NUCLEAR ENERGY IN LONG-TERM SYSTEM MODELS

A Multi-Model Perspective

Nuclear Energy in Long-Term System Models

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Abstract

Long-term energy system models—including electric sector capacity expansion models—are widely used tools for informing planning, technology assessment, and policy analysis. Recent decarbonization goals and rapid technological change have increased the need to appropriately represent economic characteristics and technical details of energy system resources, including variable renewable energy, energy storage technologies, carbon-capture-equipped capacity, and nuclear energy.

Nuclear power represents about 20% of electricity generation and 50% of carbon-free electricity in the United States as of 2021. However, there are many perspectives on the role of existing and new nuclear in the future U.S. energy system, which is reflected in the broad range of potential contributions reported in the literature.

This project aims to understand how issues central to nuclear energy are represented in long-term energy models. Building on earlier collaborations that focused on variable renewable energy and energy storage, this project convenes four modeling teams that use national-scale long-term energy system models from the Electric Power Research Institute, the National Renewable Energy Laboratory, the U.S. Energy Information Administration, and the U.S. Environmental Protection Agency to share methods and data, update models, run coordinated scenarios, and identify research needs. Improving tools can provide more insightful analyses and ensure that methods are more transparent.

Guided by inter-model comparisons and intra-model scenario analyses, we investigate how model structures and input assumptions impact projections, refine model representations of nuclear energy, and communicate findings to the research community and consumers of modeled scenario results. A greater understanding of model structures, assumptions, parameters, and limitations can improve model capabilities to effectively represent interactions under a variety of market and technology assumptions.

This report synthesizes our collective modeling experience, reviews the literature, and highlights research gaps—which results in recommendations on approaches for representing nuclear energy in long-term energy system models. Such comparisons can identify robust findings and critical assumptions impacting model projections.

Nuclear energy's role in forward-looking scenarios varies due to differences in scenario assumptions, model structure, and regional characteristics. The scenario design assumptions that have the greatest influence on nuclear deployment are policies and technological cost. Details about a policy's stringency, timing, and technology eligibility influence decarbonization outcomes and nuclear deployment. Higher shares of nuclear generation occur in scenarios and regions with favorable:

- **Policy conditions:** Deeper decarbonization targets and restrictions on other low-emitting options (e.g., constraints on carbon removal and carbon capture)
- **Regional economic characteristics:** Regions with supporting policies as well as lower wind and solar resource quality
- **Financial assumptions:** Lower nuclear capital costs and lower discount rates
- **Combinations of these factors**

Nuclear power can complement extensive additions of wind, solar, energy storage, and other resources by providing firm, zero-emissions electricity. The range of nuclear deployment in forward-looking scenarios highlights uncertainty moving forward, but it also stresses the importance of significant nuclear technology advancement and electric sector policies.

Overall, these findings point to the important roles that underlying model structure and input assumptions play in projections for nuclear energy in mitigating climate change and lowering multiple air pollutant emissions. The four participating models have undertaken a variety of nuclear-specific modifications and broader model updates over the course of this project, which have altered model outcomes and improved insights.

Model complexity can strongly impact projected electric sector investments and costs, and many considerations (e.g., parameterization of solar, wind, and storage technologies and temporal resolution) have more significant impacts with deeper decarbonization. Levelized-cost metrics are incomplete for evaluating the relative competitiveness of system resources, which requires detailed energy modeling to assess. The report also identifies several model development priorities and data needs related to nuclear and broader energy systems, including representing hybrid systems that support electric and non-electric applications, capturing integration across systems, linking modeling tools of different resolutions, and several others.

Keywords
Capacity expansion modeling
Decarbonization
Energy systems modeling
Model intercomparison
Nuclear energy
Power sector economics

List of Abbreviations

AEO	Annual Energy Outlook
BECCS	bioenergy with carbon capture and storage
BWR/PWR	boiling/pressurized water reactor
CCS	carbon capture and storage
CDR	carbon dioxide removal
CEM	capacity expansion model
CES	clean electricity standard
DOE	U.S. Department of Energy
EIA	U.S. Energy Information Administration
EMM	Electricity Market Module
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
FOM	fixed operations and maintenance
G&A	general and administration
GW	gigawatt (electric)
INL	Idaho National Laboratory
IPM	Integrated Planning Model
kW	kilowatt (electric)
LCOE	levelized cost of electricity
LOLE	loss of load expectation
MWh	megawatt-hours (electric)

NEMS	National Energy Modeling System
NERC	North American Electric Reliability Corporation
NGCC	natural gas combined cycle
NPV	net present value
NRC	U.S. Nuclear Regulatory Commission
NREL	National Renewable Energy Laboratory
NVOC	net value of capacity
NVOE	net value of energy
O&M	operations and maintenance
PV	photovoltaic
RD&D	research, development, and demonstration
ReEDS	Regional Energy Deployment System
REGEN	Regional Economy, GHG, and Energy
RPS	renewable portfolio standard
SMR	small modular reactor
t	tonne (metric ton)
TWh	terawatt-hours (electric)
U.S.	United States
VRE	variable renewable energy
WACC	weighted average cost of capital
yr	year
ZEC	Zero Emissions Credit
$	U.S. dollar

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Section 1: Introduction

Background: Nuclear Energy in Long-Term System Models

Capacity expansion models (CEMs) are tools for informing strategies to meet future electricity and energy needs under a range of policy scenarios, technology options, and market conditions. However, CEMs vary significantly in their coverage, structure, and input assumptions. As a result, model projections for similar policies can differ—sometimes dramatically. Such differences can support alternate strategies for research, development, and demonstration (RD&D); alter assessments of existing and proposed policies; and shape decisions by governments and industry. Models can influence the world they seek to understand and consequently merit detailed examinations and comparisons.

Understanding model differences and output drivers is important for improving model capabilities and resulting insights, providing context for interpreting results, and better informing users of model-based studies. Working with teams who create, update, and apply these models—as well as subject matter experts from national laboratories, industry, and research community—has led to a forum in which experts can discuss modeling assumptions and challenges, including earlier efforts focusing on variable renewables and energy storage (Cole, et al., 2017; Bistline, et al., 2020) as well as this collaboration on nuclear energy.

Nuclear power is 20% of electricity generation in the U.S. and 50% of low-carbon electricity.

Nuclear power currently represents about 20% of electricity generation in the United States, which makes it the largest source of low-carbon electricity—roughly half of emissions-free electricity and more than solar, wind, and hydropower generation combined in 2020 (EIA, 2020a). Many decarbonization studies see nuclear energy and other low-emissions firm technologies as complements to renewable energy technologies; in particular, their always-available power can fill in weekly and monthly gaps when wind and solar output are low, which can help to lower decarbonization costs (Baik, et al., 2021; Brown and Botterud, 2021; Bistline and Blanford, 2020; Jenkins, Luke, and Thernstrom, 2018; Sepulveda, et al., 2018). However, there are many perspectives on the future role of nuclear in the U.S. energy system, which is reflected in the broad range of nuclear-related scenario outputs in the literature (Bistline and Blanford, 2021; Bistline, et al., 2018) and in scenarios from this study (summarized in Figure 2-1). Although it can provide virtually emissions-free[1] electricity and heat with a relatively small land footprint, nuclear energy also

[1] Nuclear has among the lowest lifecycle emissions intensity of generation (i.e., including fuel production and material needs), even among clean electricity resources (NREL, 2021; Pehl, et al., 2017).

raises potential concerns about safety, cost, waste disposal, and non-proliferation. Advanced nuclear designs offer potential enhancements around these issues, but there is uncertainty about how these factors could shape nuclear energy's contribution.

Model intercomparison studies such as this one can identify robust findings across models, transfer learnings, and isolate critical assumptions that impact projections. Such coordinated multi-model exercises are useful in understanding differences in data, assumptions, methods, and outputs and have been used in a range of fields such as climate science and energy modeling (Weyant, 2017). Through coordinated scenario analysis, model intercomparisons can highlight which conclusions appear to be robust and which are more uncertain, which can guide future research. These exercises help to determine how differences in model outputs may reflect differences in model structure (e.g., temporal resolution, technology choice), input assumptions (e.g., technology cost and performance), and scenario specifications.

In this study, different scenarios and their associated technology and policy assumptions are used to evaluate model behavior. They do not reflect policy or market expectations of the modelers or their respective organizations. While these results may provide insight into policy and market behavior, the scenarios and report itself are not designed or intended to be interpreted as a policy development exercise.

Summary of Motivating Questions and Findings

What is the potential role of nuclear energy in the U.S. electricity mix by 2050? How does this role depend on technology and policy uncertainties?

The model intercomparison in Section 2 suggests a broad range of installed nuclear capacity across models and scenarios—ranging from 36–92 GW in 2030 and 2–329 GW in 2050 across all of the policy and technology scenarios in the analysis (Figure 2-1). With harmonized technology cost assumptions, the range of nuclear capacity narrows to 83–92 GW in 2030 and 63–120 GW in 2050.

Future nuclear cost trajectories and CO_2 policy assumptions have significant impacts on installed nuclear capacity. Decarbonization targets generally help to retain existing nuclear capacity but may not be enough to bring new nuclear capacity online in the absence of significant cost declines. Models show sizable nuclear additions in scenarios that layer power sector decarbonization policy with low-cost assumptions for new nuclear capacity. With these low costs, total installed nuclear capacity including existing plants ranges from 76–187 GW by 2050 with current policies, which increases to 285–329 GW under a zero CO_2 policy in the electric sector.

How much do models vary in their projections for nuclear energy? How does this variation compare with other technologies?

Using default model assumptions,[2] nuclear generation shares in 2050 vary across models from 7–13% in the current policies scenario and 10–17% in the 80% CO_2 policy scenario (Figure 2-3). This variation across models is similar to other generation technologies—natural gas shares span 28–61% in the current policies scenario (9–23% with an 80% power sector CO_2 cap), and wind and solar shares span 19–48% in the current policies scenario (53–69% with an 80% power sector CO_2 cap).

How does harmonizing input assumptions impact model projections?

Harmonizing technology cost assumptions narrows the variation in 2050 nuclear generation shares across models from 7–13% to 10–13% under current policies and from 10–17% to 12–14% under a power sector CO_2 policy with 80% reductions from 2005 levels (Figure 2-3). However, harmonizing discounting and financing assumptions can broaden this range to 0–13% under current policies and 6–14% under the 80% CO_2 policy, a difference largely due to changes in existing nuclear retirements in REGEN (which is investigated in detail in Section 7). These comparisons reinforce that differences across models play critical roles in projections and highlight the value of model intercomparison studies to inform planning and policy, as single-model studies may understate potential variation in outputs of interest.

Which model features and assumptions have the largest influence on projections for installed nuclear capacity?

Using inter-model comparisons (Section 2) and intra-model scenario analyses (Sections 4 through 7), the report shows how models vary in their treatments of key considerations related to nuclear energy and other electric sector resources, which can affect insights about their future roles. Key assumptions include CO_2 policy details (Figure 2-1 and Figure 4-4), cost and performance of new nuclear and other technologies (Figure 2-1), operations and maintenance costs of existing nuclear (Figure 5-2), and discounting/financing (Figure 7-4).

Differences in projections are due to a combination of these input assumptions, model structure (e.g., temporal resolution in Figure 7-1), and algorithms (e.g., age-based algorithms to represent capital expenditures for existing nuclear plants). In all cases, having transparent and public data are important for validating and comparing across models and against observed trends, as appropriate.

[2] Default assumptions include technological cost and performance projections and policies that were in place when the modeling was completed in 2021. Section 2 discusses scenario assumptions in detail, and Appendix B summarizes policies included in all scenarios.

This report discusses several additional areas for future work that may impact model projections, including representing hybrid systems and capturing integration across systems in greater detail, examining economy-wide net-zero scenarios, as well as developing methods for quantifying and incorporating climate impacts and resource adequacy.

What Are Long-Term Energy and Electric System Models?

Long-term energy system models have large influences on planning and policy analysis.

Long-term energy system models—including CEMs of the electric sector—are computational tools that are created and applied by a range of organizations to answer questions and inform decisions. These models can influence planning and policy analysis, including directly informing policy-makers at federal, state, and local levels. They can inform government and private sector decisions by supporting technology assessment, policy analysis, and RD&D prioritization.

Electric sector CEMs capture both investments and operations over multi-decadal time horizons. The coupling of these decisions makes these models complex,[3] and since there is typically a focus on investments, CEMs make approximations about the representation of operations relative to other model types such as operational simulation models. These models are built to represent the competition among existing and new generation, transmission, and energy storage assets, where the typical goal is to find least-cost portfolios to balance demand across all model regions subject to technical, market, and policy constraints. These constraints include serving electric loads, meeting operating and planning reserve requirements, satisfying emissions policies, and other requirements specified by the user. Model decisions can include both investments in new resources and retirement of existing resources. The geographical scope can be regional, national, or international.

The report focuses on national-scale models that consider the evolution of the U.S. energy or electric sector through at least 2050 given their prevalence in planning and policy analysis, though many findings are transferrable to other contexts. Details of the models used in this work are presented in Section 3.

The general aim of analyses performed by long-term energy systems and electric sector models is understanding and insight to guide decisions, rather than specific numbers or predictions of particular outcomes (Huntington, Weyant, and Sweeney, 1982). All models are approximations of the complex systems they represent and make a range of simplifications to render them tractable. Model decisions involve necessary tradeoffs between the degree of simplification to ensure tractability and the accuracy of the representation (EPRI, 2021; Merrick and Weyant, 2019; Saltelli, 2019). CEMs are better suited for answering some questions (e.g., impact of capital costs or policy design on the economics of

[3] These large optimization models are sometimes linked to or embedded in broader energy systems (or economy) models to capture important interactions.

nuclear and renewable energy technologies) and less well suited for others (e.g., siting questions for specific plants, value of flexibility in preventing outages when another generator trips offline).

Project Objectives

The goals of this collaborative research project are:

- To understand how issues central to nuclear energy are modeled in long-term capacity expansion models;
- To investigate how model structures and input assumptions impact projections for the roles of existing and new nuclear power plants through inter- and intra-model comparisons under a range of technology, market, and policy conditions;
- To identify areas for refining the representation of existing and new nuclear energy options (and, to the extent feasible, implement these changes and run diagnostic tests to understand how these features could impact projections); and
- To communicate findings to the research community and consumers of model outputs.

We identify technical issues associated with model representations of nuclear energy and other system resources and develop observations from the literature on best practices.

Improving these tools can improve insights, helping stakeholders to improve their understanding of the potential role of nuclear in future energy systems. A greater awareness of model structures, assumptions, parameters, and limitations can improve the models' capability to effectively represent market interactions under a variety of market and technology assumptions, enhancing the ability of decision-makers to evaluate the value of new and existing nuclear generation.

Project Participants

This report synthesizes findings from the two-year collaborative project among DOE, EIA, EPRI, INL, NREL, and EPA.

Representing nuclear energy in long-term system models led to the current collaboration to assess current practices, share data and methods, and identify future research needs. The study is patterned after recent collaborations among EIA, EPRI, NREL, and EPA to assess and compare the model approaches, structures, and underlying assumptions that impact model outputs for variable renewable energy (Cole, et al., 2017) and energy storage technologies (Bistline, et al., 2020). The four participating models include:

- Integrated Planning Model (IPM) from the U.S. Environmental Protection Agency (EPA)
- National Energy Modeling System (NEMS) from the U.S. Energy Information Administration (EIA)

- Regional Energy Deployment System (ReEDS) from the National Renewable Energy Laboratory (NREL)
- Regional Economy, Greenhouse Gas, and Energy (REGEN) from the Electric Power Research Institute (EPRI)

Existing Literature

This report surveys the treatment of key modeling issues for nuclear energy and provides a scenario-based comparison to explore nuclear drivers.

There are multiple surveys on best practices for modeling other technologies such as variable renewables and energy storage, where nuclear energy is mentioned but is not the focus (Bistline, et al., 2020; Cole, et al., 2017). The only model intercomparison study focusing on nuclear-related outputs is a paper by Kim, et al. as part of the Energy Modeling Forum (EMF) 27 study (Kim, et al., 2014). However, that analysis used global integrated assessment models instead of detailed CEMs, and the assumptions do not reflect technological developments over the past decade. Other model intercomparisons include nuclear energy as a candidate technology but do not focus on nuclear-related drivers or technology scenarios (Baik, et al., 2021; Mai, et al., 2018).

The existing literature also includes sensitivity and scenario analysis conducted to better understand the role of nuclear in single-model frameworks, especially in decarbonization scenarios (Baik, et al., 2021; Zhang, et al., 2021; Bistline and Blanford, 2020; Bistline, James, and Sowder, 2019; Sepulveda, et al., 2018). These scenarios generally indicate large roles for variable renewable energy and battery storage technologies, but least-cost decarbonization portfolios often include low-emitting firm[4] technologies such as nuclear, carbon-capture-equipped capacity, biomass, geothermal, hydropower, and low-carbon gas-fueled plants (e.g., hydrogen).

The current report offers two unique contributions to the literature. First, we survey the treatment of key modeling issues for nuclear energy in long-term system modeling. Second, we provide a scenario-based intercomparison to investigate how different input assumptions alter model outputs related to nuclear energy for each of the included models.

Report Structure

This report is organized as follows. Following the introductory section, Section 2 discusses scenarios and results for a coordinated model intercomparison analysis. Section 3 provides high-level overviews of the four participating models.

