tCO_2$, and with no PH, CAES, nor Pathfinder Wind result in emissions reductions of 10%, 35%, and 42%, respectively (see SI for tabular data). Finally, while we demonstrate the environmental benefits of each technology-policy scenario, our results indicate that optimization models alone tend to underestimate emissions by about 18−29% relative to the total life cycle emissions for the scenarios we examine.

We also examined results calculated for mean life cycle grid emissions at hourly time steps for each of the four representative days modeled in JHSMINE (Figure 4a−d). While the general results are the same that carbon pricing scenarios were the dominant influence on emissions in the scenarios we modeled, we highlight two important ramifications of the hourly estimates. First, our results reinforce results from Siler-Evans et al.:[5] the impacts of specific interventions may be misestimated without considering their effects at the subannual level. With this approach, scenarios can be examined with regard to their ability to create interventions at specific time periods. Such scenarios can inform policy-makers about how their decisions are likely to influence the environmental outcomes of the grid. Second, while we observe only subtle changes due to the level of technology change in our scenarios, specific interventions should be explored in future research that can capture greater environmental benefits.

We note how each scenario may influence the resource cost of electricity: a higher carbon price will cut emissions while raising resource cost. For example, in the cases without PH, CAES, and Pathfinder wind power, the costs, from a carbon price of 0 to $100/Metric ton are, respectively, $30.81/MWh, $31.15/MWh, $34.22/MWh, and $35.76/MWh (see Supporting Information). Furthermore, while holding the carbon price constant, the cost impact of PH or CAES is small, just as the emissions impacts are. However, the installation of the Pathfinder wind project will simultaneously lower the system cost as well as the system emissions. For instance, in the cases where the carbon price is $58/metric ton, the 3000 MW Pathfinder wind installation will lower the system cost by $0.42/MWh on average as well as lower emissions by 6.92 Mton/year. When the BESS is allowed to be installed, and the carbon price is $100/metric ton, the installation of BESS lowers emissions but at the expense of higher resource costs, indicating that the BESS installation is primarily driven by emissions goals, as reflected through savings in carbon expenditures.

■ CONCLUSIONS AND POLICY IMPLICATIONS

Our combined LCA-optimization modeling yields an approach to understanding the implications of power system dynamics under different technology-policy configurations at higher spatial and temporal resolutions than previously modeled, leveraging data at the scale of each power plant and hourly dispatch modeling. This analysis optimized grid operations under a carbon price, examining the question from a grid planning perspective. Results show that the environmental benefits of carbon pricing and technology additions are realized both for the grid alone (i.e., JHSMINE results) and also when considering the life cycle of the grid. JHSMINE alone, however, may undercount emissions by near 30% when compared to life cycle emissions, suggesting optimization models could benefit from including upstream emissions to avoid unintended consequences. Using a systems approach enabled two contributions: (1) we capture the emissions changes at the scale of grids rather than individual technologies, accounting for their nonlinear and sometimes surprising interactions, and (2) our results capture the effects of carbon pricing applied to the electric sector on life cycle emissions outcomes while acknowledging overall resource costs.

LCA and optimization can be coupled in numerous ways; while we examine results from the perspective of the electric systems planner, life cycle emissions could be integrated within the optimization model to observe how results may change if

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the full economy is responding to carbon pricing. Our results highlight the importance of carbon policy for grid operations. Future research should consider the expansion of carbon pricing from the power sector to an economy-wide system and compare different pricing systems in terms of the overall outcomes. The effects of carbon pricing were the greatest, though we note that more ambitious decarbonization may result in more influential results for the technology options. For example, while the effects of batteries are relatively minor under our scenarios, their contribution may become significant with high penetration and more stringent policies. Related, future research may shift focus from carbon pricing alone to more rigorous considerations and comparisons with other policies. While the presence of renewable portfolio standards was treated as a boundary condition in this work and they are not analyzed independently, the effectiveness of such standards for emissions reductions is an important topic for investigation. This is especially true in large interconnected power systems without system-wide carbon pricing but with multiple local renewable standards. We also highlight that future research may consider factors other than greenhouse gases alone, particularly, or hydropower. Environmental conservation, ecosystem management, and competition for other uses, for example, may be limiting factors for scenarios with large scale pumped hydropower as energy storage options.

