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Open Source Energy System Modeling Using Break-Even Costs to Inform State-Level Policy: A North Carolina Case Study

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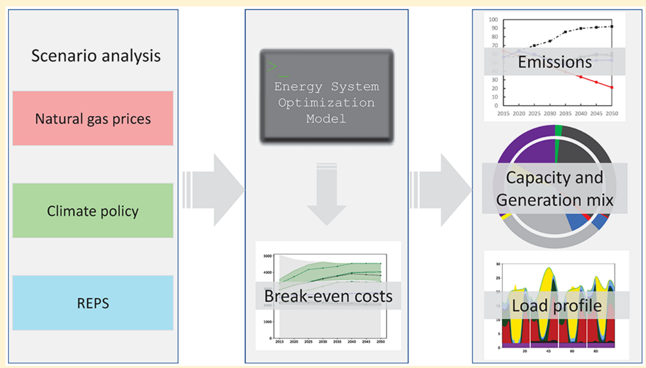
Supporting Information

ABSTRACT: Rigorous model-based analysis can help inform state-level energy and climate policy. In this study, we utilize an open-source energy system optimization model and publicly available data sets to examine future electricity generation, CO_2 emissions, and CO_2 abatement costs for the North Carolina electric power sector through 2050. Model scenarios include uncertainty in future fuel prices, a hypothetical CO_2 cap, and an extended renewable portfolio standard. Across the modeled scenarios, solar photovoltaics represent the most cost-effective low-carbon technology, while trade-offs among carbon constrained scenarios largely involve natural gas and renewables. We also develop a new method to calculate break-even costs, which indicate the capital costs at which specific technologies become cost-effective within the model. Significant variation in break-even costs are observed across different technologies and scenarios. We illustrate how break-even costs can be used to inform the development of an extended renewable portfolio standard in North Carolina. Utilizing the break-even costs to calibrate a tax credit for onshore wind, we find that the resultant wind deployment displaces other renewables, and thus has a negligible effect on CO_2 emissions. Such insights can provide crucial guidance to policymakers weighing different policy options. This study provides an analytical framework to conduct similar analyses in other states using an open source model and freely available data sets.



■ INTRODUCTION

Many U.S. states have proposed plans to address the climate change threat.[1] North Carolina is the ninth most populous state, the 14th largest CO_2 emitter (2014)[2] in the United States, and the first state in the Southeast to adopt a Renewable Energy and Energy Efficiency Portfolio Standard (REPS).[3] The NC REPS requires investor-owned utilities to meet at least 12.5% of their electricity demand through renewable energy resources or energy efficiency measures by 2021.[3] Three carve outs, representing minimum shares of specific fuel types, were also defined: 0.2% solar by 2018, 0.2% swine waste by 2020, and 900 000 MWh of poultry waste by 2016.[3] The deployment of solar PV has far exceeded the solar carve out, with 4.3% of North Carolina's total generation supplied by solar.[4] This high level of solar PV deployment is largely due to the rapid decline in investment costs and favorable contract terms for third party, utility-scale solar under the Public Utilities Regulatory Policies Act (PURPA). However, electric power producers in the state have had difficulty meeting the swine and poultry waste targets, and have repeatedly filed joint petitions to the North Carolina Utilities Commission (NCUC) seeking relief and delay.[5]

These outcomes illustrate the challenge that state policymakers face in developing policy that balances environmental performance, affordability, and stakeholder interests. Debates over energy-related policies and incentives within the state persist, often in the absence of sound, rigorous analysis available to the public. The same is true in many other states. Filling this analytical need to prospectively evaluate policy is now critical since comprehensive federal action to mitigate climate change is not imminent, and responsibility has fallen to states.

Energy system optimization models (ESOMs) represent a self-consistent framework for evaluation that can be used to probe the effects of potential policy while considering future uncertainty. ESOMs are already a crucial tool in long-term energy planning and policy making at regional to national scales, and in recent years, numerous models have been developed and applied.[6−15] ESOMs can also help planners at the state level.[16] A key advantage of such models over simple calculations is their ability to capture dynamic technology interactions across the modeled system, which can have a significant effect on the generation mix over time. Capturing such interactions is also critical when assessing the relative cost-effectiveness of different technologies.

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The break-even point, sometimes referred as grid parity point,[17,18] indicates the point at which the delivered cost of electricity from a given technology reaches a target, often assumed to be the prevailing cost of grid electricity in a particular region. Break-even cost is a useful financial metric because it indicates how close specific technologies are to achieving cost parity and therefore deployment, relative to conventional technologies. The break-even cost is typically determined based on comparisons of specific financial metrics, such as net present value,[19] internal rate of return,[20] and levelized cost of electricity,[21] which have been adopted by a wide range of studies.[22−26] However, an increasing number of studies call these metrics into question due to their oversimplified assumptions, lack of uniform standards, and failure to account for grid dynamics that can affect break-even cost.[17,21,27−30] These studies suggest break-even costs should be evaluated in a market-based framework that considers the dynamic interactions between technologies with different dispatch characteristics meeting time-varying demand. ESOMs are well-suited to identifying break-even points in a market context, but such analysis has not been a focus in previous work. While ESOMs often incorporate various forms of sensitivity analysis to determine how changes in input parameters affect outputs of interest,[31−37] this is the first application of an ESOM to formally identify break-even capital costs.

In this study, we employ an ESOM called Tools for Energy Model Optimization and Analysis (Temoa)[38] to conduct state-level analysis of North Carolina's electric sector through 2050. A key innovation in this work is the technique used in calculating break-even costs, which are directly derived from ESOM solutions, and thus reflect the system-level values of each technology. Such information is particularly useful since state energy policy often aims to incentivize the deployment of technologies that are not currently cost-effective. Information on break-even investment costs that vary over time and under different scenarios can provide critical insight by helping policy makers to develop targets and financial incentives.