Sections 4–7 of the report describe key modeling issues for incorporating nuclear energy into long-term energy systems analysis. Each provides a summary of approaches for a specific issue, related literature, intra-model comparisons, and research gaps. Instead of making prescriptive suggestions about appropriate model features, these sections emphasize that distinct considerations are

[4] Firm resources are "technologies that can be counted on to meet demand when needed in all seasons and over long durations (e.g., weeks or longer)" (Sepulveda, et al., 2018).

important for different research questions and that navigating these tradeoffs requires judgment from modeling groups that accounts for their unique circumstances. Model development decisions depend on the analysis type; motivating questions; energy system characteristics; and available staff, funding, and computational resources for development and analysis (Merrick and Weyant, 2019; Saltelli, 2019).

Section 8 recaps insights from the report and describes opportunities for additional research. Appendix A discusses model-specific enhancements that were undertaken during this project.

Section 2: Model Intercomparison

Summary

- To understand impacts of different input assumptions and model structures, this section summarizes results of a model intercomparison, where the four participating models ran scenarios with native and harmonized inputs across a range of future technology and policy assumptions.
- Results suggest that installed nuclear capacity can span a broad range across models and scenarios (Figure 2-1). Installed nuclear capacity ranges from 36–92 GW in 2030 and from 2–329 GW in 2050. With harmonized technology cost assumptions, the range of nuclear capacity narrows to 83–92 GW in 2030 and 63–120 GW in 2050. Under current policies, differences in nuclear FOM costs and capital costs for other generation technologies largely explain the range of nuclear capacity retirements. Differences across models in the generation mix and capacity deployment are due to input assumptions about technological cost, financing, and demand.
- Results across models indicate the pronounced impact that stringent power sector carbon policies could have on the future U.S. electricity supply mix. Under a policy that reduces electric sector CO_2 by 80% from 2005, there are several robust findings across models, including keeping most existing nuclear capacity online; lowering coal generation significantly; and deploying considerably more wind, solar, and energy storage (though magnitudes vary by model). The role of nuclear increases under more stringent climate policy scenarios—decarbonization targets generally help to retain existing nuclear capacity but may not be enough to bring new nuclear capacity online in the absence of significant cost declines. In scenarios that layer a deep decarbonization policy with low capital cost assumptions for new nuclear (moving from harmonized assumptions of $5,000/kW by 2050 to $2,000/kW), models show significant nuclear capacity additions, which are concentrated in the U.S. South and West.
- Zero CO_2 emission scenarios in the electric sector entail additional wind, solar, energy storage, hydrogen, and nuclear capacity, though shares vary by model. These scenarios generally indicate large roles for variable renewables and battery storage, but their variability and energy-limited discharge mean that least-cost decarbonization portfolios often include other technologies, especially zero- and low-emitting firm technologies such as nuclear, carbon-capture-equipped capacity, biomass, geothermal, hydropower, and zero-carbon gas-fueled plants (e.g., hydrogen).

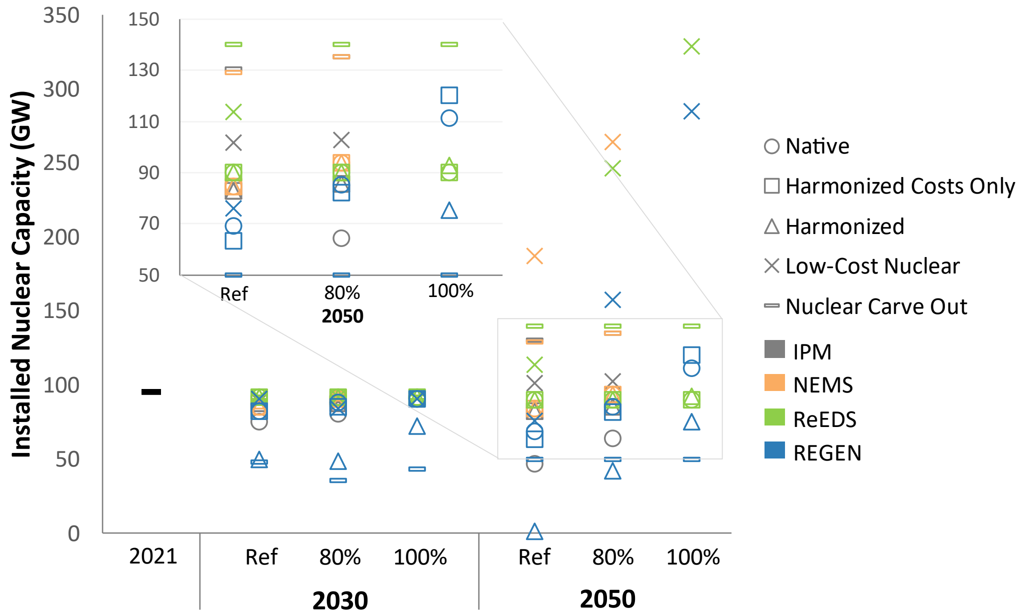

Figure 2-1
Total installed nuclear capacity by year and electric sector CO_2 policy scenario across all models and technology sensitivities. Policy scenarios include a current policies reference ("Ref") and "80%" or "100%" reductions in electric sector CO_2 by 2050 from 2005 levels.

- Assumed cost reductions and financing parameters for new nuclear have the greatest influence on the range of simulated nuclear additions under decarbonization scenarios. Model responses to alternate policy and technology assumptions vary across models. Differences in projected nuclear shares are due to differences in underlying assumptions and model structures, including retirements of existing reactors, the competitiveness of future technologies, and various model features described in other sections of this report.
- While these scenarios should not be interpreted as predictions, they are informative for understanding differing model assessments of the relative competitiveness of nuclear energy under a range of policy and technology conditions. The simulated magnitude of nuclear generation across scenarios could also provide insights for fuel, supply chain, and planning discussions.

Overview

Later sections of this report describe how the representation of nuclear energy varies across models. To understand impacts of these differences, this section summarizes *inter*-model comparisons, where all four participating models (IPM, NEMS, ReEDS, and REGEN) run the same scenarios with a common set of input assumptions and compare outputs of interest. These comparisons complement qualitative comparisons and *intra*-model comparisons in later sections, where a single model runs a series of diagnostic or scenario-based experiments.

Comparing outputs across models, technology assumptions, and policy scenarios informs model understanding, interpretation, and development decisions.

These diagnostic scenarios can inform model understanding, interpretation, and development for a range of stakeholders, and many insights may be able to inform decision-making. These policy and technology scenarios are designed to span a wide (but incomplete) range of futures to observe model behaviors for nuclear capacity expansion, retirement, and operation under different environments. While the results in this section can help inform discussions related to U.S. energy policy and RD&D priorities for nuclear power, they do not represent explicit policy analysis, recommendations, or critiques of ongoing discussions.

The results of this analysis should not be interpreted as predictions or indications of technology, market, or policy preferences. Instead, their primary role is to offer two primary forms of comparison—similarities and differences across the four participating models for a given scenario, and comparisons across technology and policy sensitivities for a given model. These comparisons offer insights into the model features and parameters that have the greatest influence on the simulated role of nuclear power plants across a range of future scenarios.

Scenarios

Scenarios in the model intercomparison include different combinations of assumptions about policy and technologies. For each scenario, models determine the least-cost mix of generation, energy storage, and transmission assets that can meet market and policy requirements through 2050. Later sections describe key differences in model structure and assumptions, which were not harmonized for these scenarios, including annual and peak demand assumptions, temporal resolution, spatial aggregation, transmission costs, foresight, and many others.

There are three policy-related sensitivities:

- **Reference ("Current Policies"):** This scenario reflects all on-the-books state and federal policies and incentives.[5] The goal of this scenario is to estimate how existing and new nuclear technologies (e.g., Gen III+, Gen IV, and SMR designs) could compete on a status quo economic and policy basis. State and regional policies include renewable portfolio and clean electricity standards, energy storage mandates, ZEC policies, and CO_2 caps/taxes both in the electric sector (Regional Greenhouse Gas Initiative, Colorado) and economy-wide (California) if models can represent these policies. Federal policies and incentives include production and investment tax credits with phasedowns, 45Q tax credits, and Clean Air Act § 111(b) CO_2 performance standards. Appendix B provides a more detailed list of U.S. federal and state policies represented in this scenario.

[5] Modeling for this study was completed in 2021 before the Bipartisan Infrastructure Law was passed, which means that the Civil Nuclear Credit Program and incentives for other electric sector resources (e.g., carbon capture, long-duration energy storage, transmission, hydrogen, advanced nuclear) were not included in these scenarios. Scenarios also do not include economy-wide or electric sector targets from the updated U.S. Nationally Determined Contribution.

The "Deep Decarbonization" scenarios explore nuclear's competitiveness in relation to other low-emitting technologies.

- **Deep Decarbonization (80-by-50 and 100-by-50):** The goal of the deep decarbonization scenarios, which reflect a policy push to lower CO_2 emissions, is to explore the competitiveness of nuclear energy in relation to other low- and zero-CO_2 technologies.[6] The national power sector cap begins at current levels and linearly decreases to meet 80% and 100% CO_2 reductions by 2050 (relative to 2005 levels), as shown in Figure 2-2. These cap-and-trade policies are implemented as national caps with "where" flexibility (i.e., free national trade), no banking or borrowing, and no offsets or alternative compliance payments.[7] The national CO_2 cap is implemented alongside the federal, regional, and state policies in the Reference ("Current Policies") scenario.

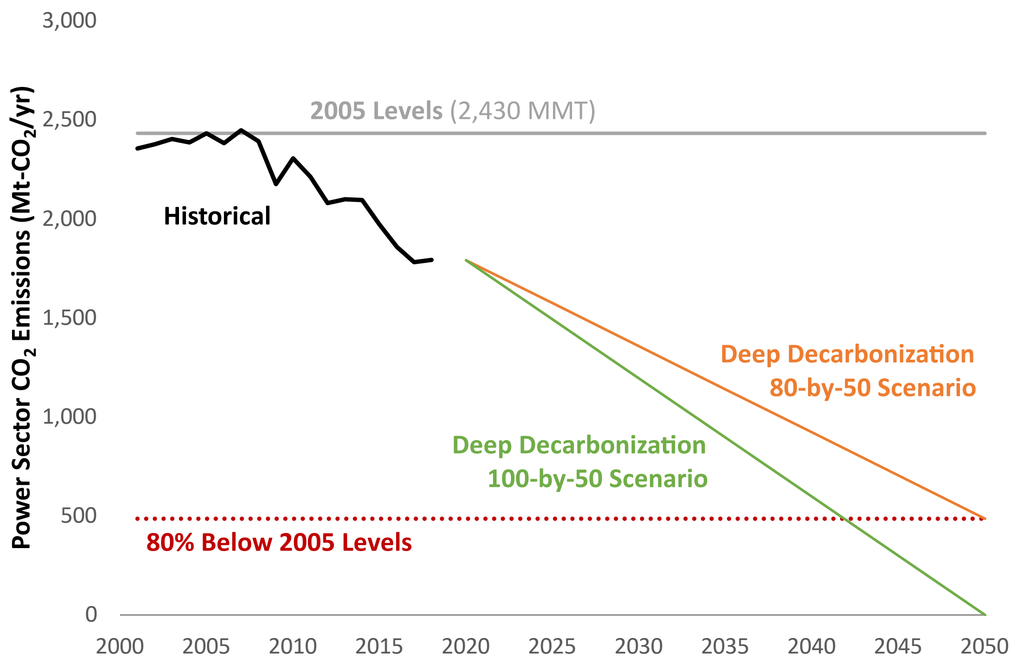

Figure 2-2
Historical U.S. electric sector emissions and proposed cap trajectories for the Deep Decarbonization scenarios.

The 100% by 2050 scenarios represent a transformational shift in the U.S. electricity supply. As a result, only the REGEN and ReEDS models were able to run these scenarios. Note that some mitigation options that could play important roles in achieving such a transformational change were not considered in these scenarios, including negative emissions technologies (such as direct air capture or bioenergy with carbon capture and sequestration) and demand-side approaches.

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[6] Note that CO_2 caps are more technology-neutral emissions reduction approaches relative to technology-specific tax incentives, mandates, or portfolio standards that only include a subset of electric sector resources.

[7] The NEMS model implemented a carbon tax proxy instead, which was designed to achieve a similar level of emissions reductions.

These policy scenarios are run for different technology assumptions:

- **Native Assumptions:** These technological assumptions use all modeling teams' default assumptions for technology cost and performance. Native capital costs over time are compared in Figure 6-1. The goal of this scenario is to understand the competitiveness of existing/new nuclear technologies, using the models as they are currently parametrized.
- **Harmonized Costs Only:** These scenarios align costs only in order to quantify the relative magnitudes of cost assumptions and discounting/financing in driving model outputs. Here, the cost and performance assumptions from the Harmonized Technology Assumptions section are used, but each model uses its native assumptions about financing and discounting.
- **Harmonized Assumptions:** In this scenario and where existing model structure allows, all models use a common set of input assumptions for capital costs, FOM costs, discounting, and financing. The goal is to evaluate the role of input assumptions versus model structure in projections of nuclear energy in the power sector. Specific assumptions include:
  - Cost and performance assumptions for new investments: Use NREL's 2020 Annual Technology Baseline (NREL, 2020), due to its public availability and transparency. All costs are exogenous over time (i.e., endogenous technological learning is turned off in all models). Native capital costs by technology over time are shown in Figure 6-1, and assumptions from ReEDS are used for the harmonized values.
  - FOM costs for existing nuclear: FERC Form 1 FOM plus EUCG maintenance capital costs are assumed. A comparison of native FOM costs are shown in Figure 5-1, and assumptions from REGEN are used for the harmonized values, which do not change over time.
  - Financing: Discount rate (Weighted Average Cost of Capital, real dollar terms) of 3% and capital recovery period (economic lifetime) of 30 years for all investments (including all nuclear and non-nuclear generation options). Native and harmonized discount rates and economic lifetime assumptions are shown in Figure 7-2 and Figure 7-3, respectively.
  - Construction time: Construction time for SMRs is assumed to be 5 years, while other new nuclear capacity is assumed to be 10 years.
- **Harmonized Assumptions with Low-Cost Nuclear:** Another scenario uses the same harmonized assumptions from above, but considers much lower cost assumptions for new nuclear capital costs and existing nuclear FOM costs. Although new nuclear capacity is available in each model and scenario beginning in 2028 or 2030, this scenario adjusts new nuclear costs to $2,000/kW beginning in 2035 (Table 2-1).[8] This stylized sensitivity examines how much lower costs for new nuclear impact deployment

[8] This stylized trajectory is informed by breakeven costs from the analysis in Bistline, James, and Sowder (2019).

outcomes under different policy conditions. Additionally, FOM costs for existing nuclear are 25% lower than the reference values, assuming plant modernization can lower net costs (including modernization costs[9]).

- **Harmonized Assumptions with Nuclear Carveout:** In addition to harmonizing input assumptions, this scenario harmonizes model outputs for new nuclear additions over time, which illustrates how a nuclear capacity carveout impacts outputs of interest across models. This scenario enforces a national-level capacity[10] constraint in which total installed new nuclear capacity meets the following stylized glidepath: 5 GW by 2035, 15 GW by 2040, 30 GW by 2045, and 50 GW by 2050.

Table 2-1
Overnight capital cost assumptions for new nuclear power plants ($/kW) for the "Harmonized" (NREL, 2020) and "Low Costs" sensitivities

Sensitivity	2020	2035	2050
Harmonized	$6,200/kW	$5,600/kW	$5,000/kW
Low Costs	$6,200/kW	$2,000/kW	$2,000/kW

The following assumptions are harmonized across all scenarios:

- **Fuel Prices:** These scenarios use EIA's Annual Energy Outlook 2021 "Reference" fuel prices for natural gas, coal, petroleum, and uranium. Fuel prices are typically represented as inelastic.[11]
- **Carbon Removal ("Negative Emission") Technologies:** All scenarios assume that bioenergy with carbon capture, direct air capture, and other negative-emission technologies are not included. The intra-model sensitivity in Section 4 shows how the availability of carbon removal impacts nuclear and other technology investments under deep decarbonization scenarios.
- **Retirements:** All scenarios incorporate a list of announced retirements for all capacity types (e.g., coal, nuclear, and gas), and assume that endogenous economic retirements can occur in any period. Models use an exogenous assumption that all remaining nuclear plants can operate for 80 years if economic (which is represented as an upper bound constraint).

[9] Information about nuclear plant modernization can be found in the EPRI Nuclear Plant Modernization Toolbox (https://www.epri.com/NuclearPlantMod) and guide to plant modernization research (https://www.epri.com/research/programs/111344). For an example of how modernization can impact existing nuclear plant operations, see the modernization white paper analysis in US-REGEN (Bistline and Austin, 2019).

[10] Since NEMS does not represent capacity constraints, this scenario is approximated with a nuclear-only generation share requirement.

[11] Natural gas prices in the ReEDS scenarios use elastic regional supply curves which are rooted in fuel price and consumption projections from the AEO2021 "Reference" case.

Several assumptions are not harmonized for this study, including the long-term growth of energy services, electricity demand, and hourly load profiles. Impacts of these factors are left for future work.

Results: Trends Across Technology Sensitivities

Differences in technology cost and financing assumptions have a strong influence on the future electric sector technology mix.