This analysis speaks to the importance of scenarios to understand the effects of potential decisions at the grid-scale, beyond individual technologies, but also to the importance of improving the spatiotemporal resolution of LCA. The former enables LCA to investigate the influence of policies on product systems (in this case, emissions dispatch and investment decisions) rather than the effects of fuel switching alone. Our results also point to the need for LCA to improve systems-level analysis by modeling with spatially- and temporally-resolved data. Future adjustments of our modeling approach may include the locations of not only the fuel supply chain but also spatial details about manufacturing plants and transportation distances. Recent research suggests that transportation of coal, for example, can be substantial for specific cases and may range up to 35% of power plant emissions.[64] Detailed evaluations of regional grid impacts of technology-policy can uncover more realistic estimates of life cycle trade-offs resulting from planning decisions.

We note that even our most robust temporal modeling can be further improved, particularly for deep decarbonization scenarios with higher intermittent renewable and storage capacity than what we examined here. The accuracy of our estimation is limited by the temporal resolution of the operation simulation in JHSMINE (i.e., four daily cycles), and it is noteworthy that the length of a day can underestimate the impacts of long-duration storage options such as PH and CAES. Such underestimation cannot be ignored if the system penetration of nondispatchable wind and solar is much higher, such as 80−90%. That said, we anticipate such under-estimation (if any) will not compromise the results showed in this paper, where the model estimated that solar and wind penetration would be the highest at 27.6% when the carbon price is $100/metric ton with all PH, CAES, and pathfinder wind added into the system. The quantification of accuracy improvement from higher temporal resolution and longer operation period length is a valuable direction of future research.

As a proof-of-concept, the present analysis captures power plants at the site-level and develops reasonable upstream impacts using uncertainty analysis (i.e., Monte Carlo Simulation) with published literature estimates (NREL's harmonization studies). While we account for time in terms of hourly dispatch of electricity, we note that the upstream emissions across the life cycle are related to the generation of electricity rather than the exact timing and location of the resulting upstream emissions. In contrast to materials extraction, manufacturing, and extraction of specific fuels combusted (for example), the dispatch of electricity is tracked with frequently published data, and these data informed the development of our model. For example, the exact time and place of materials extracted for the manufacture of battery or power generation equipment are not tracked in a readily accessible database. Thus, our estimates are of the aggregate life cycle impact associated with the generation of electricity, bounding the uncertainty of the emissions across life cycle stages with NREL's harmonization studies.

Although our work here focuses on the LCA emission estimations of technologies and carbon price levels, it is fair to pose the same question to storage and transmission facilities, such as how much carbon emission is induced by transmission and storage. Our LCA systems boundaries are in line with the NREL harmonization studies and focus on the electricity generated rather than delivered, excluding transmission and distribution (T&D) losses as well as the emissions associated with construction. The Energy Information Administration reports that the average T&D losses in the United States amount to approximately 5%. The associated emissions may present an interesting area of future inquiry, particularly in terms of regional variability and for studies that focus specifically on the electricity delivered as the functional unit.

Our analysis provides a needed improvement in temporal and spatial modeling in LCA while considering the power sector as a system. However, in general, methodology for characterizing temporal and spatial dimensions of LCA is relatively under-developed, with few LCA studies having addressed it. Future research may capture important dynamics by integrating both spatially and temporally resolved data across the life cycle, as sufficient data becomes available to do so. Temporal and spatial accounting methodologies in LCA are relatively immature, meaning that comprehensive analyses of spatial and temporal interactions across the supply chain have yet to be fully developed. Research addressing this challenge is commencing to emerge[65] with temporal accounting having been found to lag spatial methodology in LCAs of electricity generation.[66] Additional model adjustments could yield interesting conclusions, for example, by exploring the effects of improving the modeling of heat rates through dynamic ramping and the inclusion of impact categories other than greenhouse gas emissions alone. The results are presented using 100-year global warming potentials; while not the focus of the present analysis, future work could explore the effects of applying different time horizons.

Our analysis further demonstrates that the application of combined LCA-optimization scenario modeling can provide useful insights not just for different technology changes but particularly for the implications of policies. While we examine the electric grid that constitutes the Western Interconnection, our approach is broadly applicable for evaluating the environmental outcomes energy policies at the systems-level. For example, the approach may be applied to improve life cycle

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comparisons of regional vehicle fleets under different policies, such as electric vehicle incentives and limitation of the number of vehicles on the road by their license plates.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.0c01861.

Life cycle assumptions used in calculations for batteries (XLSX)

Full report of all input distributions and output distributions for Monte Carlo simulations (XLSX)

Results from Monte Carlo Simulation and relevant calculations (XLSX)

Resource cost estimations (XLSX)

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All authors contributed to the writing of the manuscript. All authors have given approval to the final version of the manuscript.

Notes

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