We begin by examining future electricity development pathways for North Carolina while considering fuel price uncertainty, a hypothetical CO_2 cap, and an extended REPS. Next, we examine the break-even costs under these different scenarios and use them to inform the consideration of a hypothetical tax credit under the extended REPS. Finally, we examine total electric sector CO_2 emissions and CO_2 abatement costs under all modeled scenarios. The objective of this analysis is twofold: develop policy-relevant insights that are both specific to North Carolina and generalizable to other states, and demonstrate an open source analytical framework that can be used to explore policy options in different states, regions, or countries. A key feature of Temoa is publicly archived source code and data, which enables third party replication and can serve as the basis for further analysis and exploration. The model source code and data are available through GitHub,[39] and an exact copy of the files used to produce this analysis is archived through Zenodo.[40]

■ MODEL AND DATA

Model Overview. We use Temoa,[38] an open-source, Python-based ESOM, to examine electric sector capacity expansion and associated emissions from 2015 to 2050. Temoa represents an energy system as a process-based network in which technologies are linked together by flows of energy commodities. Each process is defined by an exogenously specified set of techno-economic attributes such as investment costs, operations and maintenance costs, conversion efficiencies, emission rates, and availability factors. Temoa is similar in structure to other ESOMs such as MARKAL,[41] TIMES,[9] MESSAGE,[42] and OSeMOSYS.[43]

Temoa is formulated as a linear program that minimizes the total system cost of energy supply over the user-specified time horizon, subject to both physical and operational constraints and user-defined constraints. Physical and operational constraints include conservation of energy at the individual process level, the global balance of commodity production and consumption, and the satisfaction of end-use demands. User-defined constraints include emission limits, maximum technology growth rates, and bounds on technology capacity and activity. Temoa minimizes the total system-wide cost of energy supply by optimizing the installation of new capacity and utilizing both new and existing capacity to meet demand. The complete algebraic formulation of Temoa is presented in Hunter et al.[38]

Temporal Considerations. In this study, the model time horizon spans 2015 to 2050, with each period consisting of five years. The results for each year within a given period are assumed identical. Note that although 2015 is a historical year, the first optimized period spans 2015 to 2019 and therefore the optimization results differ slightly from historical values.

NC electricity demand is projected to grow at 1.2% annually between 2015 and 2030,[44] based on forecasts from the Integrated Resource Plans (IRPs) of Duke Energy Progress and Duke Energy Carolinas,[45] which constitute the largest utility serving North Carolina, as well as Dominion Energy, another electricity utility whose service territory includes the northeastern corner of North Carolina.[46] We extend this annual growth rate to 2050, and use the historical NC electricity consumption in 2015 as the base year value, as displayed in Supporting Information (SI) Table S2 and Figure S1.

ESOMs typically represent intra-annual variations in energy supply and end-use demands by dividing one year into a limited number of time slices that represent combinations of different seasons and times-of-day. Modeling supply and demand with fine-grained temporal resolution is necessary to capture the energy and capacity value of variable renewable energy sources.[47,48] Several papers attempt to model long time horizons with sufficient temporal detail to capture power sector operation in ESOMs.[8,11,12,49] In this study, one year is divided into 96 time slices: four seasons, with each season including 24 times-of-day to create a representative hourly profile for each season. This configuration allows us to capture average hourly variations in renewable resource availability and electricity demand. The load in each time slice comes from seasonal average load of that time-of-day, which is drawn from historical hourly electricity load in 2014.[50] All scenarios utilize the same fixed, exogenously specified demand profile.

In addition, two constraints capture temporal aspects of power system operation: a system-wide reserve margin constraint and a ramp rate constraint. The reserve margin constraint requires that the total system capacity value must exceed the peak hourly demand by at least 15%[45] during each period to ensure adequate capacity reserve to meet demand during plant outages. Technology-specific capacities are multiplied by a capacity credit in the reserve margin constraint, where the capacity credit represents the fraction of capacity

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that can be relied on during peak demand periods. The assigned capacity credits are 5% for solar PV,[51] 20% for onshore wind,[51] 35% for offshore wind;[52] the remaining capacity credits for dispatchable generators are drawn from NERC.[53] Solar PV receives a low capacity credit due to limited solar availability during cold winter mornings when the system reaches its peak.[51] For simplicity, we assume that the capacity credit remains constant through time, though previous work indicates that the capacity credit of wind and solar declines with increasing penetration.[54,55] The ramp rate constraint requires that the change in electricity generation from a specific technology between two adjacent time slices must be bounded by its ramping capabilities. The mathematical formulation of these constraints is provided in the SI.

Technology Cost and Performance Data. The North Carolina electric sector is modeled as a single region and does not include a representation of the transmission network. Net interstate trade has constituted less than 10% of NC's total electricity supply[56] and is not included in this analysis. We performed an offline analysis of hourly imports and exports to the Duke Energy Progress system, which constitutes most of North Carolina, and did not observe large seasonal or diurnal variations in electricity trade that would have a significant effect on capacity expansion. We consider 28 electricity generating technologies, which can be categorized into nine groups based on their primary fuel types: natural gas, coal, diesel, uranium, biomass, geothermal, solar, wind, and hydro. Combustion technologies are defined based on their primary sources of power, including steam turbines, combustion turbines, or combined-cycle turbines. Advanced natural gas combined cycle and coal-fired steam with carbon capture and sequestration (CCS) plants are included, and state-of-art SO_2, NO_X, and CO_2 emissions control retrofits are also available for both existing and future units. Nuclear technologies include both conventional light water reactors (LWRs) and LWR-based small modular reactors (SMRs) as an advanced alternative. We consider three groups of renewable technologies: solar PV, wind, and biomass. Solar PV is further split into residential and utility-scale PV, differentiated by their investment costs and capacity factors. Wind power is categorized into onshore and offshore. Due to limited resource potential in North Carolina, onshore wind is capped at 5 GW in total.[57] Biomass-based integrated gasification combined-cycle (IGCC) is also included. Consistent with previous work,[6,58] we model the input feedstock as a composite of corn stover, energy crops (grassy and woody), urban wood waste, agricultural, forest, and primary mill residues. Since end-use energy efficiency (EE) is a part of the current REPS, we model it as a generic technology. A literature review indicates EE costs ranging from 29 to 258 \$/MWh,[59−66] and the median variable cost of 43 \$/MWh is used in this data set. In addition, we consider four utility-scale electricity storage systems: lithium-ion battery, zinc−carbon battery, flow battery, and compressed air energy storage. The model treats the time slices as an ordered set and optimizes both the charge−discharge capacity and amount of energy stored or dispatched each time slice. In each model time period, the storage charge level is initialized to zero and must be fully discharged by the end of the period. The storage duration is fixed at 4 h for simplicity.