Figure 2-3 presents the national installed capacity and generation[12] results in 2050 from across the technology sensitivities under the Current Policies scenario. Looking first at scenarios with Native cost assumptions, all models indicate a prominent role for solar, wind, and natural-gas-fired technologies. However, there are modest differences in generation and capacity shares across models. For example, the Native ReEDS mix involves a greater role for energy storage, which primarily takes the form of batteries. The Native REGEN mix indicates significantly less installed capacity due to lower VRE deployment (i.e., with lower capacity factor wind and solar buildouts) and peak load. Note, however, that the total electricity demand is similar across models—as indicated by the similar height of the generation mix in the bottom panel of Figure 2-3—and it is met via higher utilization of natural-gas-fired generation in REGEN.

[12] The generation panel does not include net or gross contributions from energy storage. The "Hydrogen+Other" category includes hydrogen, biomass, municipal solid waste, landfill gas, imports, and fuel cells.

Under current policies, models differ in their projections for nuclear retirements, and new builds only occur in scenarios with very low nuclear costs and prescribed builds.

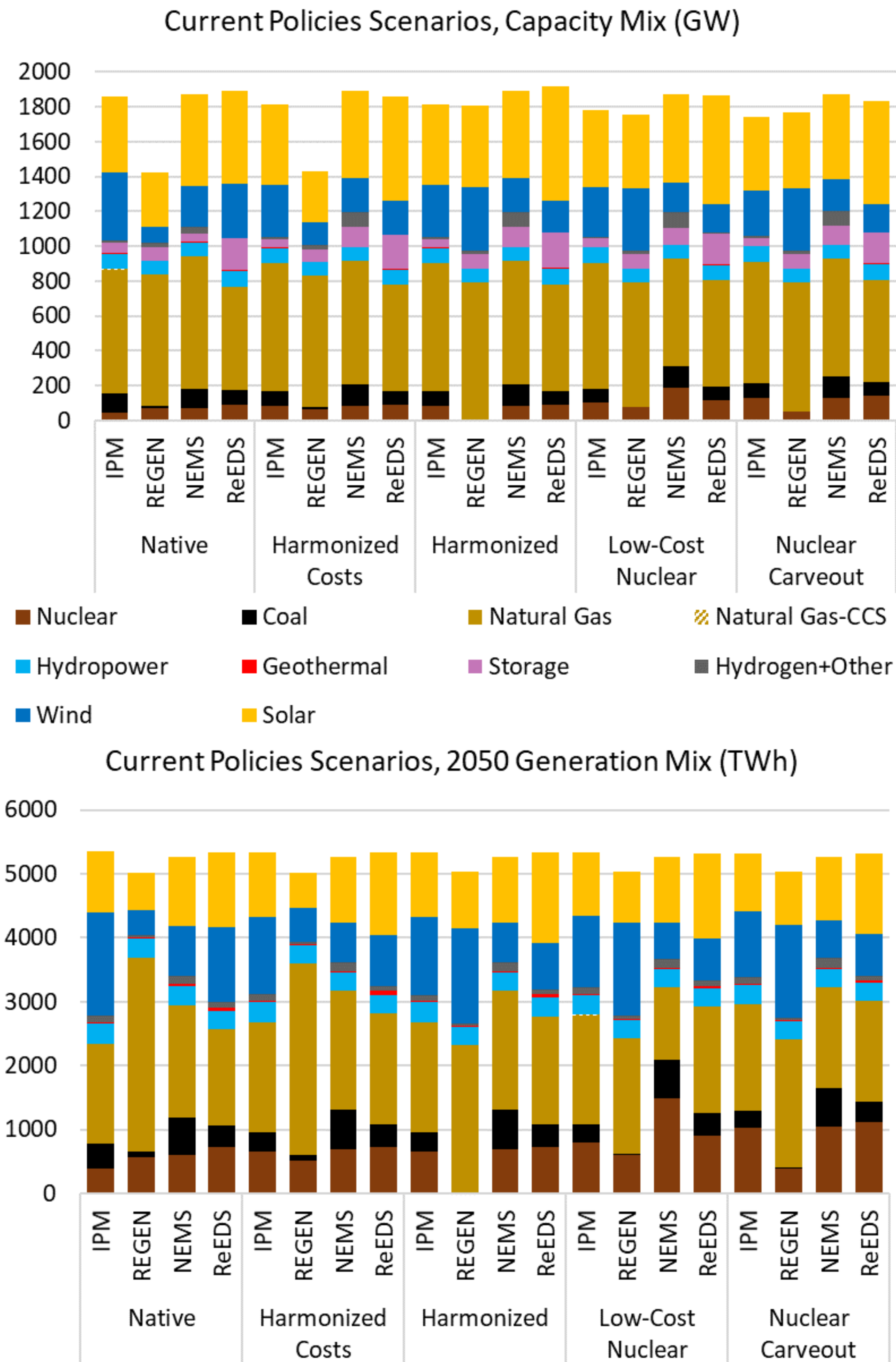

Figure 2-3
2050 capacity and generation across the technology sensitivities by model under reference ("current policies") scenarios.

The magnitude of nuclear power plant retirements by 2050 varies strongly across models with Native cost assumptions: ReEDS includes almost no nuclear retirements (beyond announced retirements), NEMS and REGEN retire approximately 30 GW of existing nuclear capacity, and IPM retires about 50 GW. Comparing the Native and Harmonized Costs scenarios indicates that much of this variation can be explained by disparate capital cost assumptions for all technologies (Figure 6-1) and nuclear FOM costs (Figure 5-1). In other words, harmonizing these input cost assumptions brings greater agreement among the nuclear retirements for most of models, such that nuclear retirements by 2050 differ by 27 GW across models with harmonized cost assumptions (compared to 43 GW with native assumptions).[13]

Aligning input cost assumptions reduces differences across models in overall generation and capacity results.

Overall capacity and generation mixes across models come into closer agreement in the three technology sensitivities that involve harmonized cost and financing assumptions: the Harmonized, Low-Cost Nuclear, and Nuclear Carveout sensitivities (Figure 2-3, rightmost columns). This growing similarity suggests that differences in the native cost and financing assumptions can explain many of the apparent discrepancies in model projections under Current Policies scenario. Yet differences remain in terms of the role of nuclear power across these technology sensitivities. For example, adopting the harmonized financing assumptions brings REGEN's total installed capacity in line with the other models, but it results in the retirement of nearly all nuclear and coal capacity. This visible difference is primarily driven by the harmonized discount rate (3%), which is significantly lower than REGEN's native discount rate (7%).[14] More modest changes in the other model solutions reflect that their native discount rates are more similar to the harmonized value, as shown in Figure 7-2.

Under the "Low-Cost" nuclear scenario, the very low-cost assumptions for new nuclear are sufficient to drive new deployment in each model: NEMS, ReEDS, IPM, and REGEN deploy 100 GW, 25 GW, 15 GW, and 3 GW of new nuclear capacity by 2050, respectively, in the absence of new power sector policies. Models with more competitive natural gas generation in the reference tend to have lower nuclear deployment in this low-cost scenario (and vice versa). As shown in Figure 2-4, new nuclear deployment is primarily concentrated in the South and West Census regions due to lower wind and solar resource quality and higher gas prices in the South and supporting state policies in the West. This new nuclear capacity primarily displaces additions of natural gas, wind, and solar capacity in these regions (and, to a lesser extent, energy storage).

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[13] The intra-model comparison using IPM in Section 5 illustrates how different nuclear FOM cost assumptions can alter deployment projections.

[14] Intra-model comparisons in REGEN illustrating the impacts of different discount rates are discussed in Section 7.

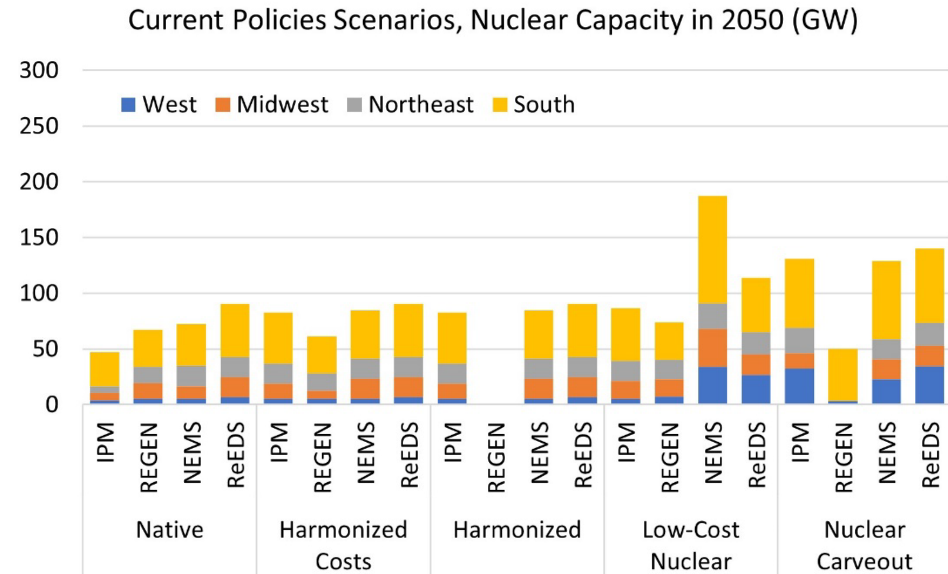


Figure 2-4

Regional distribution of nuclear capacity (existing and new) in 2050 for all combinations of models and technology sensitivity assumptions under reference ("current policies") scenarios. Regional definitions are based on U.S. Census regions.

The final technology sensitivity explores a Nuclear Carveout scenario, culminating in 50 GW of new nuclear capacity by 2050, which is a binding constraint across all models and policy scenarios. The same regional and technology displacement trends generally hold as in the Low Costs scenario. A unique response occurs in the REGEN solution, which retires the existing nuclear fleet in conjunction with adding 50 GW of new nuclear capacity, as mandates for this new dispatchable capacity lower market prices and consequently the revenues for existing generators with similar operational profiles (hence, earlier retirements of existing nuclear). This value deflation is akin to decreasing market value associated with other technology mandates in the literature including for variable renewables (Bistline, 2017).

Existing and new nuclear tend to run with high capacity factors (90% to 94% annually) across scenarios and models.

Finally, combining the capacity and generation results provides insights into the utilization (or capacity factors) for nuclear technologies. Nuclear power's low variable costs make it well-suited for higher capacity factor operations, which are consistently high across models and scenarios. Each model solution includes modest seasonal differences in nuclear capacity factors, due to a combination of seasonal changes in load and forced outages. However, despite the potential flexibility of these plants (see "Dispatchability and Flexibility" in Section 5), the annual average across all models and scenarios with Current Policies is between 90% to 94%.

Results: Effects and Interactions of Policy Sensitivities

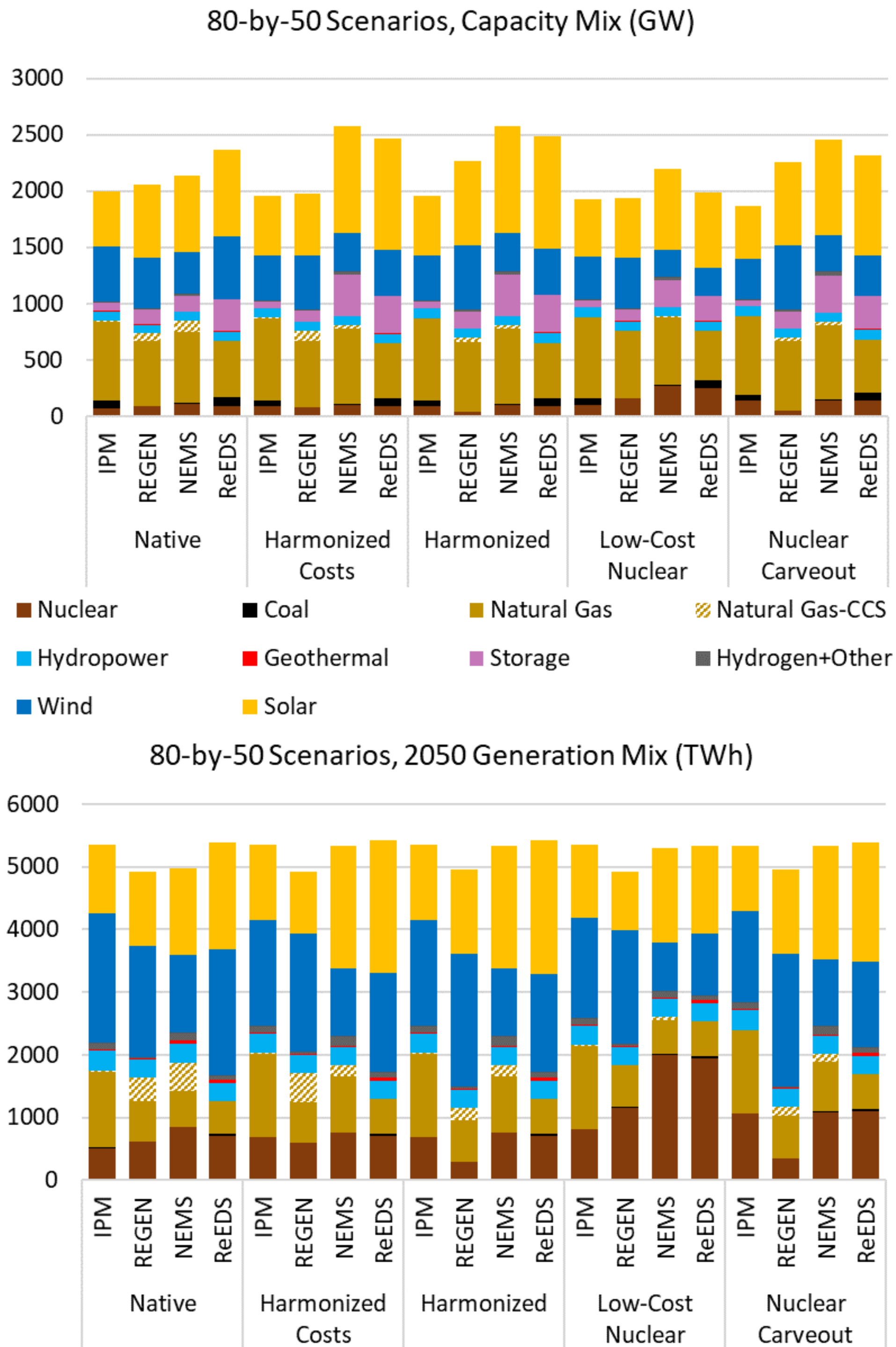
This section explores results where technology sensitivities are layered with hypothetical power sector carbon policies. All models explored a set of "80% by 2050" policy sensitivities, in which power sector CO_2 emissions linearly decline to reach 80% reductions by 2050 from 2005 levels (Figure 2-2). REGEN and ReEDS further explored a set of "100% by 2050" sensitivities.

As before, discussion in this section is primarily focused on comparing results across models, to understand similarities and differences. To avoid repetition with the previous section, comparisons here are typically rooted in incremental effects of the policy dimension across models, as well as interactions between technology and policy assumptions. Unless otherwise stated, the same trends were observed in terms of variation across technology sensitivity assumptions.

"80-by-50" Policy Results

Layering an "80-by-50" power sector policy with the previously described technology sensitivities has significant impacts on the least-cost mix of generation, storage, and transmission investments through 2050 (Figure 2-5). In general, the policy signal increases the value of low- and zero-carbon generation technologies. But while there are commonalities among the model responses, there are also noticeable differences across models and technology sensitivities.

An "80-by-50" electric sector policy has significant impacts on the least-cost mix of generation, storage, and transmission in 2050.



Under an 80-by-50 CO_2 cap, models align in keeping existing nuclear capacity, lowering coal capacity, and deploying more renewables and energy storage.

Figure 2-5
2050 capacity and generation for all models and technology sensitivities under an 80% by 2050 power sector policy.

Under Native cost assumptions, there are several common responses to the 80% CO_2 policy across models:

- Avoiding nuclear power plant retirements that were present under the Current Policies scenarios. Existing nuclear capacity increases from the reference to the 80-by-50 scenario: IPM from 47 to 64 GW, NEMS from 70 to 88 GW, REGEN from 69 to 85 GW. ReEDS installed nuclear capacity is 89 GW for both scenarios.
- Retiring a large portion of the existing coal fleet and significantly reducing coal generation.
- Increasing deployment of wind, solar, and energy storage (though magnitudes vary across models), which leads to higher installed system capacity.

These high-level trends generally align with the existing deep decarbonization literature for the U.S. power sector (e.g., Jenkins, Luke, and Thernstrom, 2018; Bistline, et al., 2018). NEMS, REGEN, and ReEDS retain nearly all existing nuclear capacity, whereas IPM retires nearly 30 GW of existing nuclear capacity. All four models see a growing role for solar, wind, and energy storage under the hypothetical 80-by-50 policy, which results in an increase in total installed capacity (Figure 2-5) compared to the Current Policies scenarios (Figure 2-3).

Nuclear plant flexibility is employed more under deeper decarbonization scenarios, though annual capacity factors are still high (between 80% and 94% across models).

In terms of nuclear capacity factors, all four models see growing value in employing the flexibility (or ramping) options for nuclear power capacity under 80-by-50 scenarios (Figure 2-6). This response is generally modest (one to two percentage point reductions across models), though changes in annual capacity factors are larger for REGEN (moving from 93% to 83% between the Current Policies and 80-by-50 scenarios).[15] Nuclear power plants reduce their capacity factors and draw on their flexible capabilities under higher variable renewable deployment. The value of flexible resources more broadly—including energy storage, demand response, dispatchable fossil-fueled capacity, hydro, nuclear, and others—increases in scenarios with higher wind and solar penetration (Gils, et al., 2022; Bistline, 2019; Jenkins, et al., 2018b). Lower capacity factors for nuclear power plants are due to reduced utilization of nuclear in non-summer months (Figure 2-7).

[15] Many factors may drive the lower capacity factors for nuclear plants in REGEN, which could be due to the model's higher temporal resolution (which may better capture flexibility needs), endogenous representation of load shapes, or other model features.

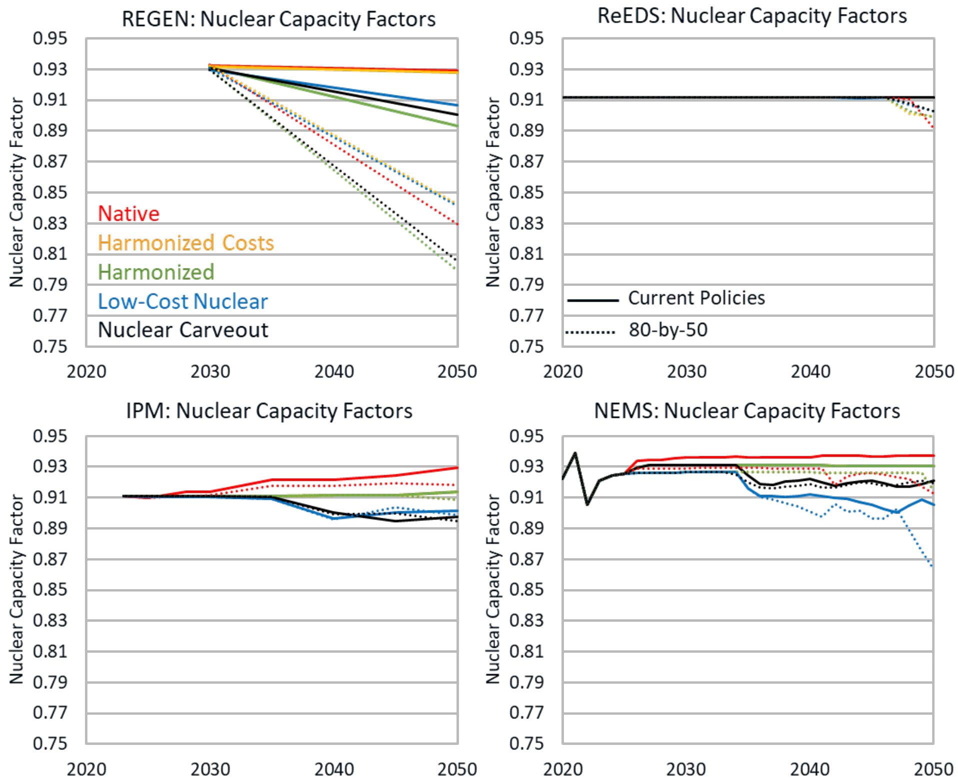


Figure 2-6
Annual average capacity factors over time for nuclear (existing and new) across technology and policy sensitivities. Panels show different models. Note that vertical axes are truncated at 75%.

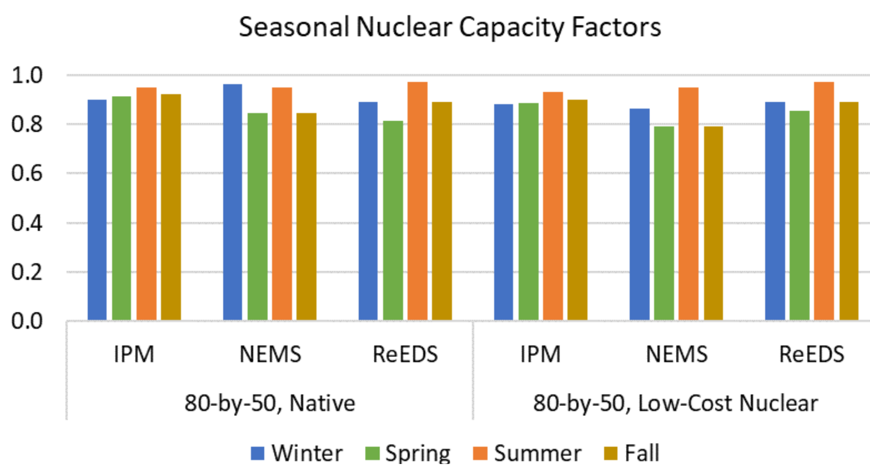


Figure 2-7
Nuclear capacity factors by season for select 80-by-50 policy sensitivities from the models that provided a seasonal breakdown of generation from nuclear power plants.

Under the 80-by-50 policy environment with native costs, models differ in their assessments of the future role of coal- and gas-fired generation. The REGEN and NEMS solutions involve retiring nearly all coal-fired capacity by 2050, whereas the IPM and ReEDS models retain more of the existing coal fleet and operate it with lower capacity factors. This difference is maintained under the harmonized cost and financing assumptions, suggesting that there are differences in how the models treat the economics and retirements of the existing coal fleet.

Models differ in their extent of fossil capacity installations, including CCS-equipped gas. Harmonizing cost assumptions better aligns results across models.

Finally, there is variation across models in the deployment of CCS-equipped capacity under deep decarbonization. The IPM and ReEDS solutions indicate a very modest role for gas CCS under such an 80-by-50 policy, whereas NEMS and REGEN involve 92 GW and 65 GW (respectively) of new gas CCS capacity by 2050. Figure 6-1 shows how capital costs for gas with CCS are similar over time across models (with the exception of higher costs in REGEN), which suggests that gas CCS costs are not primary drivers of differences in gas CCS deployment across models. However, the lower gas CCS deployment in NEMS and REGEN when moving from Native to Harmonized Costs assumptions suggests that renewables and energy storage costs could play a larger role in more pronounced deployment of gas CCS, wind, solar, and batteries. Moreover, nuclear and CCS-equipped capacity are substitutes in REGEN scenarios, as indicated by the lack of gas CCS in the Low Costs case.

Although models differ in their temporal resolution, spatial resolution, and sectoral coverage (Table 3-2), these features do not uniquely determine technology-specific shares, including nuclear-related outputs. High and low contributions of different technologies are observed in models of different types. Intra-model comparisons in later sections provide ceteris paribus comparisons to illustrate how some of these features shape outputs (e.g., temporal resolution in Section 7).

Combining very low cost assumptions for nuclear with more stringent CO_2 policy leads to higher nuclear deployment than when these drivers are considered separately.

Combining very low-cost assumptions for new nuclear with an 80-by-50 policy drives new nuclear deployment across all four models (Figure 2-8). Responses to cost and policy drivers (separately and in combination) differ in magnitude across models. For example, NEMS produces the strongest response to each driver, with the very low-cost nuclear resulting in nearly 100 GW of new nuclear capacity by 2050, and the 80-by-50 policy resulting in 17 GW of new nuclear capacity by 2050. When combined, the corresponding NEMS solution involves 175 GW of new nuclear capacity, which is significantly more than the sum of each individual driver. Therefore, the results indicate that interactions between policy and technology sensitivities can produce synergies in terms of the magnitude of potential deployment. Similar interactions are apparent in the other models, but with smaller magnitude effects overall.

Significant economic deployment of new nuclear capacity requires both a stringent electric sector CO_2 policy and very low cost assumptions for new nuclear.

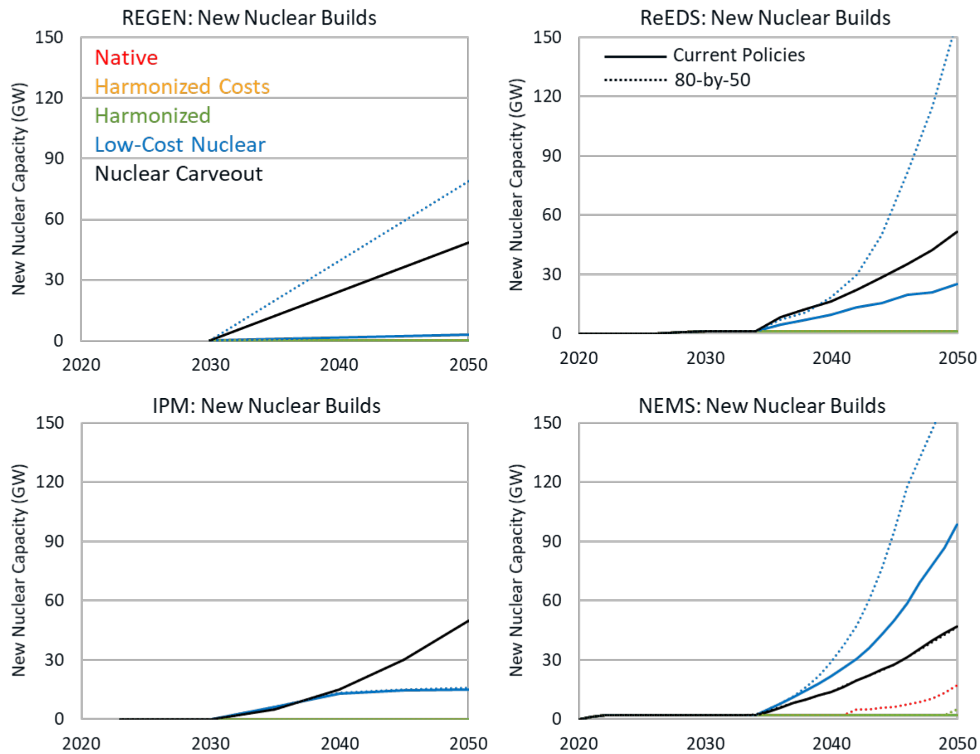


Figure 2-8
New nuclear capacity over time across all technology and policy sensitivities. Panels show different models. Note that there are no new additions in many models and scenarios.

New additions of nuclear capacity are highest in the Southern and Western U.S. regions.

The regional distribution of nuclear capacity (Figure 2-9) follows similar trends as in the previous section, with the greatest deployment in the South and West Census regions for most models. In the Nuclear Carveout scenario, incremental deployment is highest in the South and West.

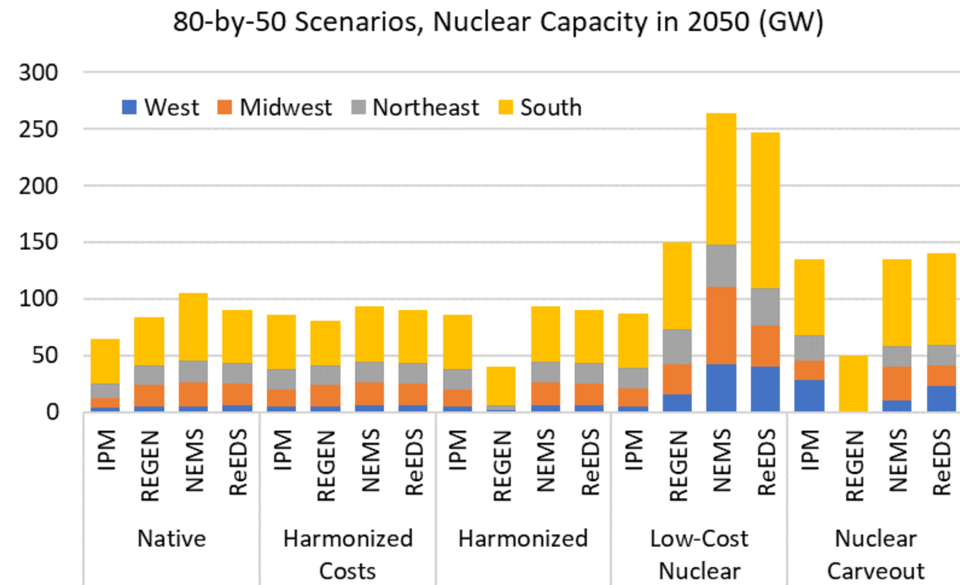


Figure 2-9
Regional distribution of nuclear capacity (existing and new) in 2050 for all combinations of models and technology sensitivity assumptions with an 80-by-50 power sector policy. Regional definitions are based on U.S. Census regions.

"100-by-50" Policy Results

Reaching zero emissions in the electric sector entails some combination of additional wind, solar, energy storage, hydrogen, and nuclear capacity, though shares vary by model.

Due to challenges with representing the transformational change of transitioning to a 100% carbon-free electricity supply, results from only the REGEN and ReEDS models are presented in this section. As in the previous section, the policy on its own drives substantial changes to the least-cost capacity and generation mix (Figure 2-10). Since the scenarios do not allow for consideration of negative emissions technologies, only zero-emitting resources can contribute to the generation mix in 2050. As a result, the capacity and generation mixes are dominated by solar, wind, energy storage, hydrogen-based combustion turbines (using hydrogen produced by electrolysis), and nuclear technologies, with contributions from geothermal and hydropower.

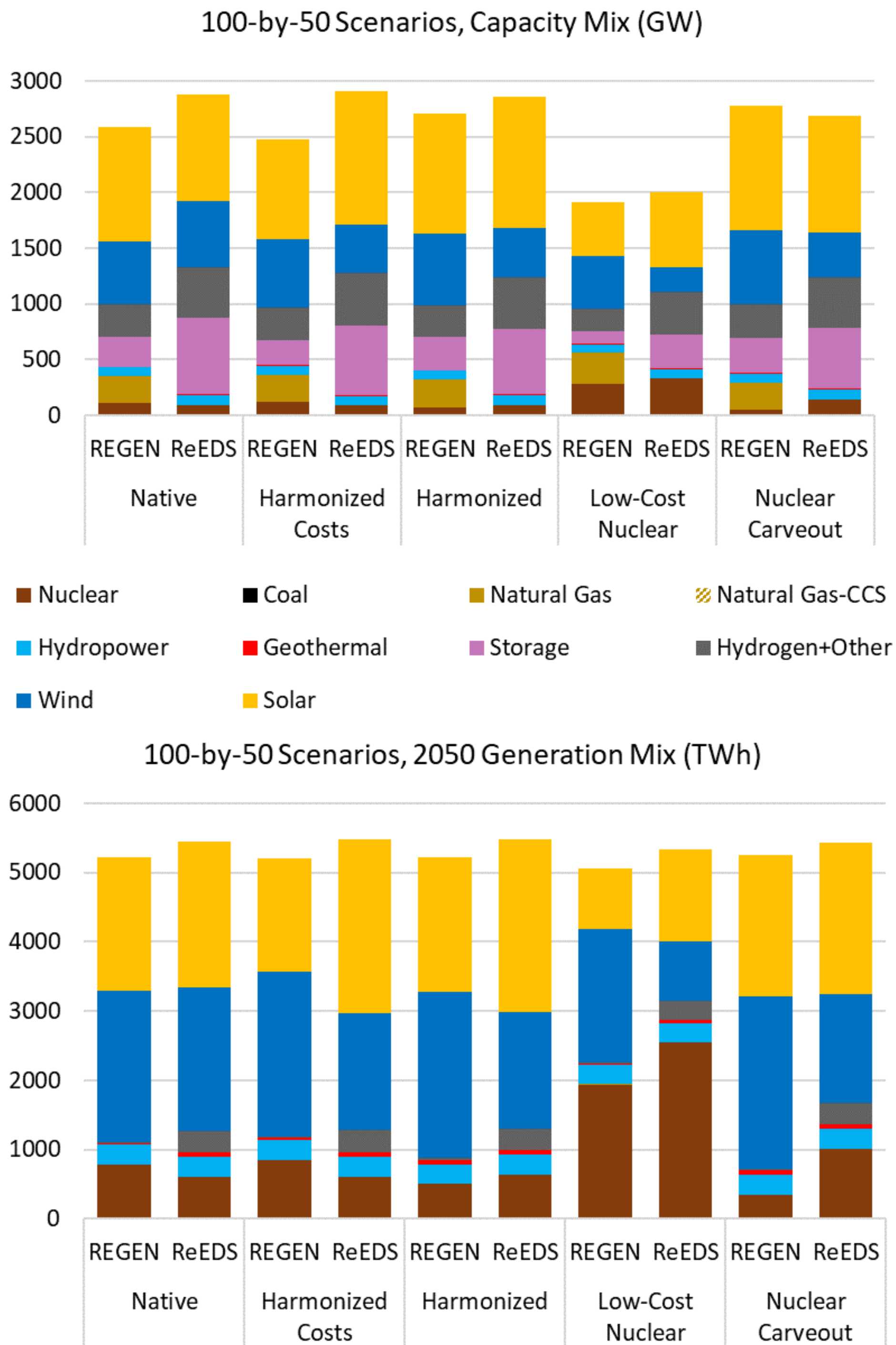


Figure 2-10
2050 capacity and generation results across the technology sensitivity scenarios and models under a 100-by-50 power sector policy.

These insights are consistent with the intra-model comparison in Section 4 ("Intra-Model Comparison: Policy Design") and with the emerging literature on reaching zero-emissions targets (Bistline and Blanford, 2021; DOE, 2021).

Even in scenarios that achieve 100% decarbonization of U.S. electricity supply in 2050, financing assumptions have a pronounced influence on new nuclear buildout.