Existing capacities are drawn from EIA Form 860 and calibrated with EIA's state electricity profile.[56,67] Technical parameters for most technologies, including costs, performance, and emission factors, are taken from EPA's MARKAL 2016 database supplemented by EIA's Annual Energy Outlook 2017.[6,68] Capital costs of new electricity generating technologies are drawn from NREL's 2018 Annual Technology Baseline.[69] Solar PV costs in 2015 are taken from a market report from NREL.[70] A complete list of technologies and their techno-economic parameters are provided in SI Section 2.

Modeled Scenarios. All modeled scenarios include EPA's Cross-State Air Pollution Rule (CSAPR), which limits SO_2 and NO_X emissions[71] as well as the current REPS law. We model the current NC REPS with annual percentage targets for minimum renewable electricity generation and energy efficiency (EE). It requires at least 12.5% of electricity generation from renewable sources or EE in 2021 and beyond. We include the solar carveout, but not the ones for swine or poultry waste given their low targets. Consistent with the REPS law, the maximum allowable EE fraction starts at 25% in 2015, reaches 40% in 2025,[3] and remains fixed at 40% thereafter. The percentage requirements by model time period is detailed in SI Figure S10.

Future electricity system pathways can be affected by several factors, but we choose to focus on three high-level issues: natural gas prices, an extended REPS, and a limit on CO_2 emissions. In North Carolina, as elsewhere, low natural gas prices enabled by hydraulic fracturing have led to a rapid transition away from coal and toward combined-cycle gas turbines (SI Figure S1). Thus, the future generation mix will be sensitive to realized natural gas prices. In addition, there are active and ongoing discussions about future energy and climate policy, including Executive Order 80, which aims to reduce statewide CO_2 emissions by 40% below 2005 levels by 2025.[72]

In this study, we utilize future fossil fuel price projections from EIA's Annual Energy Outlook 2017 (AEO 2017).[68] Fuel prices from three AEO2017 scenarios are selected to encompass the full range of natural gas prices included in AEO 2017: Low Oil and Gas Resource, Reference, and High Oil and Gas Resource, which have the highest, intermediate, and lowest natural gas prices, respectively. The price trajectories are shown in SI Figure S8. As noted in the results, the large variation in projected natural gas prices has a significant effect on capacity deployment.

We also consider a hypothetical cap on CO_2 emissions. In addition to Executive Order 80, Duke Energy, the largest investor-owned utility in North Carolina, has committed to reducing its emissions 40% below 2005 levels by 2030.[73] This goal is meant to be consistent with a scenario in which the world collectively limits climate change to no more than 2 °C above preindustrial levels.[73] In our analysis, we provide a linear extrapolation of this goal to achieve a 70% reduction below 2005 levels by 2050. We assume for simplicity that proportional reductions are undertaken by all states, and thus leakage effects across state lines are minimal. While Duke models their CO_2-constrained scenario as a carbon price, the assumed value is not publicly available in their integrated resource plan.[45] Historical CO_2 emissions from the electric sector and the modeled future emission limits from 2025 to 2050 are given in SI Figure S9.

Finally, we consider a revised and extended REPS that represents a linear extrapolation of the current REPS target, reaching a 30% share of renewable electricity in 2050 (SI Figure S10). The existing REPS has already been achieved, and active discussions about an extended REPS or clean energy standard are currently taking place. In the extended REPS scenario, the EE fraction of all renewable electricity is assumed

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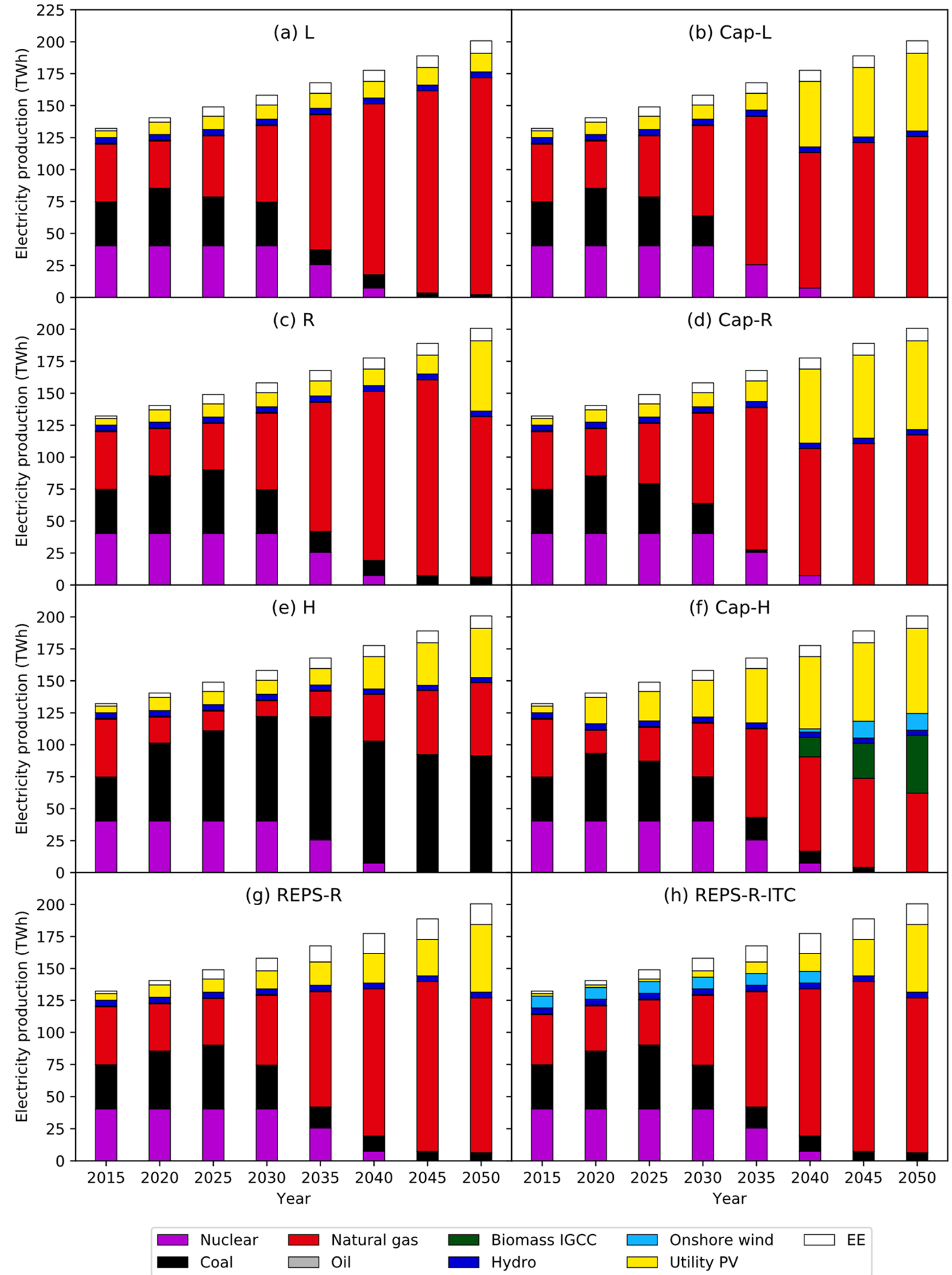