Figure 2-11 shows existing and new nuclear capacity across the range of scenarios that include a 100% decarbonized U.S. electricity supply in 2050.[16] Under the Native and Harmonized Costs scenarios, the 100-by-50 policy avoids retiring large shares of existing nuclear plants. Moreover, REGEN builds about 30 GW of new nuclear capacity by 2050, whereas the ReEDS model does not build new nuclear capacity (beyond advanced nuclear reactor demonstration projects). Comparing with the harmonized cost *and financing* scenario[17] ("Harmonized") results indicate that this discrepancy can be attributed, in part, to the different investment lifetime and weighted average cost of capital assumptions in REGEN and ReEDS, since REGEN builds are much lower in the Harmonized case (relative to the Harmonized Costs only case).[18]

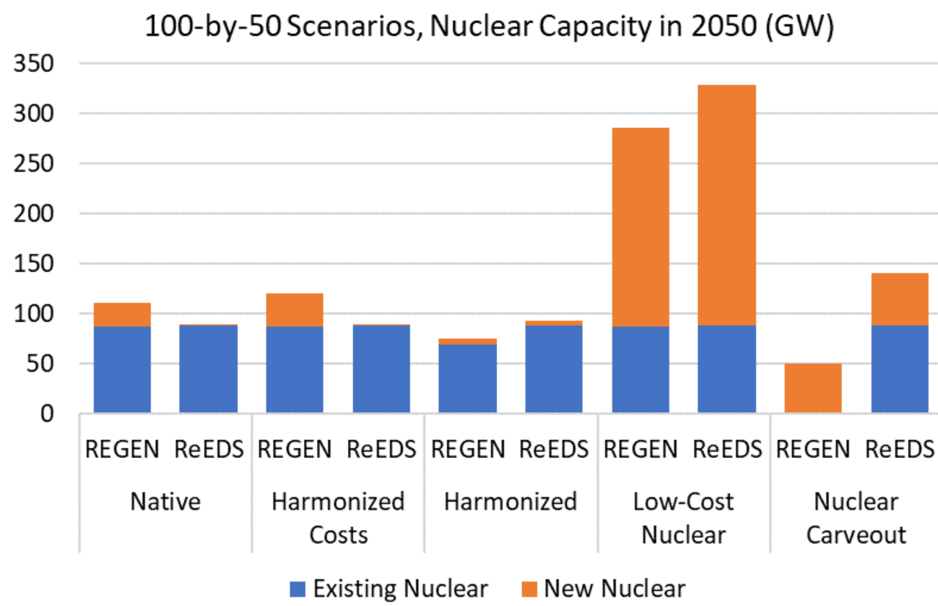


Figure 2-11
New and existing nuclear capacity across the 100-by-50 policy scenarios and technology sensitivities.

Nuclear power provides up to a third of U.S. electricity generation in 2050 in scenarios that combine very low-cost nuclear assumptions with a 100% by 2050 power sector policy.

Finally, both models respond strongly to the combination of a 100-by-50 power sector policy and very low-cost assumptions for new nuclear capacity. The new nuclear cost reductions that are assumed in this scenario are sufficient to enable nuclear power to play a significant role in a fully decarbonized U.S. electricity

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[16] We focus on 2050 results due to the more limited impacts in 2030, where the assumed policy stringency remains relatively modest.

[17] REGEN's native discount rate is 7% versus 3% in the harmonized scenario, which is the native assumption in ReEDS. REGEN's native economic lifetime for nuclear is 80 years versus 30 years in the harmonized scenario, which also is the native assumption in ReEDS. See the "Discounting and Financing" discussion in Section 7 for additional detail.

[18] Similar to earlier Carveout scenario results, REGEN retires the existing nuclear fleet in conjunction with adding 50 GW of new nuclear capacity, as mandates for this new dispatchable capacity lower market prices and consequently the revenues for existing generators with similar operational profiles (hence, earlier retirements of existing nuclear).

supply, with both models indicating on the order of 300 GW of new nuclear capacity by 2050 (Figure 2-11). In turn, the combination of very low-cost nuclear assumptions and a 100% by 2050 policy results in nuclear power plants contributing between a quarter and a third of total electricity generation in 2050. While this result should not be interpreted as a prediction of the future, the magnitude of deployment is informative for understanding the potential impacts of substantial cost reductions or subsidies and associated implications for permitting, siting, and fuel supply chains (see the "Deployment Barriers" discussion in Section 6).

Figure 2-12 compares 2050 capacity mixes across models for the three policy scenarios (assuming native technological costs). This comparison highlights the considerable changes in the investment mix and extent of capacity growth under the 100-by-50 policy.

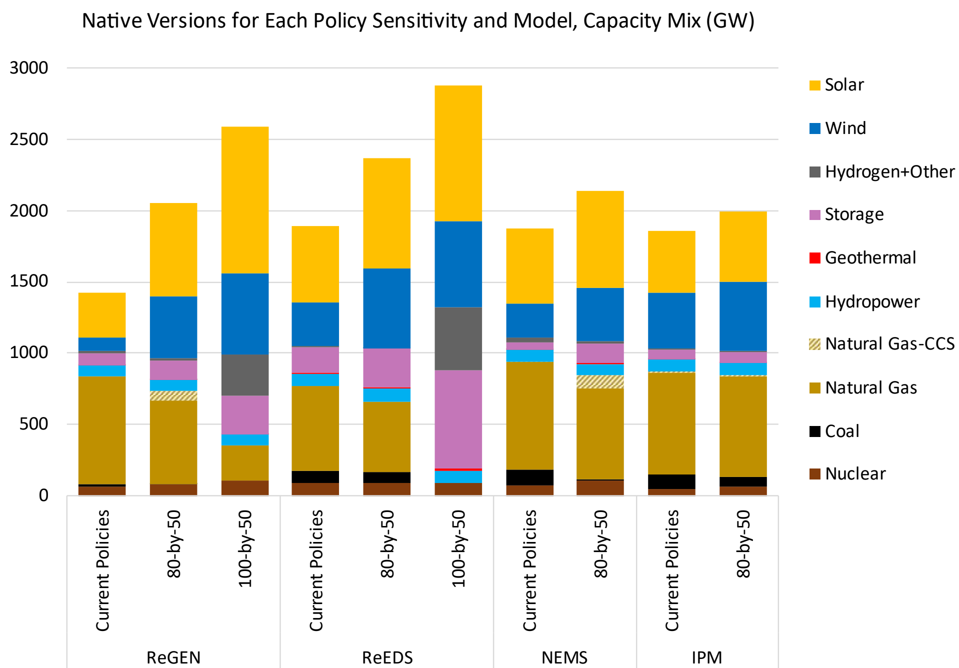

Figure 2-12
2050 capacity results across policy scenarios by model (with native technology assumptions).

Table 2-2 shows annual capacity factors by technology, model, and policy scenario. Even under deep decarbonization of the electricity sector with extensive deployment of wind and solar, capacity factors of nuclear plants tend to be high (77% in ReEDS and 81% in REGEN). Capacity factors of natural gas combined cycle (NGCC) plants without and with CCS tend to be much lower, especially under scenarios with stringent CO_2 policies.

Table 2-2
2050 annual capacity factor by technology, model, and policy scenario

Policy	Model	Nuclear	NGCC	NGCC-CCS
Reference	IPM	93%	50%	27%
	NEMS	94%	46%	44%
	ReEDS	91%	41%	N/A
	REGEN	93%	61%	N/A
80-by-50	IPM	92%	39%	45%
	NEMS	91%	18%	55%
	ReEDS	89%	14%	N/A
	REGEN	83%	25%	64%
100-by-50	ReEDS	77%	N/A	N/A
	REGEN	81%	N/A	N/A

Other Results

The results presented in this section have focused on the capacity and generation outcomes, which provide the most direct means of comparison across models and scenario. Additional model outputs can provide insights into the implications of various technology and policy assumptions, though some metrics reflect scenario definitions rather than endogenous model outputs. The remainder of this section highlights emissions and system cost results for a subset of scenarios.

Power Sector Emissions

The most meaningful insights regarding power sector emissions are those associated with the Current Policies technology sensitivities.[19] Across the Current Policies scenarios, power sector CO_2 emissions from a given model typically vary by less than 10% across all years and technology sensitivities. In other words, for most models, the optimal generation mix is similar across these technology sensitivities with Current Policies, and/or the primary form of competition is among low-emitting resources (i.e., nuclear and renewable energy technologies). This finding holds even for the Low-Cost Nuclear and Nuclear

[19] The policy sensitivities—80% and 100% CO_2 reductions by 2050 from 2005—are binding in the models, and therefore prescribe CO_2 emissions pathways. Greater variation exists among the NO_x and SO_2 emissions results from the models given differences in coal and gas generation. We leave explorations of such dynamics for future work.

Carveout scenarios for IPM, NEMS, and ReEDS, such that increases (or decreases) in the role of zero-emitting nuclear generation are primarily offset by decreases (or increases) in generation from solar and wind technologies.

One exception lies in the REGEN model solutions, for which all of the scenarios with harmonized cost and financing assumptions involve 20-40% reductions in power sector CO_2 emissions, relative to the Native and Harmonized Cost scenarios (with Current Policies). This result follows from the generation results presented earlier, where harmonized financing assumptions lead to significant declines in coal-fired generation, which is replaced by lower-emitting resources.

Power Sector System Costs

Power sector system cost results are another common output across models, which provide insights into the relative costs of various investment portfolios. Interpretation of such results can be challenging across technology sensitivities and models due to scenario- and model-specific assumptions. System cost results and valuation over time can change if input assumptions differ (e.g., capital costs in the Low Costs nuclear scenario, discount rates in the Harmonized costs scenario). Technology-specific interpretations can be misleading in such settings, especially across models. Finally, the scenarios with harmonized costs involve increases for some technology cost categories and decreases for others, which makes it challenging to disentangle competing effects on the power sector system cost results (Figure 6-1).

Under the Current Policies assumptions, the Nuclear Carveout sensitivity involves 2-3% increases in annualized power sector system costs in 2040, and 5-8% increases in 2050 (compared to the Harmonized sensitivity results). Since both scenarios involve the same technology cost and financing assumptions, this incremental increase in power sector system costs provides an estimate for how much additional investment and operational expenditure would be needed to displace some of the least-cost generation resources with 50 GW of new nuclear capacity.

System costs indicate that new nuclear capacity is close to being competitive with the least-cost solution under an 80% by 2050 power sector policy.

Performing the same comparison for the corresponding 80-by-50 scenarios reveals that the system cost implications of forcing in 50 GW of new nuclear capacity could be significantly reduced when combined with a policy constraint. In the NEMS and ReEDS solutions, the incremental annualized system cost impact of the Nuclear Carveout sensitivity remains at 2-3% in 2040 and 2050 (compared to the Harmonized sensitivity results), whereas similar system cost impacts are observed in IPM as in the previous paragraph. The reduced system cost implication of the Nuclear Carveout assumptions in NEMS and ReEDS suggests that, under an 80% by 2050 policy, additional nuclear capacity is close to being competitive with the least-cost solution in the absence of that constraint.

Section 3: Overview of Models

The four participating models—IPM, NEMS, ReEDS, and REGEN—are national-level CEMs that vary in their coverage and detail across a range of model dimensions. Table 3-1 and Table 3-2 compare several key features across models. Given that intended model applications often guide development decisions, differences in characteristics of these four models are driven in part by differences in their applications.

This project compares four models—IPM, NEMS, ReEDS, REGEN—which have a diverse range of modeling decisions, scopes, and uses.

Note that all four models are long-term electric sector models (in some cases with linkages to broader energy systems and the economy). These differ from smaller-scale, shorter-time-horizon models (e.g., production cost models) and with larger-scale tools (e.g., global integrated assessment models). Production cost or operational simulation models assess short-run electric system operations using detailed simulations of unit commitment and dispatch typically over a year with a fixed capacity mix (unlike CEMs, where the capacity investments and retirements are model outputs). In contrast to detailed power sector models, global integrated assessment models are better-suited for exploring interactions across countries, global technological change and transfer, feedbacks between energy and land-use systems, and cross-sectoral impacts, but they are not as well-equipped for informing questions related to detailed technological interactions across system resources or to those requiring spatial/temporal detail.

The four participating models have undertaken a range of nuclear-specific modifications and broader model development efforts over the course of this project, which have altered model outcomes and helped to improve insights. Nuclear-related improvements implemented by many modeling teams include adding small modular reactor technologies, allowing existing nuclear plants to operate for 80 years when economic, and adding/refining representations of flexible nuclear operations. Broader model updates from some participating models include running zero-emissions scenarios, increasing temporal resolution, adding new technologies (e.g., carbon removal, hydrogen, hybrid resources), and refreshing technology cost assumptions. Appendix A discusses these model enhancements in detail.

Integrated Planning Model (IPM) from the U.S. Environmental Protection Agency (EPA)

IPM®, developed by ICF, is a multi-regional, dynamic, deterministic linear programming model of the contiguous U.S. electric power sector. It provides estimates of least-cost capacity expansion, electricity dispatch, and emissions control strategies while meeting energy demand and environmental, transmission, dispatch, and reliability constraints. EPA has used IPM for almost three decades to better understand power sector behavior under future business-as-usual conditions and to evaluate the economic and emissions impacts of prospective environmental policies. As a result, EPA has focused considerable effort on the representation of fossil-based generator technologies and associated emissions and environmental impacts. IPM® is a registered trademark of ICF Resources, L.L.C. For further details, see the documentation available at: https://www.epa.gov/airmarkets/power-sector-modeling

National Energy Modeling System (NEMS) from the U.S. Energy Information Administration (EIA)

NEMS is EIA's primary tool to provide projections for its Annual Energy Outlook (AEO) and related reports, which provide a baseline examination of U.S. energy markets and facilitate better understanding of the impact of future policies and market evolution on U.S. energy supply and consumption. NEMS links the U.S. energy and macro-economy sectors to allow it to evaluate the impact of economic feedback with endogenous energy sector development on the evolution of U.S. energy markets. NEMS consists of twelve major modules representing various key players in the U.S. energy market. One of them is the Electricity Market Module (EMM). The NEMS EMM consists of five submodules representing load and demand, capacity planning, fuel dispatching, finance and pricing, and renewables and energy storage. These five sub-modules are designed to collectively simulate major decision points within the U.S. electricity market by estimating the actions taken by electricity producers to meet demand in the most economical manner using a least-cost optimization approach. EMM then outputs electricity prices to the NEMS demand modules, fuel consumption to the NEMS fuel supply modules, emissions to the Integrating Module, and capital requirements to the macroeconomic module. These modules then return updated electricity demand, fuel price, and macro-economic parameters back to the EMM. The model iterates until a stable supply and demand solution is reached for each forecast year.

Regional Energy Deployment System (ReEDS) from the National Renewable Energy Laboratory (NREL)

ReEDS is an electricity-sector-only model with a focus on the contiguous U.S. power sector (Ho, et al., 2021), though representations currently exist for an expanded North American model (Canada, U.S., Mexico) and India. ReEDS has high spatial resolution, representing the U.S. with 134 model balancing areas, and representing wind and solar resources with up to 50,000 individual sites each.

Transmission lines connecting each of these 134 regions and spur lines connecting to each of the wind and solar sites are modeled in ReEDS alongside generation and storage buildouts.