Figure 1. NC electricity generation mix through 2050 under eight scenarios: (a) low natural gas prices [L], (b) carbon cap with low natural gas prices [Cap-L], (c) reference natural gas prices [R], (d) carbon cap with reference natural gas prices [Cap-R], (e) high natural gas prices [H], (f) carbon cap with high natural gas prices [Cap-H], (g) extended REPS with reference natural gas prices [REPS-R], and (h) extended REPS with reference natural gas prices and an investment tax credit for onshore wind [REPS-R-ITC]. Given the low cost of energy efficiency (EE) measures, it is used to the maximum extent under both the existing and extended REPS.

to remain the same as in the current REPS, that is, it starts at 25% in 2015 and reaches 40% in 2025. In this revised REPS, the target includes utility and residential solar PV, onshore and offshore wind, hydro, and biomass IGCC with no carve outs or additional financial incentives.

The scenario analysis therefore includes the following scenarios: no new policy with high (H), reference (R), and low (L) natural gas prices; the carbon cap with high (Cap-H), reference (Cap-R), and low (Cap-L) natural gas prices; and the extended REPS under reference level natural gas prices (REPS-R). We only include the extended REPS under reference natural gas prices, as results in the REPS under different fuel price projections are very similar. An additional REPS run is conducted with an investment tax credit (REPS-R-ITC) for wind, which is informed by the break-even analysis described

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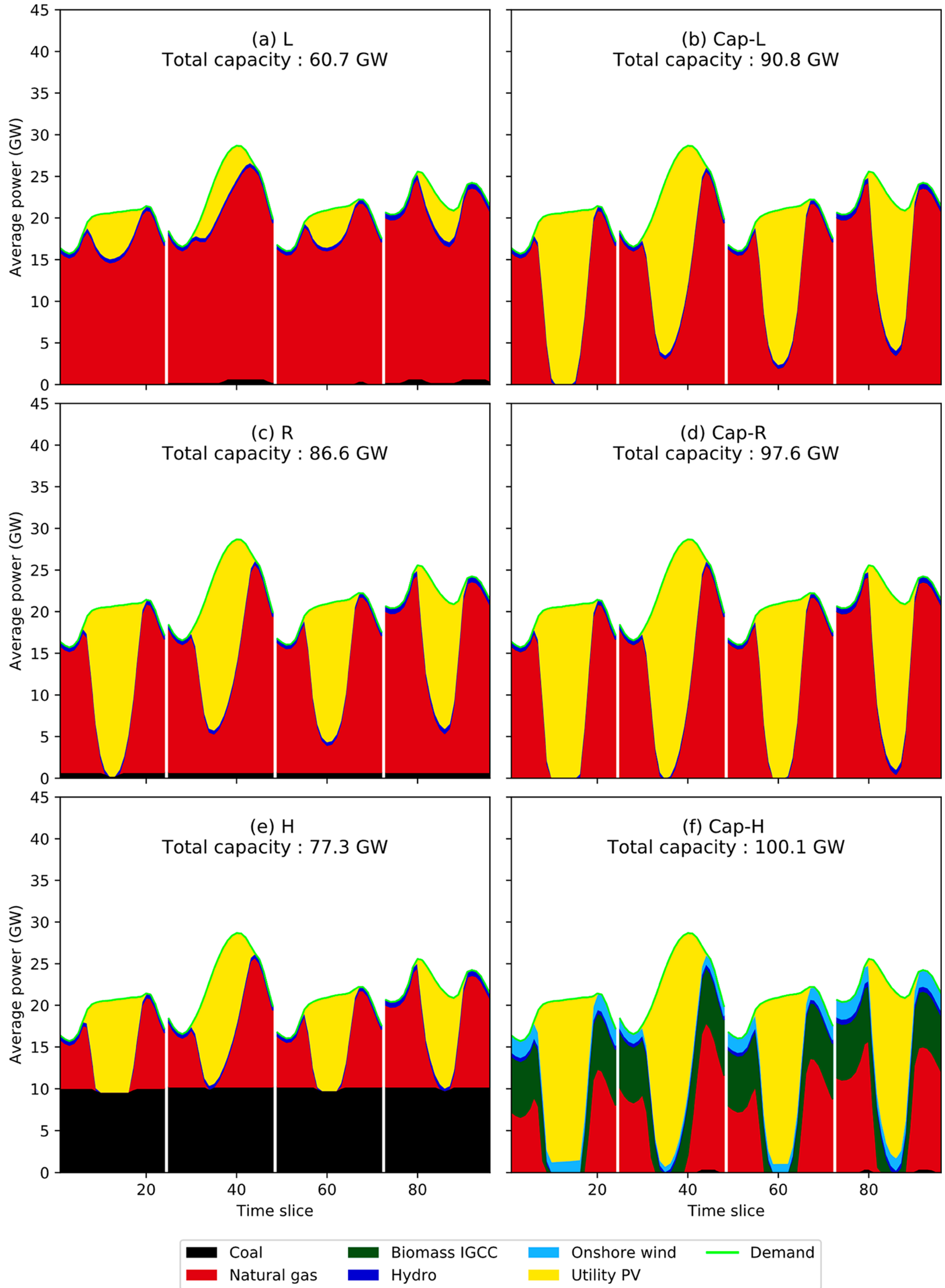

Figure 2. Average power production in 2050 from different sources in each time slice. Results from six scenarios are shown here: (a) L, (b) Cap-L, (c) R, (d) Cap-R, (e) H, (f) Cap-H. The seasons are ordered left-to-right beginning with spring. White gaps represent the boundaries between seasons, and each season is divided into 24 h time slices. Note that net load, the total electric load minus wind and solar generation, is represented by the upper edge of the dark blue band.

below. Thus, a total of eight scenarios are modeled. SI Table S12 summarizes the modeled scenarios.

Break-Even Analysis. In most ESOMs, optimal solutions only consist of a subset of all available technologies, and they fail to reveal how close some technologies are to being deployed. We quantify the technology-specific break-even capital costs required to achieve deployment under the eight modeled scenarios. In this analysis, the break-even cost represents the capital cost at which a given technology will be deployed, all else equal. Examining break-even costs for technologies that are not deployed in a given scenario and period indicate the necessary capital cost reduction to make them cost-competitive. We focus on break-even capital costs because new low carbon technologies—including wind, solar, carbon capture and sequestration, and nuclear—are capital-intensive. In addition, capital costs also serve as a convenient

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metric, and can be readily compared with future cost projections from other sources.[69,74] Such information can help inform policy.

In this analysis, we use the reduced costs returned by Temoa's solver to estimate break-even costs. In linear programming, the "reduced cost" associated with a specific decision variable in the objective function is the amount by which its coefficient must improve before it can enter the optimal solution.[75] In Temoa, the reduced cost vector returned by the solver contains updated objective function coefficients associated with the technology-specific capacity variables that are not part of the initial optimal solution. These reduced cost coefficients indicate the level to which the fixed cost of each technology must drop—all else equal—to enter the solution. In simpler terms, the Temoa objective function represents a present cost calculation over the model time horizon. Our break-even cost calculation effectively estimates the required capital cost for each technology to make its present cost competitive with other technologies. This is not a static calculation, but rather determined endogenously by the model, as it depends on the dynamic interaction among all technologies meeting demand over time and subject to a set of performance constraints. A more detailed discussion on reduced cost and its relationship to break-even capital cost is provided in SI Section 4. In addition, SI Section 4.3 compares results produced with our proposed method to a simple levelized cost of electricity comparison, and illustrates how the latter can lead to misleading insights by ignoring system-level constraints. Previous work points out the utility of reduced cost as a metric in energy system optimization models,[76−79] but it has not been formally applied to quantify break-even costs.

One limitation of this approach is that break-even costs for a given technology and scenario will be contingent on all other cost and performance assumptions in the model. To address this limitation, we perform sensitivity analysis on the technology-specific investment costs. We perform this sensitivity in the L and Cap-H scenarios, which span the full range of break-even costs for each technology. Thus, for a specific technology and scenario, the break-even costs are calculated three times, assuming the following for all generating technologies other than the one under consideration: (1) baseline capital costs, (2) a 20% increase in capital costs, and (3) a 20% decrease in capital costs. This uniform variation in capital cost across all generating technologies provides a simple way to roughly assess the relative sensitivity of technology-specific break-even costs to scenario assumptions and the capital costs of all other generating technologies.

■ RESULTS AND DISCUSSION

Capacity and Generation Mixes. The electricity generation mix is shown in Figure 1. Low (L), reference (R), and high (H) fuel price scenarios affect the trade-off between natural gas, solar PV, and coal. In 2050, coal alone contributes over 50% of the total electricity generation in the H scenario, compared to less than 5% in the R and L scenarios. The H scenario results are consistent with previous studies,[80,81] which report that in the absence of climate policy, the U.S. energy system continues fossil fuel use between 2010 and 2050. This observation aligns well with McCollum et al.,[82] which found that the global energy system might see a future expansion of coal and low-carbon energy under high oil and natural gas prices. While the model results suggest that a limited resurgence of coal is possible under high natural gas prices, utilities are unlikely to make a 50 year investment in coal given the possibility of future climate policy.

A direct trade-off between natural gas and renewables can be observed in the Cap scenarios. Natural gas contributes 31% of the 2050 electricity generation in the Cap-H scenario, whereas natural gas alone accounts for over 62% of electricity generation in the Cap-L scenario. In addition, the high natural gas prices in the Cap-H scenario produce a significant shift toward renewable energy. Solar PV, wind, and biomass collectively account for over 62% of the 2050 electricity generation in the Cap-H scenario, which represents the highest renewable penetration across all scenarios. The high natural gas prices in the Cap-H scenario lead to continued coal utilization, but coal is reduced to less than 1% of the generation mix by 2050. Although all scenarios have the same annual demands, the Cap scenarios typically have higher total capacities (SI Figure S11). The Cap scenarios include higher penetrations of wind and solar, which have relatively low capacity factors, and therefore require higher capacities to produce the equivalent amount of electricity as a conventional plant. Consistent with the Duke IRP,[45] we consider CCS associated with pulverized coal and integrated gasification combined cycle (IGCC), but do not see its deployment in the carbon constrained scenario.

Figure 2 indicates that the future contribution of solar PV under all scenarios is significant, and the model results replicate the "duck curve" effect observed in California.[83] As shown in Figure 2f, the Cap-H scenario includes significant amounts of biomass, which are deployed to address the steeper ramps of net load resulting from a high solar PV penetration. The highest solar PV penetration in the Cap-H scenario creates steep ramps of net load during late-afternoon, especially in summer. As shown in Figure 2, net load in the Cap-H scenario in summer 2050 rises from 3 GW at 1 pm to 25 GW at 8 pm, creating a much steeper ramp than in the H scenario. However, natural gas only provides around 15 GW of ramping capacity due to high natural gas prices and therefore limited utilization of gas turbines. The model instead utilizes biomass IGCC, which is assumed to be a carbon-neutral process that enables fast-ramping through syngas combustion. While biomass IGCC alone provides over 7 GW of ramping capacity in 2050, NC biomass energy potential is estimated to be around 2 GW,[57,84] which implies that an additional 5 GW of biomass resource must be imported from other states. Interestingly, storage is not deployed. We speculate that this may have to do with the fixed storage duration and the use of average 24 h diurnal profiles per season that do not capture the full benefit of shifting supply from low to high demand periods. To better characterize the potential role of storage, additional work with higher temporal resolution of supply and demand and different parametrizations of storage technology is required.[85] For example, recent work using a model with hourly resolution indicated cost-effective deployment of lithium-ion battery storage in North Carolina by 2030.[86]