ReEDS models seven years of hourly, chronological data of wind, solar, and load in order to capture the value of variable renewable energy (VRE) resources and energy storage. Non-VRE, non-storage generators are typically dispatched at a 17-time-slice resolution, though that can be customized by the user, while VRE and storage rely on the chronological hourly representation for many key modeling parameters. The ReEDS model is publicly available at: https://www.nrel.gov/analysis/reeds/request-access.html

Regional Economy, Greenhouse Gas, and Energy (REGEN) from the Electric Power Research Institute (EPRI)

The U.S. Regional Economy, Greenhouse Gas, and Energy (REGEN) model was developed by the Electric Power Research Institute (EPRI). REGEN integrates a detailed electric sector capacity planning and dispatch model and an economic model of non-electric sectors capturing end-use technology tradeoffs (EPRI, 2020a). The electric sector model makes simultaneous decisions about capacity investments, transmission expansion, and dispatch, including load profiles that reflect the evolving end-use mix. The model includes hourly resolution for investment and operations, which better characterizes the economics of variable renewables, energy storage, and firm low-carbon resources. The end-use model captures technology choices at the customer level with heterogeneity across different sectors, structural classes, and regions. Online documentation is available at: https://us-regen-docs.epri.com

Table 3-1
Overview comparison of participating models and their key features

Model	Institution	Objective Function	Computational Requirements	Planning Horizon	Foresight	Sectoral Coverage
IPM	U.S. Environmental Protection Agency (EPA) and ICF	Minimize the NPV of the power sector's total system cost	~10 hour run time on computational server	Non-chronological, all periods solved simultaneously	Perfect foresight	All grid-connected generators
NEMS	U.S. Energy Information Administration (EIA)	Least cost optimization for the U.S. electric power sector; the EMM projects capacity planning, generation, fuel use, and transmission, subject to inputs and interactions with other modules in NEMS	~8-12 hour run time as part of integrated NEMS runs, ~4 GB memory	Annually through 2050; in EMM each solve-year optimizes over a three-period planning horizon to examine costs over a 30-year period	Convergent perfect foresight within the 2050 planning horizon by using prior run results as input to the current run; out-of-horizon years use adaptive foresight	All fuel supply and conversion, electricity and end use demand sectors, macroeconomic
ReEDS	National Renewable Energy Laboratory (NREL)	Minimize total system cost using the 20-year NPV	~8 hour run time, ~12 GB memory	Customizable; 2-year increments through 2030, 5-year increments through 2050	Foresight only for natural gas and CO_2 prices when running in sequential solve; intertemporal and sliding window foresight is available as an option at computational cost	Electric sector only
REGEN	Electric Power Research Institute (EPRI)	Maximize NPV of surplus over the model time horizon (accounting for end effects); minimize NPV if electric sector only model	Depends on spatial/temporal resolution: ~1 hour run time, ~32 GB memory for 48-state runs	Customizable; for most analyses, five-year increments through 2050	Intertemporal perfect foresight	Electric and all end-use sectors

Table 3-2
Comparison of power sector constraints and implementation across models used in this study

Model	Temporal Resolution	Spatial Resolution	Plant Retirement Dynamics	Deployment Dynamics	Technological Change	Fuel Prices	Demand Levels/Shapes
IPM	72 time slices for each run year (3 seasons x 24 segments) through 2030; 60 time slices (3 seasons x 20 segments) for all post-2030 run years	67 regions covering the contiguous U.S. (64 power market regions and 3 power switching regions), with 11 provincial regions for southern Canada	Economic retirements for all non-VRE technologies; VRE assumed to incur life extension costs to continue operation indefinitely	Electric sector capacity planning and dispatch is a least-cost linear program	Exogenous cost and performance estimates over time	Endogenous coal, biomass and natural gas prices, other fuel prices based on AEO	Seasonal load duration curves: 3 seasons, 6 categories (base to peak), 4 time-of-day categories, for a total of 72 segments
NEMS	3 seasonal periods (summer, winter, and spring/fall) divided into 3 groups: peak (highest 1%), intermediate (next 49%), and base (lowest 50%), totaling 9 segments	The generation of electricity is accounted for in 25 supply regions that resemble the NERC reliability assessment regions	Announced retirements are a model input; the model also evaluates retirement decisions for fossil/nuclear based on whether continuing operation costs exceed revenues	Linear programs for capacity planning and dispatch, and a third to solve renewable and storage dispatch (576 time slices); each model minimizes total system costs	Endogenous learning-by-doing is modeled in the electric sector for new build costs, based on assumed learning rates	In integrated runs, the electric sector uses supply curves from the fuel supply models and iterates based on demand/price response	End use models provide annual demand by sector and end use; the EMM has initial regional load shapes that can change over time
ReEDS	17 Time slices (4 per day x 4 seasons + summer afternoon super-peak) across one year	Contiguous U.S. with 134 load balancing areas and 18 resource adequacy regions; some representation of Canada/Mexico	Age-based retirements for all technologies; additionally, minimum capacity factor-based retirements for coal	Electric sector capacity planning and dispatch is a least-cost linear program	Exogenous cost and performance estimates over time	Endogenous regional natural gas fuel supply curve	Demand levels and hourly shapes are exogenous inputs to ReEDS
REGEN	Customizable; typically 100+ "representative hours" (Blanford et al. 2018) per year or 8,760 hourly	Contiguous U.S. states and Canadian provinces; customizable regions based on state and provincial boundaries	Exogenous retirements due to announced closures and age-based retirements for some capacity; endogenous retirements for most capacity	Electric sector capacity planning and dispatch is a least-cost linear program; end-use decisions are based on lagged logit choice models	Exogenous cost and performance estimates over time	Exogenous fuel prices for most runs (sensitivities with supply elasticity are possible in the electric model)	Demand levels and hourly shapes are endogenously determined in the REGEN end-use model

Section 4: Grid Value Streams and Market Participation

Summary

- The relative magnitudes of different electric sector value streams vary by technology, model, region, and scenario. In many instances, nuclear capacity operates with high capacity factors due to its low variable costs, and energy is generally the primary value stream. However, a stringent CO_2 policy can shift the capacity value stream and make it larger than the energy value. Out-of-market payments—including federal tax credits, state-level zero emissions credits, and other policy incentives (Appendix B)—also can be significant revenue sources for eligible technologies.
- CO_2 emissions policy assumptions are a first-order driver of nuclear capacity additions and retirements. Details about the policy's stringency, timing, and technology eligibility influence decarbonization planning and costs, as illustrated by the model comparisons in this section. Zero-emissions policies supporting carbon removal technologies lower deployment of nuclear and renewables relative to policies that do not support negative emissions options.
- Traditional levelized-cost metrics are not indicative of the relative competitiveness of system resources, which requires detailed energy modeling to assess.
- The section concludes with a list of modeling and analysis needs.

Overview of Considerations and Approaches

Nuclear energy can provide value for a range of electric sector services, including energy, firm capacity (or long-term resource adequacy products more broadly), ancillary services, and potential non-power value streams such as hydrogen production or policy requirements. Long-term systems models attempt to capture these value streams under scenario-specific variations, potential changes to market depth as different resource are deployed, competition across technologies to provide the same service, and ability for resources to participate in multiple markets. The balance of these values may differ by technology, region, and scenario.

Employing long-term planning models that simulate the bulk power system can provide detailed insights into the relative competitiveness of candidate generation technologies. Such models simulate investments in utility-scale electricity generation technologies based on the net value provided by competing alternatives. CEMs, in particular, can evaluate the impacts of varying technology and policy futures, both of which are known to have a pronounced impact on the least-cost portfolio of generation, energy storage, and transmission assets.[20]

Levelized-cost metrics are not indicative of the relative competitiveness of system resources, which require capacity expansion models to accurately assess.

In contrast, the levelized cost of electricity (LCOE) is a common metric to assess technology-specific costs of electricity generation. It represents "the average revenue per unit of electricity generated that would be required to recover the costs of building and operating a generating plant… during an assumed financial life and duty cycle" (EIA, 2021). While the LCOE metric is commonly used to assess various technologies' costs, it is an incomplete metric whose limitations have been well documented (Bistline, 2021b). For example, a recent report emphasizes that, "LCOE does not consider the monetary value of that energy to the system, which varies by location and time, and LCOE ignores the value of other services altogether" (Mai, Mowers, and Eurek, 2021).

Table 4-1 summarizes market participation assumptions across models, which are discussed in detail in the following subsections.

[20] While capacity expansion modeling can provide insights and quantitative estimates, results from such modeling should not automatically be interpreted as predictions.

Table 4-1
Comparison of market participation across models

Model	Resource Adequacy Requirement	Ancillary Services Markets and Eligibility	Non-Power Value Streams
IPM	Reserve margin requirements are based on the regional margins reported to NERC. Capacity credits for wind, solar, hydro, and storage are less than 100% and a function of technology, year, and location; all other technologies contribute 100% of net summer capacity.	Operating reserves constraints can be modeled. However, given their significant computational overhead and small impact on results, these constraints are applied on an as-needed basis.	Able to incorporate incentivizing policies (e.g., CES, tax credits).
NEMS	Reserve margin values are set based on the regional reserve margins reported to NERC. Capacity credit is the estimated portion of capacity that will be available during the peak demand, available capacity is affected by transmission imports and exports in each region.	Ancillary services are captured in the Electricity Fuel Dispatch Submodule. Dispatch accounts for spinning reserve requirements with several operating options to allow for co-optimization of the production of energy with the deployment of spinning reserves. Dispatch is done for three time slices in each of three seasons to account for seasonal variation in electricity demand and available generation.	NEMS captures Electricity Tax Credits, Production Tax Credits, Zero Emission Credit, and other clean energy credits (e.g., RPS).
ReEDS	Each region holds sufficient capacity to meet seasonal peak demand plus a planning reserve margin consistent with NERC guidance. Non-variable generation technologies receive full capacity credit, storage and VRE capacity credit considers 7 years of hourly load and resource profiles.	Each region and time slice requires spinning, regulation, and flexibility reserves. Spinning reserves are 3% of load and can be provided by generators with a 10-minute ramp time. Regulation reserves are 1% of load 0.5% of wind generation, 0.3% of PV and can be provided by resources with a 5-minute response time. Flexibility reserves cover 10% of wind and 4% of PV and can be served by resources with a 60-minute response time. PV/wind are not eligible to contribute to operating reserves. All other technologies provide reserves for a fraction of their capacity (Ho, et al., 2021).	Policy incentives applied at national, regional, or state level, including CES, RPS, and ZEC policies; hydrogen production options.
REGEN	Planning reserve margin constraint applied to all model regions (equal to 7% above peak residual load); endogenous resource contributions to the reserve margin (dispatchable technologies contribute full nameplate capacity); single weather year (often 2015).	Spinning and quick start reserve constraints for each hour and region; includes contingency reserves, frequency regulation reserves, and wind/solar forecast error reserves; high computational costs for these constraints and relatively small impact on most model outcomes mean that these constraints are typically not included in model runs.	Policies and incentives (e.g., CES, ZEC, tax credits); hydrogen production options.

Policy Representation and Design

Policy assumptions are first-order drivers of model outputs, including nuclear capacity builds and retirements.

The inclusion and implementation of high-value markets and policies within the models are often first-order drivers of power systems investments and operations. Approaches for valuing energy using locational marginal prices are well-established in both power system models and in existing markets. By comparison, there is a greater diversity in approaches for modeling other grid services and policies (Table 4-1) relative to the actual implementation for how these grid services are valued.

As the intra-model comparison described later in this section suggests, policy design details (e.g., stringency, timing, technology eligibility) influence model outputs related to nuclear and other technologies. Tax credits, emissions caps, Clean Electricity Standards (CESs), Renewable Portfolio Standards (RPSs), and Zero Emissions Credits (ZECs) each create different incentives for generator entry, exit, and operations, and their overlap can lead to unanticipated electric sector outcomes. Appendix B summarizes U.S. federal and state policies and incentives represented in these models. The level of model granularity (summarized in Table 3-2) and participation rules for a given policy influence how much of an effect it will (or will not) have on the model solution.

The existing literature indicates that nuclear energy tends to have a larger role under deeper decarbonization scenarios (Duan, et al., 2022; Bistline and Blanford, 2021; Jenkins, Luke, and Thernstrom, 2018; Bistline, et al., 2018), a conclusion that is supported by the intermodel comparison in Section 2.

Existing studies indicate that clean firm technologies can lower decarbonization costs.

Existing studies also indicate that the availability of nuclear and other "clean firm" technologies[21] lowers the costs of decarbonization (Baik, et al., 2021; Bistline and Blanford, 2020; Bistline, James, and Sowder, 2019; Sepulveda, et al., 2018; Kim, et al., 2014). Clean firm technologies include nuclear, carbon-capture-equipped capacity, biomass, geothermal, hydropower, and low-carbon gas-fueled plants (e.g., hydrogen). The value of nuclear in lowering decarbonization costs depends on the cost and availability of substitutes across different functional roles (e.g., generation, firm capacity, different ancillary services). Baik, et al. (2021) quantify diminishing returns to additional zero-carbon resources but also the important functional role of at least one clean firm technology and greater value for multiple resources given different cost structures and system roles.

Energy Markets

The market value of generation from nuclear and other system resources is typically captured through an electricity market-clearing constraint, which stipulates that net supply (including generation, energy storage, and trade) equals demand for each model region and intra-annual period. Shadow prices on this

[21] Firm resources are "technologies that can be counted on to meet demand when needed in all seasons and over long durations (e.g., weeks or longer)" (Sepulveda, et al., 2018).

constraint are intended to capture dynamics of competitive wholesale electricity markets, which dispatch a least-cost combination of resources in "merit order" (i.e., from lowest to highest short-run marginal costs) subject to technical and market constraints. Such dynamics are influenced by model design choices related to temporal resolution (i.e., whether models capture market-clearing on every hour of the year or only a handful of periods) and spatial resolution (i.e., the number of regions where locational clearing occurs), which are described in Section 7.

Nuclear's low variable costs mean that plants often runs with high capacity factors.

For nuclear plants, their low short-run marginal costs typically mean that they run with high capacity factors, even under high variable renewable grids (as the model comparison in Section 2 illustrates). Variable costs of nuclear are related to uranium fuel costs, which is a smaller component of cost profiles relative to coal and gas plants that are dominated by fuel costs. The low variable costs of nuclear make many plants price-takers for most hours, which means that their revenues are dependent on market outcomes and competition between higher-marginal-cost resources. These dynamics have historically lowered revenues to nuclear plants as natural gas price declined (Jenkins, 2018a) and increase potential exposure to future VRE price impacts (Mills, et al., 2020), though the dispatchability and flexibility of nuclear plants can mitigate such losses (as discussed in Section 5).

Planning Reserve Margin

A planning reserve margin is designed to ensure sufficient surplus capacity is available to avoid a generation shortfall during periods of high demand (or net load). Ensuring that sufficient capacity is available to meet expected demand depends on the temporal resolution of a model (Bistline, et al., 2021) as well as the way that the planning reserve is represented. The North American Electric Reliability Corporation (NERC) provides guidance on capacity requirements based on a probabilistic standard—loss of load expectation (LOLE). This guidance is communicated to regional reliability councils that must determine how to act on the guidance.

Many U.S. markets have dedicated capacity markets or other resource adequacy mechanisms to compensate generators for providing firm capacity. CEMs often do not capture intricacies of these markets and instead represent capacity values of resources through planning reserve margin constraints. To model a planning reserve margin, CEMs typically include a constraint that total firm capacity must exceed peak load by a specified margin. The spatial and temporal granularities used for this constraint vary depending on model structure (Table 3-2). Determining which technologies are allowed to contribute firm capacity, and how much, is an impactful area of difference across models. While such a determination is relatively straightforward for nuclear, coal, natural gas, and geothermal technologies (which are typically given full credit), it is more complicated for weather-dependent resources (e.g., wind, solar) and energy-limited resources (e.g., energy storage), as described in Cole, et al. (2017). Therefore, care should be taken to assess how much firm capacity solar photovoltaics, wind, hydropower (especially run-of-river), and energy storage

The capacity value of nuclear and other system resources is typically modeled through a planning reserve constraint.

can contribute toward meeting this requirement, and how that contribution evolves as such technologies achieve greater levels of deployment. Most models endogenously determine capacity contributions of different resources (Table 4-1). The declining capacity credit (and value deflation more broadly) of variable renewables and other system resources as a function of their penetration is typically a reason why other technologies come into the mix with deeper decarbonization, even with very high renewable shares.[22]

All models discussed in this report use a version of a planning reserve constraint. Most models implement reserve margins consistent with published NERC guidance. VRE resources are also generally eligible to contribute to this constraint; while the participating CEMs employ different approaches in determining how much capacity counts, the overall formulation is similar across the CEMs.

Operating Reserves and Ancillary Services

While the planning reserve focuses on longer timescale needs for the power system, operating reserves and ancillary services are designed to ensure that the bulk power system can respond to unexpected shifts in the balance of generation and load. The corresponding services provided address needs on a sub-hourly time scale and can be grouped into two categories: spinning reserves and non-spinning reserves.

Spinning reserves—including regulation reserves and longer-duration spinning reserves—are designed to address needs which can only be satisfied by generation assets that are already online (or "spinning"). Regulation reserves maintain the instantaneous balance of the system, with participating generation units adjusting output automatically to meet needs. Longer-duration spinning reserves are also maintained to address the loss of a major generation asset, with the need being satisfied on the order of tens of minutes. By contrast, non-spinning reserves address needs with sufficient lead time, such that an offline generation (capable of starting quickly enough) can be brought online to meet the need. This type of reserve typically addresses forecast errors in load and VRE output.

In addition to spinning and non-spinning reserves, finer timescale services also exist (e.g., frequency response or fast frequency response) to varying degrees across U.S. markets. However, these finer timescale services tend to fall outside of the scopes of many models, which typically employ more aggregate temporal resolutions and reduced-form representations of dispatch.

Operating reserves generally have smaller impacts on investments compared with energy and capacity services.

The models in this report have similar capabilities for representing operating reserves, with all making a distinction between spinning and non-spinning reserves (Table 4-1). Most models seem to have similar formulations, but a major difference between models is whether reserves are enabled by default. Compared to energy and capacity services, operating reserves are small and usually have

[22] For instance, Cole, et al. (2021a) show that, even at 95% renewable penetration, roughly half of firm capacity is procured from non-renewable, non-storage resources.

minimal impacts on investment decisions (Sergi and Cole, 2021; EPRI, 2021); therefore, questions remain about when these constraints are worth the computational costs, given their limited impacts on utility-scale capacity and generation results. Note that firm capacity needs are typically addressed through the planning reserve margin constraint, as detailed in the earlier subsection.

Non-Power Value Streams

Power and energy sector policies introduce so-called non-power value streams, which can be an important driver of model outcomes. All four models include options to represent proposed and implemented policies that impact the power system (Table 4-1). Policies are implemented either as a system of constraints, requiring the solution to satisfy a specified need, or through explicit costs or subsidies that shift a model solution.

Decarbonization policies offer concrete examples of how policy implementation approaches yield non-power value in the model. A carbon tax increases the cost of generating power for emissions-intensive resources, which can alter wholesale electricity prices and consequently revenues received by generators. Power sector incentives—including the federal investment tax credit for solar, the federal production tax credit for wind, and state-level zero emissions credits for existing nuclear—reduce eligible generator costs, thus increasing their relative competitiveness. Appendix B lists U.S. policies and incentives captured in these models.

Cap-and-trade systems and other policies that create tradable compliance instruments also generate value streams of different generators, which can alter decisions related to dispatch, entry, and exit. Emissions cap policies such as California's economy-wide cap and the electric sector Regional Greenhouse Gas Initiative (RGGI) in the Northeastern U.S. are implemented as emissions constraints in applicable regions. The shadow price associated with this type of constraint can be interpreted as the price of an emission credit. RPS and CES policies, which are widely adopted at the state level, require specified levels of eligible technologies to supply electricity. These standards can be implemented in multiple tiers with carveouts for key technologies and differentiation between in-state and out-of-state resources. The shadow price associated with these constraints is equivalent to price of a renewable energy or clean energy credit and increases the competitiveness of eligible technologies.

Finally, plants also can receive revenues from the sale of hydrogen, synthetic liquid fuels, and potable water produced from high-temperature heat (Sowder, 2021). Some participating models capture hydrogen production, including the ability to use electricity from nuclear and other resources to produce electrolytic hydrogen (Table 4-1). None of the participating models currently represents the possibility of using nuclear for industrial heat applications. These types of products are becoming more common in analyses of economy-wide deep decarbonization, and they highlight the value of models that can capture cross-sector interactions.

Intra-Model Comparison: Value Stream Analysis

Value streams are measures that indicate the system value of technologies and better reflect the underlying decision framework for CEMs relative to commonly reported metrics such as the LCOE. These values allow for the inclusion of a holistic mix of plant values and costs. Alternative metrics also can be used that normalize the value streams into a value that is comparable to LCOE (see Table 3-2).

Table 4-2
Examples of electricity price metrics

Metric	Typical Units
LCOE	Cost/Energy [$/MWh]
Net Value of Energy (NVOE)	(Value-Cost)/Energy [$/MWh]
Net Value of Capacity (NVOC)	(Value-Cost)/Capacity [$/kW]
Normalized Value	(Value-Cost)/Value [%]

Figure 4-1 provides an example of how a plant's value streams can be understood. Plant costs include all outlays associated with constructing and operating resources (including costs to connect a plant to the grid). Next are the sources of value, which come from the value of the electricity generated by the plant and the value of its contributions toward the planning reserve margin. Operating reserves and ancillary services can be both a cost and a revenue source for a generator: They represent a revenue source for generators that can provide the services, whereas they represent a cost for VRE generators (based on the increase in reserves required to address forecast errors). The stacking of value streams and costs reflect the underlying mathematics of the optimization model; if, at equilibrium, the net value of a plant is greater than or equal to zero, then that plant will be selected as part of the model solution.

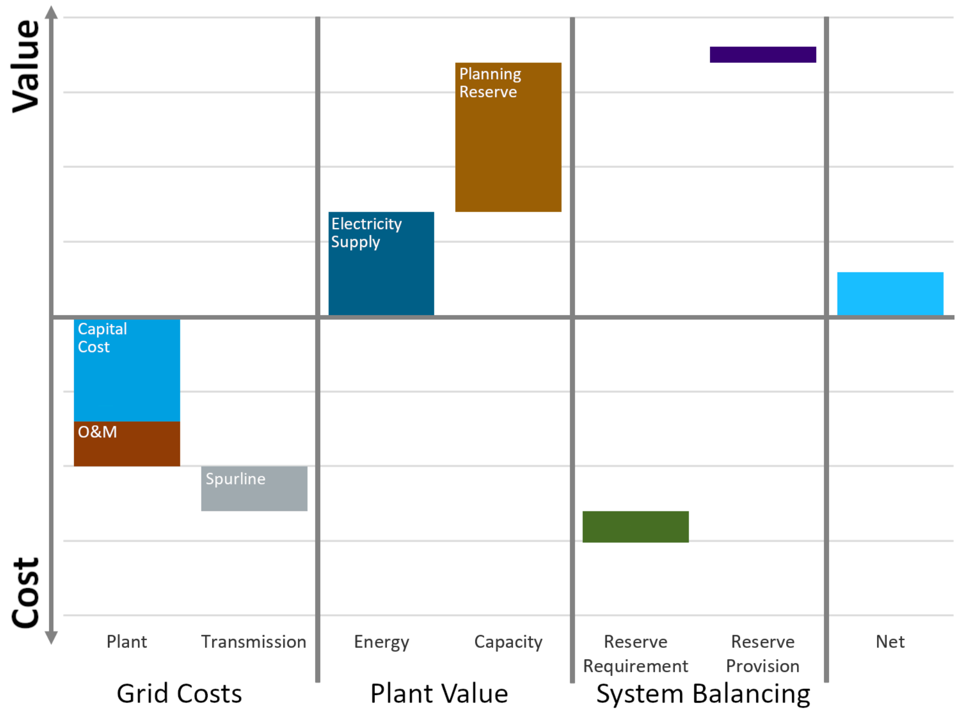

Figure 4-1
Stylized example of plant value streams and costs decomposed by category grouping.

Value stream analysis can illustrate model dynamics and technology-specific outputs across scenarios.

Calculating value streams offers an important tool to explore a range of key questions. The mix of revenues that a technology receives quantifies the value that technology offers to the power system as represented by the model. Examining the value streams also helps to validate and understand model behavior by allowing for comparison against known uses and revenues for varying plant types. Finally, because value streams are representative of the optimization model at equilibrium, measuring value stream changes in response to policy sensitivities provides a deeper understanding of how that policy influences a technology's competitiveness, in greater depth than capacity and generation results can provide by themselves. In addition to generating value streams for developed technologies, model outputs can also provide insights into value streams for technologies that were not included in the model solution (i.e., not deployed). Knowing how an unbuilt technology would have earned revenue is valuable for understanding how the model is assessing that technology. The calculated net negative value of a technology further provides insights into what level of cost reduction (or increase in revenue) would cause the model to start choosing to invest in that technology.

To demonstrate the value of such an approach, we use ReEDS to perform a value streams analysis across three scenarios that mirror the intercomparison scenarios in Section 2: a Reference (or business-as-usual) scenario, a Low-Cost Nuclear scenario, and a Nuclear Carveout scenario (in which 50 GW of new nuclear capacity was required for investment through a constraint that is analogous to a nuclear-only clean electricity standard [CES]). This analysis is designed to facilitate a comparison of how a technology's sources of revenue—and net-value—varies across a range of technology and policy assumptions, similar to those presented in Section 2 of this report. The outcomes of this value streams analysis provide insights for all generation and storage technologies, but the following presentation focuses on insights for nuclear power plants.

Figure 4-2 presents the outcomes of our value streams analysis for existing plants in a given year (as opposed to new investments) under the Nuclear Carveout scenario; this scenario is unique in certain ways, but the results also highlight more consistent trends from across the explored scenarios. For example, it is apparent from this figure that the primary value streams for all technologies are rooted in energy services and the planning reserve margin (which determines capacity value). On the other hand, the relative importance of energy versus capacity value varies depending on the generation technology in question.

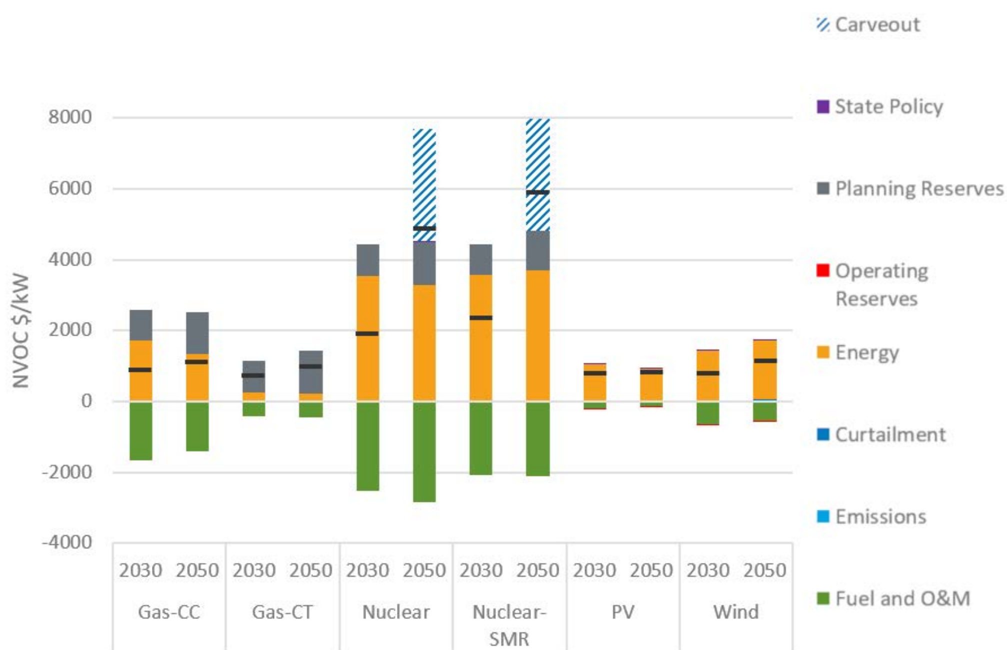

Figure 4-2
Value streams for key existing generation technologies (as opposed to new investments) in a Nuclear Carveout scenario performed by the ReEDS model. Black lines indicate the profitability of the technologies (i.e., revenues minus costs). NVOC is the net balance of a plant's revenues and costs normalized by installed capacity.

Table 4-3
National average revenue by category for key existing generation technologies in the ReEDS model's Nuclear Carveout scenario

Technology	Year	Energy	Planning Reserves	Other
Gas-CC	2050	55%	45%	0%
Gas-CT	2050	17%	83%	0%
Nuclear	2050	74%	26%	0%
Nuclear-SMR	2050	78%	22%	0%
PV	2050	98%	0%	2%
Wind	2050	94%	0%	6%

Nuclear plants see revenues from both energy and capacity services, though energy is primary value stream.

For solar PV and wind technologies, energy accounts for most of their total value (yellow bars in Figure 4-2). While these plants can contribute to the planning reserve margin, their capacity value declines as they capture higher fractions of the generation mix. The opposite is true for gas combustion turbines, for which the vast majority of value is derived from contributing capacity towards the planning reserve margin. NGCC plants fall in between, with an even split between capacity and energy value. Nuclear power plants also see revenues from both energy and capacity services, although the majority of nuclear power plant revenue comes from energy services. Finally, it is important to note that other revenue sources—including operating reserves and state RPS policies—represent a small fraction of revenue by 2050. The low operating reserves revenue is driven in large part by the substantial deployment of energy storage in 2050 in these scenarios (Section 2), which both serve a large portion of operating reserve and depress operating reserve prices.

Unique in this scenario is the impact of the Nuclear Carveout, which drives a measurable shift in the value streams. With the additional nuclear capacity above what would have been procured otherwise, the value of energy was reduced for all technologies by ~10%. The value of capacity for the planning reserve remained constant, due to a significant reduction in battery storage capacity. Finally, the carveout appears in the value stream stack as an additional revenue source, analogous to CES credit payments. For this level of carveout, the additional revenue was on the order of $3,000/kW. Put another way, the carveout value indicates how much nuclear development costs would need to be reduced to see new development in the absence of the carveout constraint.

Examining value streams for new nuclear development in 2050 across the three explored scenarios reveals the technological competitiveness at different levels of deployment (Figure 4-3). In these scenarios, SMRs reach a lower cost for development compared to conventional nuclear. Under the Reference, costs fail to decline sufficiently to allow for new nuclear investment, which is why no value stream information is presented for this scenario. However, the ReEDS value stream results indicate that nuclear technology capital costs would need to decline by approximately $1,104/kW to achieve parity with their expected value (i.e., for new nuclear power plants to become part of the model solution). Under the Low-Cost Nuclear assumptions, approximately 24 GW of new nuclear capacity was deployed by 2050 (at a reduced cost of $2,822/kW). Together with the Carveout scenario results, the full suite of value analysis scenarios reveals both the range of cost assumptions under which new nuclear power plant deployment could be expected and a corresponding estimate for the degree of response from the model.

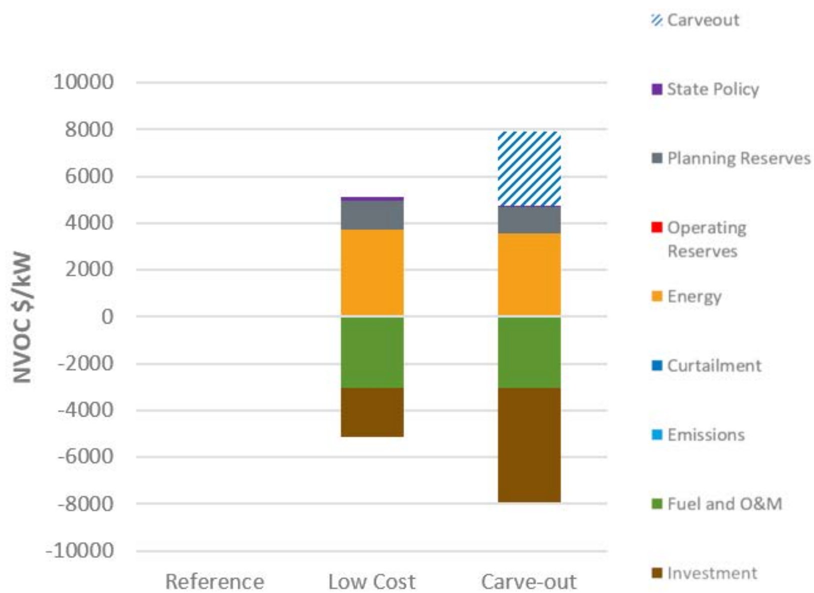

Figure 4-3
Value stream balance for nuclear SMR capacity built in ReEDS in 2050.

The value streams provide a useful tool for breaking down the complex balance of decisions that a CEM is making. Using the carveout and alternate scenarios, we could identify the competitiveness of the technology across a range of development. These same techniques can be applied to estimate the response to alternate policy scenarios including how decarbonization improves the technological competitiveness.

Intra-Model Comparison: Policy Design

Given the importance of policy assumptions for nuclear deployment, this intra-model comparison uses REGEN to illustrate how policy timing and eligible technologies interact within a CEM to affect capacity builds and system costs.

There are three scenario dimensions explored in this analysis:

- **Eligible technologies in a power sector net-zero emissions target:** One scenario assumes a "Net-Zero" (NZ) emissions target, where all technologies are eligible and net CO_2 emissions equal zero. This broad and technology-neutral definition of zero implies that any emissions produced from operations are balanced by an equivalent amount of carbon removal. A second scenario looks at a "Carbon-Free" (CF) target, where the only eligible resources are renewables and nuclear. This is the definition used in the zero-emissions scenarios in Section 2.
- **Timing of zero-emissions target:** Scenarios vary whether the (net) zero emissions goal is reached in 2035 or 2050.
- **Costs of new nuclear:** "Reference Costs" and "Low Costs" scenarios use the same harmonized assumptions as the model intercomparison in Section 2. Reference costs decline over time to approximately $5,000/kW by 2050 (Figure 6-1). The low-cost scenario assumes a $2,000/kW capital cost beginning in 2035.

For additional detail on net-zero scenarios and role of carbon removal, see Bistline and Blanford (2021) and Blanford, et al. (2021).

Nuclear is 25% of the generation mix for a 2035 zero-emissions goal. This share drops to 13% if the target is delayed to 2050.

For the scenarios with reference technology costs, the Carbon-Free scenarios entail rapid builds of energy storage and nuclear to balance large deployment of solar and wind (Figure 4-4). Nuclear represents a quarter of the generation share in the 2035 target case, and slightly less than half of this generation is from new nuclear. Delaying the zero-emissions target to 2050 lowers nuclear generation in both absolute and relative terms (13% generation share). The main reason is that, although nuclear costs are assumed to decline through 2050, relative declines for solar and batteries are assumed to be larger, hence a much larger role for these technologies. New nuclear capacity additions are 62 GW in the Carbon-Free by 2035 scenario and 24 GW in the 2050 scenario.

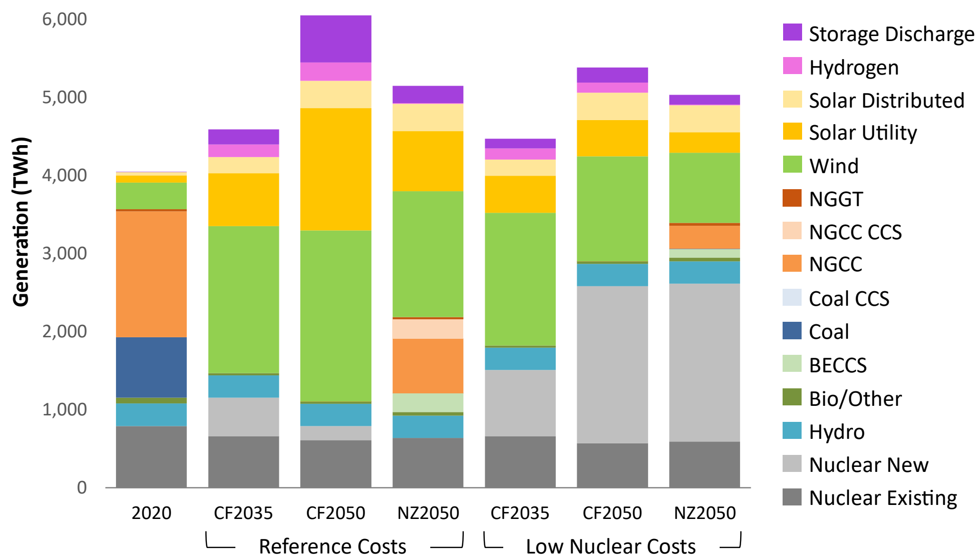

Figure 4-4
Generation by technology in 2035 and 2050 across the zero-emissions policy design and technology sensitivities in REGEN.

Note that total generation (inclusive of energy storage discharge) is higher under the Carbon-Free targets relative to Net-Zero ones due to the losses associated with deployment and utilization of energy storage, especially from the production, storage, and use of electrolytic hydrogen, which has low roundtrip efficiencies. Total load increases between 2035 and 2050 from end-use electrification.