Break-Even Costs. The trade-offs among low carbon options in the modeled scenarios largely revolve around utility-scale solar photovoltaics, biomass IGCC, and onshore wind. Decision makers may wonder how close to cost-effective other low carbon technologies may be under these different scenarios, and break-even costs can provide insight that helps inform policy. The break-even capital costs for six selected technologies are presented in Figure 3. In Figure 3, the upper

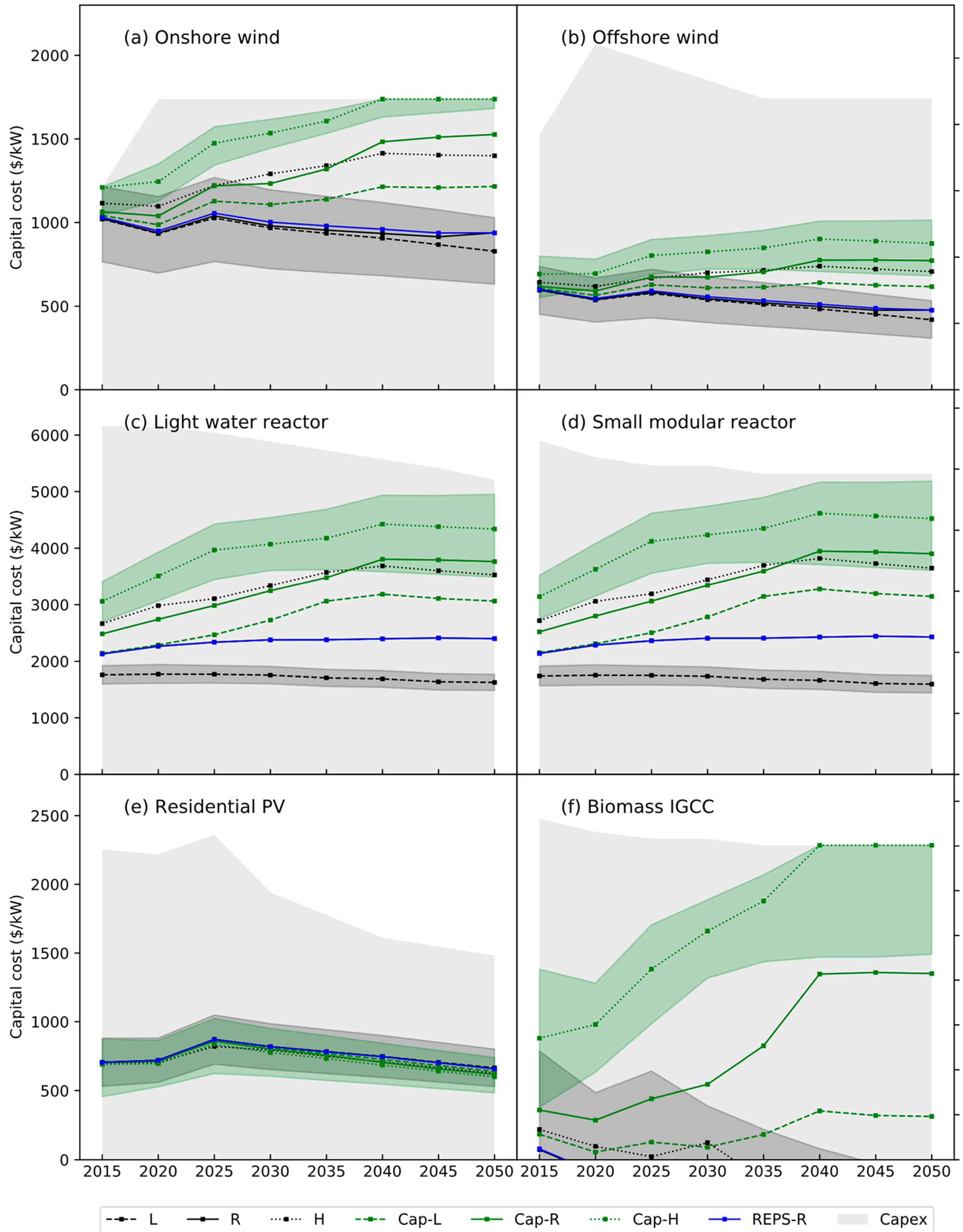

Figure 3. Break-even investment costs associated with (a) onshore wind, (b) offshore wind, (c) light water reactors, (d) small modular reactors, (e) residential solar PV, and (f) biomass integrated gasification combined-cycle. The dark gray and green bands represent the variation in break-even cost for a given technology when capital costs of all other generation technologies are simultaneously increased and then decreased by 20%. Note that in (c) and (d), the solid blue curve (REPS-R) is overlapping the solid black curve (R). In (f), the break-even costs of the L, R, H, and REPS-R scenarios are negative and are not displayed.

edge of the light gray area represents the exogenously specified capital cost for each technology within the model. In the case of wind and solar technologies, the increase in investment cost from 2015 to 2020 is due the expiration of federal tax credits (see SI Section 3 for details). Declines in the specified capital costs over time represent the effect of technological learning, which are exogenous to the model. The markers occurring within the lighter gray area indicate that the investment costs must be reduced to that amount—all else equal—before the technology will be deployed during that period and scenario. When the markers overlap the upper edge of the lighter gray area, it implies that the technology has been deployed during that period. Dark gray and green bands around the L and Cap-H scenarios represent the variability in break-even capital cost for a given technology when all other technology capital costs are increased and decreased by 20%. Caution must be exercised when interpreting these results. The scenarios are selected to form a cost envelope, enabling a wide range of

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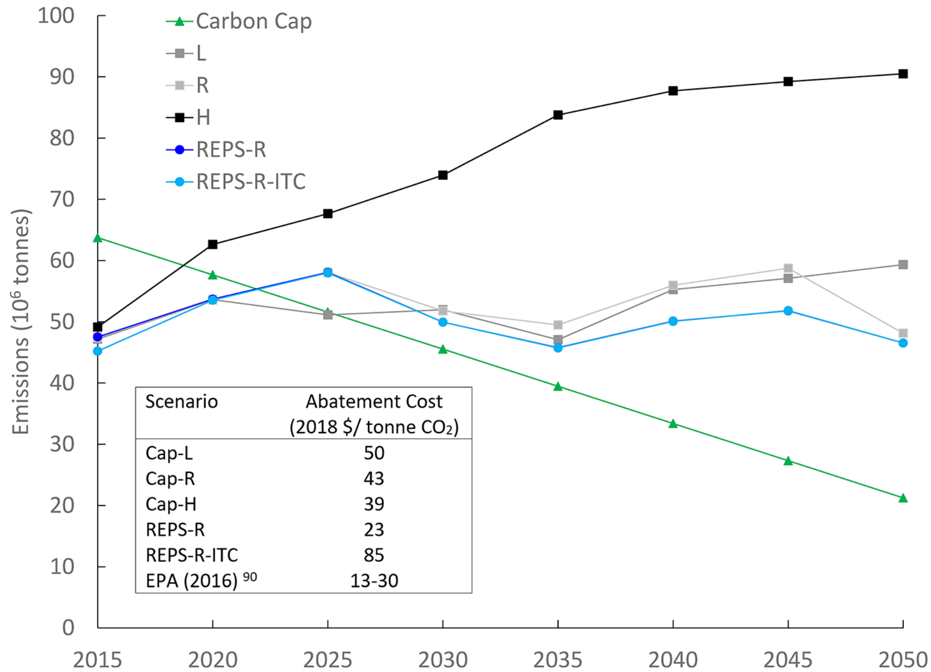

Figure 4. CO_2 emissions across all tested scenarios. The CO_2 cap is binding regardless of the prevailing fuel price projections in the cap scenarios. The table near the bottom left provides the average abatement costs calculated from the model results; the EPA social cost of carbon range from 2015 to 2050 at a 5% discount rate is included for comparison. All abatement costs are in 2018 dollars.

break-even costs across scenarios. However, the break-even costs plotted in Figure 3 are illustrative, and should be interpreted as discrete results drawn from a continuous space.

We chose to focus the break-even cost analysis on low carbon options, including renewables (onshore and offshore wind, residential solar PV, biomass IGCC) and nuclear (conventional light water reactors, small modular reactors). Utility-scale PV is excluded since it is already cost-effective in all modeled scenarios. Figure 3 indicates how the break-even costs vary under different scenario assumptions. In most cases, the break-even costs reach a maximum under the Cap-H scenario, which offers the best economic conditions under which to deploy low carbon technologies. Likewise, break-even costs are at a minimum under the L scenario, where low natural gas prices and no emissions limit make renewables and nuclear less cost-effective. The dark gray and green bands representing capital cost variation produce changes in the break-even cost that are comparable to the shift from one scenario to another. Variations in band thickness are also discernible. For example, the green band in Figure 3a is narrower than the gray band, indicating higher sensitivity of onshore wind breakeven costs to other technologies under the L scenario than under the Cap-H scenario. By contrast, the width of the green bands are wider than the gray bands in Figure 3c,d, indicating that breakeven costs of nuclear technologies are more sensitive to variations in the capital costs of other technologies if the CO_2 cap is in effect.

Figure 3c indicates that new light water reactors are cost-effective under the Cap-H scenario with a capital cost of 4500 \$/kW, but the break-even capital cost drops below 2000 \$/kW in the L scenario. Thus, the cost-effectiveness of conventional nuclear is highly sensitive to both fuel prices and the presence of the CO_2 cap. Small modular reactors share a very similar break-even cost pattern to conventional light water reactors given their similar cost and performance characteristics. Because offshore wind is much more expensive than onshore wind, onshore wind is deployed in the Cap-H scenario and the capital cost reductions required in the other scenarios are smaller compared with offshore wind. However, given offshore wind's higher capacity factors, it can be cost-effectively deployed at a higher capital cost than onshore wind. Surprisingly, biomass IGCC exhibits negative break-even costs in the fuel price scenarios without a carbon cap, indicating that there is no break-even capital cost that makes it cost-effective in those scenarios. Even with zero capital cost for biomass IGCC, it still has high fixed operations and maintenance (O&M) costs: the present cost of the fixed O&M represents over 50% of its capital cost, but is less than 30% for most other technologies.

The Extended REPS Scenario. Suppose that state legislators decide to pursue the extended REPS (REPS-R). Compared with the R scenario (Figure 1c), the REPS-R (Figure 1g) includes additional solar PV generation, which displaces natural gas generation. Legislators might wish to consider an additional provision under REPS-R to promote diversity in renewables supply. Using the break-even cost information in Figure 3, further suppose that lawmakers decide to target the deployment of onshore wind. The break-even cost for onshore wind under the REPS-R scenario ranges from 930 to 1060 \$/kW between 2020 and 2050 (Figure 3a), corresponding to a capital cost reduction between 32 and 39%.

This break-even cost information can be used in at least four different ways to inform the extended REPS. First, the required capital cost reduction can be used to calibrate an investment tax credit for wind to stimulate its deployment. Second, policy makers could decide to create a carve out for onshore wind, and the breakeven price could be used to set a cap on the incremental cost of wind Renewable Energy Certificates (RECs) that are allowed to be passed on to rate payers. Third, a carve out for wind can be created, and the break-even price used to calibrate an alternative compliance payment (ACP), which provides a price ceiling in the RECs market.[87]

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ACPs are penalty payments that a utility pays to the utilities commission or other governmental body if renewable energy goals are not met. As they are typically not recoverable from ratepayers, it is important to set the ACP at an appropriate level to encourage compliance with REPS laws. Wiser et al.[88] provide additional details about ACPs and values previously used in different U.S. states. Fourth, the break-even prices could be used to guide electricity system regulators in long-term energy auctions for renewables. While not applicable in the vertically integrated NC electric sector, these prices could potentially serve as the basis for designing appropriate subsidies to promote competition and achieve the lowest bids by generation source in competitive power markets.[89]

For simplicity, we consider an investment tax credit for onshore wind—Option 1 above—by performing an additional run with an assumed 40% reduction in the wind capital cost, which is slightly higher than the 32−39% required reduction derived from Figure 3a. As indicated in Figure 1h, the proposed ITC allows onshore wind to achieve 6% of the 2040 generation mix under the extended REPS.

CO_2 Emissions and Abatement Costs. The CO_2 emissions across all scenarios are shown in Figure 4. The CO_2 cap is binding across the three carbon constrained scenarios, and is represented by the green line in Figure 4. Only the H scenario shows a substantial rise in CO_2 emissions—80% above the 2015 level in 2050—driven by the resurgence of coal. In the L, R, and REPS-R scenarios, the emissions reduction between 2020 and 2035 reverses in later time periods due to demand growth coupled with higher natural gas utilization. Cumulative CO_2 emissions in the REPS-R scenario are 5% lower than the R scenario, indicating that the extended REPS only has marginal effects on CO_2 emissions. In addition, Figure 4 shows the CO_2 emission profile of the REPS-R scenario with and without the investment tax credit for wind are nearly the same, implying that the wind ITC leads to the deployment of wind at the expense of solar rather than increasing their overall combined deployment. Thus, the wind ITC has negligible effects on fossil-based generation.

In addition, we calculate the average CO_2 abatement costs ($ per tonne CO_2) by computing the ratio of the difference in total costs to the difference in total emissions between each pair of scenarios consisting of a cap scenario and a scenario of the same fuel price without the cap. Similarly, the REPS-R scenario is compared with the R scenario. Therefore, the CO_2 abatement costs are proportional to increases in total costs, and inversely proportional to CO_2 emission reductions. The CO_2 abatement costs are included in Figure 4. The Cap-H scenario has the lowest average CO_2 abatement cost due to the proportionally larger CO_2 emission reduction than in the other two cap scenarios. Although the CO_2 emission reductions in the Cap-L and Cap-R scenarios are similar, the cost increase from the L to the Cap-L scenario is higher than from the R to the Cap-R scenario due to the higher cost of replacing natural gas technologies with renewables in the L scenario. In the REPS-R-ITC scenario, we include the cost of the ITC in the calculation of abatement cost. Note that the ITC pushes the abatement cost above 80 $/tonne CO_2 because it does not increase the level of emissions reductions. In such a scenario, policy makers must weigh whether such additional cost is worthwhile in light of other objectives, such as supply diversification and rural economic development. For comparison, Figure 4 also includes EPA's social cost of CO_2 (SC−CO_2) values from 2015 to 2050 at a discount rate of 5%,[90] which is the same global discount rate used in our model. Though the modeling approach is different, the CO_2 abatement costs in the three cap and REPS-R scenarios are generally higher but overlap the EPA estimates.

Policy Implications. In North Carolina, solar PV is the most cost-effective low carbon technology, and would likely be used to meet future REPS or CO_2 cap requirements, consistent with past development. However, uncertainty in future capital costs could lead to different outcomes. The break-even cost represents the capital cost required to achieve the deployment of a technology that is not cost-effective under baseline assumptions. Our analysis indicates that the technology-specific break-even costs can vary significantly across scenarios. For example, the break-even nuclear costs vary by more than 20% of their baseline capital cost across some modeled scenarios. In addition, as indicated in Figure 3, variations in the capital cost of other generating technologies can shift the break-even cost of a given technology by roughly the same magnitude as switching between scenarios.

The break-even cost analysis presented here could be particularly helpful for states trying to formulate new energy or climate policy by allowing decision makers to compare the relative cost-effectiveness of different technologies under a wide variety of scenarios. Such information can be used in several ways. First, comparing break-even costs can help policy makers incentivize the deployment of technologies that deliver the highest public benefit at the lowest cost. Second, break-even costs can be used to determine alternative compliance costs, or the cap on a utility's allowable recovery of incremental REC costs from ratepayers. Third, break-even costs could be used to inform technology research and development aimed at achieving a particular cost target. Fourth, while the break-even costs in this analysis are based on future capacity expansion, it could be adapted to estimate the zero emissions credit levels necessary to maintain the existing fleet of nuclear over the next few decades. Several states, including Illinois, New Jersey, and New York have implemented zero emissions credits[91,92] for existing nuclear generators. The credits represent the zero emissions attribute of each megawatt-hour produced by a qualified nuclear power plant. Previous analysis indicates that the preservation of existing nuclear is a cost-effective carbon avoidance strategy.[93]

Federal action on climate is not imminent. The United States plans to withdraw from the Paris Agreement, and the EPA Clean Power Plan has been repealed. However, several states have pledged to uphold the Paris Agreement,[94] and many states have already taken actions, such as the Regional Greenhouse Gas Initiative[95] and California's cap-and-trade system.[96] The requisite policy planning would benefit from ESOM-based analysis, which can help states achieve their desired emissions targets cost-effectively. This analysis provides a blueprint that can be replicated in other states with a publicly available model.

Caveats. In this analysis, we try to place focus on our modeling approach and generalized insights that are robust to the model limitations and high future uncertainties. Nonetheless, several caveats are worth noting. First, scenario-specific results pertaining to future electricity generation, break-even costs, and emissions are dependent on the baseline assumptions used in the model. The capital cost sensitivity performed in break-even cost analysis demonstrates how technology-specific cost-effectiveness can change when the

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baseline capital cost of other technologies are varied. Though not presented here, we also tested a ±40% range on other capital costs and observed a linear increase in the width of the gray and green uncertainty bands presented in Figure 3. Second, using a single solver occasionally returned anomalous results. SI Section 4 explains in detail the procedure we implemented to work around this difficulty. Third, while the increased number of time slices, capacity reserve constraint, and ramp rate constraint help constrain system performance within reasonable bounds, the model does not perform hourly unit commitment and dispatch[97] or consider the need for operating reserves.[98] Additional effort is required to increase the temporal resolution in ESOMs to better represent power system operation. Fourth, we assume a fixed exogenous demand across all scenarios. Price-responsive demands would lower electricity demand in cap scenarios with higher electricity prices, but would not fundamentally change the relative grid mix or technology cost-effectiveness. Finally, while we demonstrate the utility of break-even cost analysis, it represents one of many sensitivity and uncertainty analysis methods that should be brought to bear on model-based analysis aimed at informing policy.[99]

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.9b04184.

> Additional constraints, including the reserve margin constraints and the ramp rate constraints; Overview to the electric system of North Carolina, the electricity consumption history and future demand predictions (Table S2 and Figure S1); Environmental regulations, emission limits (Figure S5); Fuel costs (Figure S8); Supplementary results, capacity mixes (Figure S11) (PDF)

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Notes

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