Net-zero emissions targets favor carbon removal technologies and lead to lower deployment of nuclear and renewables.

Adopting a Net-Zero target instead of a Carbon-Free one leads to the deployment of carbon removal technologies to enable natural gas to balance wind and solar variability. Negative emissions from bioenergy with CCS (BECCS) are roughly three times larger (in t-CO_2/MWh terms) than the positive emissions intensity from NGCC units. Using gas-fired generation to balance renewables lowers generation and capacity from other firm resources, including nuclear.[23] New nuclear is not deployed in this Net-Zero policy, though existing nuclear still plays an important role. Wind and solar are just over half of the generation mix in the Net-Zero scenario, which is lower than the 68% in the Carbon-Free scenario.

[23] The finding that the availability of carbon removal (i.e., negative emissions) technology tends to displace nuclear is reflected in other studies in the literature (Bistline and Blanford, 2021; Daggash, et al., 2019).

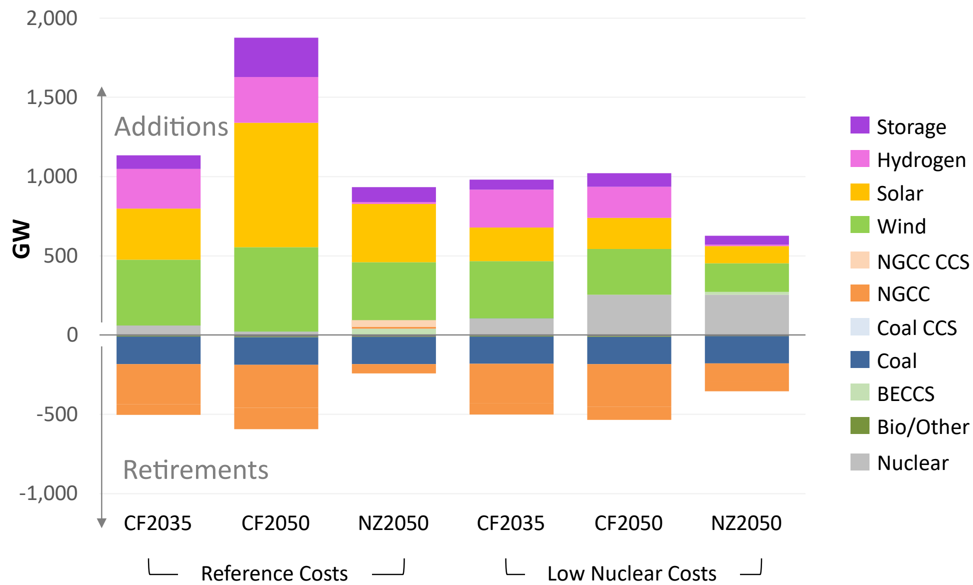

Figure 4-5
Cumulative capacity additions and retirements by technology across the zero-emissions policy design and technology sensitivities in REGEN.

States in the eastern and southern U.S. are most impacted by zero-emissions target definitions since these regions have lower quality wind and solar resources. New nuclear and CCS-equipped gas are primarily deployed in the south.

Lower nuclear costs alter projected roles for new nuclear under all policy scenarios (Figure 4-4). Nuclear generation shares range from 12–25% with reference nuclear costs to 34–52% with lower costs. Nuclear's role is less sensitive to target definitions and timing when its capital costs are low, in part due to the significant cost reductions assumed in this scenario. Displaced generation with lower nuclear costs varies by scenario: Renewable generation is lower in all scenarios, hydrogen and storage are lower in the Carbon-Free scenario, and gas-fired generation is lower in the Net-Zero scenario.[24]

Policy timing and technology eligibility impact electric sector costs, as shown in the U.S. average generation prices in Figure 4-6.[25] Expanding technology options decreases the cost of electric sector decarbonization, and prices in the Net-Zero scenario are 41% higher than the Reference in 2050 and 66% higher in the

[24] The four participating models have reporting horizons that end in 2050. Although models have different methods of treating so-called "end effects" (Section 7), capacity mixes across these scenarios have different implications for post-2050 system investments and operations. For instance, the shorter physical lifetimes of batteries, solar, and wind capacity imply more frequent asset replacements than mixes with longer-lived capacity. See the "Discounting and Financing" discussion in Section 7 for more information.

[25] Reported prices reflect generation and new bulk transmission costs (Bistline, 2021b).

Carbon-Free scenario. Accelerating the target to 2035 requires a faster introduction of new technologies and creates a higher electricity price spike than the 2050 scenario.

Policy targets, policy timeframes, and technology assumptions jointly influence decarbonization planning and costs.

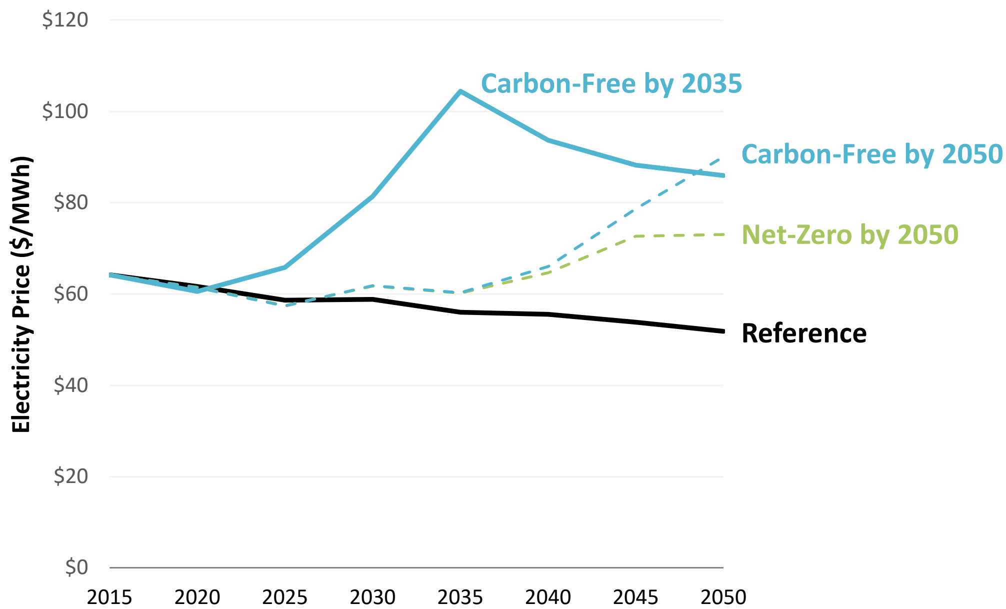

Figure 4-6
U.S. generation-weighted average electricity prices over time by scenario in REGEN.

This analysis illustrates how policy targets, policy timeframes, and technology assumptions interact within a CEM to influence value streams for technologies such as nuclear and in turn help determine decarbonization planning and costs. Policy design (especially eligible technologies) have first-order impacts on nuclear deployment. Zero-emissions policies allowing carbon removal technologies (Net-Zero) lower deployment of nuclear and renewables relative to policies that do not allow negative emissions options (Carbon-Free). Policy-related value streams are important drivers of nuclear and other low-emitting technologies, but impacts depend on details about the policy's stringency, timing, and technology eligibility.

Recommendations for Future Modeling RD&D

Based on the comparisons in this section and discussions from workshops, several areas are identified for future model RD&D efforts:

- *Understand future changes in value streams and demand for grid services:* Potential changes in planning reserve margins and operating reserves should be studied in futures with higher renewables penetration, electrification, and deep decarbonization (EPRI, 2018).
- *Characterize a range of low-emitting technologies:* Because nuclear technologies see much greater deployment in scenarios that require significant decarbonization, properly capturing the value of nuclear technologies requires

that other low- and zero-carbon technology options are adequately modeled. Not adequately representing the portfolio of candidate technologies and pathways that are being considered to meet such power sector and economy-wide targets could incompletely characterize the competitiveness of nuclear relative to these other technologies.

- *Select appropriate levels of model resolution:* Modeling zero- or very-low-emitting energy systems might require additional temporal or spatial resolution to properly capture the value of the different generator types. Additional work is needed to understand the importance of model resolution on outcomes for these zero and low-carbon solutions.
- *Improve time-series data:* Models often use a single year of historical meteorological data. Given that many low-carbon futures depend heavily on variable renewable technologies, multi-year variability in wind resources, solar resources, and load are particularly important (Diaz, et al., 2021). Improved understandings of the impact of multi-year variability (of load and renewables) can inform resource adequacy estimates and contributions of different resources. If infrequent but impactful wind lulls or cloudy periods are not captured in the model, then firm capacity resources such as nuclear could be undervalued. Similarly, capturing the extreme events that seem to be increasingly common can ensure that power sector solutions are more robust no matter the composition of the resulting generation fleet produced by the model. Future work to understand the importance of representing compensation for uncaptured attributes (e.g., inertia) would also be valuable.
- *Incorporate hybrid operations and sectoral integration:* Pathways towards achieving a net-zero energy system in the United States typically involve growing interactions among electricity supply, energy supply, and energy demand (including electricity, direct fuel use, and heat). Hybrid energy systems—including those that comprise a nuclear power plant and electrolyzers—have been proposed as a candidate technology for flexibly contributing to the full spectrum of demands across the energy system (Arent, et al., 2021). Planned demonstration projects will help to evaluate the operational capabilities of such hybrid energy systems, but their ultimate competitiveness will depend on the incremental costs and benefits of their ability to contribute products and services across different parts of the U.S. energy sector. A better understanding of the future demand for, and value of, hydrogen is a key component of evaluating the incremental value of hybridization, particularly for models that represent interactions across different segments of the U.S. energy sector.

Section 5: Representation of Existing Nuclear

Summary

- Maintaining a large fraction of the existing nuclear fleet is a robust element of electric sector decarbonization pathways; however, retirement risks exist for some plants absent additional policies that support their continued operation, though the extent varies across models and scenarios.[26]
- Representations of retirements for nuclear and other technologies differ by model. Projections of nuclear plant retirements vary by model and scenario, especially for scenarios with less stringent climate policy and low natural gas prices.
- Nuclear FOM cost assumptions vary widely by plant, over time, and across different models. These cost assumptions are first-order drivers of model projections of nuclear retirements, as the intra-model comparisons in this section illustrate.
- A best practice for representing existing nuclear plants is for models to include endogenous retirement decisions in most instances. Dispatchability and flexibility assumptions should reflect technical capabilities of plants. License renewals, state-level ZEC policies, and uprate assumptions can be important for regional assessments.
- The section concludes with a list of modeling and analysis needs related to existing nuclear.

[26] Modeling for this study was completed in 2021 before the Bipartisan Infrastructure Law was passed, which means that the Civil Nuclear Credit Program and incentives for other electric sector resources (e.g., carbon capture, long-duration energy storage, transmission, hydrogen, advanced nuclear) were not included in these scenarios.

Overview of Considerations and Approaches

Existing nuclear is about a fifth of U.S. generation and half of zero-emitting electricity, so their representation in models can impact outputs.

The existing nuclear fleet in the United States consists of nearly 100 GW nameplate capacity. Existing nuclear currently represents about a fifth of electricity generation in the U.S. and half of all zero-emissions electricity. Studies generally indicate that least-cost decarbonization portfolios include maintaining a large fraction of this nuclear capacity and that mitigation costs would be higher if these plants retire during outlook horizons, though magnitudes vary by plant and scenario (Kim, Taiwo, and Dixon, 2021; Bistline and Blanford, 2020; Bistline, et al., 2018; Roth and Jaramillo, 2017).

Table 5-1 summarizes each model's characteristics most relevant to the representation of existing nuclear capacity. This section first reviews retirement dynamics and cost assumptions, then discusses dispatch and flexibility assumptions, and finally reviews the implementation of various polices that directly affect the existing nuclear fleet.

Table 5-1
Comparison of the representation of existing nuclear across models

Model	Source(s) of Fixed O&M Costs	Representation of ZEC Policies	CES Eligibility	Uprates	Existing Nuclear Retirements	Flexibility Assumptions	Fuel Cost Assumptions
IPM	AEO2020 and Sargent & Lundy analysis, function of age	States with ZEC policies cannot endogenously retire nuclear	Policy-specific, able to model with or without credit	Exogenous, based on AEO	Endogenous, up to 80 years	Capacity factor based on AEO assumption	AEO2020
NEMS	Updated in AEO2018 based on INL (2016) report	ZEC policies included in NEMS for qualifying states	Credit where specified in state legislation	Exogenous uprates revised yearly based on announced and NRC requests	Endogenous, up to 80 years	Existing nuclear has multiple dispatch options for spinning reserves and demand. Minimum output in a given slice is 50%	Exogenous input assumption
ReEDS	EIA NEMS Plant Database; increases at 1.5%/yr beginning in 2020	States with ZEC policies cannot endogenously retire nuclear; lifetime retirements only	Eligible to contribute in CA, CO, MA, NM, NY, WA, VA	Only included if in NEMS Plant database	Endogenous, up to 80 years	Nuclear cannot provide operating reserves	Exogenous input assumptions from AEO
REGEN	Electric Utility Cost Group (maintenance capital costs); ABB Energy Velocity (non-maintenance costs)	Represented as lower bound on eligible nuclear capacity in applicable model regions	Eligible for state and federal CES policies; nuclear receives full credit	Exogenous (based on announced uprates)	Endogenous, up to 80 years	Existing nuclear can be dispatched down to 70% of nameplate capacity; no ramping constraints; output limited by monthly availability factors	Exogenous input assumptions from AEO

Retirement Dynamics

Model-driven retirements in all four models are based on the premise that existing capacity will generate electricity if that capacity is able to recover the costs on the market (or if the cost of generating electricity is less than the cost of purchasing).[27] Those costs vary over time (e.g., periodic large capital expenditures), and each model evaluates cash flows over their respective time horizons, comparing the net present values of costs to potential payments. These retirement dynamics are similar for nuclear plants and other asset types, though the drivers of such retirements and policy impacts vary (Bistline, et al., 2018). While these models are based on assumptions of foresight, the existence of uncertainty introduces complexity into this evaluation for each unit. This uncertainty is likely a key driver of the notable amount of existing capacity observed to operate unprofitably in recent years.

Economics have been an important factor in many of the nuclear plant closures in the U.S. to date. Energy revenues are a key value stream for nuclear plants (see Section 4). Declining wholesale electricity prices from low natural gas prices have historically been a primary driver of economic pressures for nuclear plants (Jenkins, 2018a), but future policy changes and VRE deployment can also alter pricing dynamics and the economic outlook for nuclear plants. Retiring (zero-emitting) nuclear plants are generally replaced by fossil-fueled generation, which leads to increases in CO_2 and criteria pollutants, as several regional studies in the U.S. have shown (ISO New England, 2017; EIA, 2016; Davis and Hausman, 2016). Studies have illustrated how extending the lifetimes of nuclear plants can lower decarbonization costs (Kim, Taiwo, and Dixon, 2021; Bistline and Blanford, 2020; Roth and Jaramillo, 2017).

Each model captures retirement dynamics differently:

- **IPM:** Retirements of existing nuclear capacity are modeled endogenously in IPM—in each run year, the model compares the net present value of revenue from each model plant to the net present value of all future costs, and projects a retirement if the latter exceed the former. However, there are two key elements in IPM that affect the time path of those projections. The first is a constraint on near-term retirements, which prevents retirements in the first year of the model horizon beyond the trajectory of what has been observed recently (in the most recent version, total nuclear retirements are assumed not to exceed 4 GW in 2025, inclusive of planned retirements). Additionally, the model includes an uncertainty adjustment which decreases fixed operations and maintenance costs through 2030. This near-term adjustment reflects the potential impact of clean energy and/or carbon regulation optionality that nuclear units may consider while making retirement decisions.

[27] Models also incorporate announced retirements (e.g., for coal plants in many models) and exogenous retirement schedules based on asset age in some instances (e.g., existing gas-fired capacity in REGEN).

- **NEMS:** In the NEMS model, projected retirements are based on an economic evaluation in each year of the model looking at two separate factors—net revenues and reserve requirements. The model calculates net revenues in each year based on projected marginal energy prices as compared to going-forward costs and counts the number of years that each plant is projected to experience a negative net revenue. The model also determines whether the capacity from each plant is required to meet reserve constraints in a future year, including in that determination the cost of new capacity. The model retires an existing nuclear unit if the projected net revenue is negative for at least six years, and if the model is not using the capacity to meet a reserve or demand constraint in the future. Planned retirements reported to EIA through survey mechanisms (primarily near-term) are assumed to occur as-reported by plant owners; all other retirements are based on the economic evaluation described above.
- **ReEDS:** The ReEDS model incorporates both exogenous and endogenous retirements. Lifetime assumptions can range from 50 to 80 years, based on scenario design, with a default lifetime of 80 years. The model also allows for endogenous retirements of capacity prior to the maximum lifetime assumed for each unit. The net present value of the projected revenue is compared to the net present value of going-forward costs, and the model retires existing nuclear capacity for which a percentage of the cost is able to be recovered. The scenarios supporting this paper assume a 50% cost recovery requirement for going-forward costs, though that value can be changed by the user.
- **REGEN:** In REGEN, existing nuclear capacity is grouped together in a single representative block in each region. As in the other models, endogenous retirements are able to occur where the net present value of going-forward costs exceeds the projected revenues. Each regional block is dispatched together, and the model is able to retire a fraction of that block's capacity across time periods.

As discussed in Appendix A, retirement assumptions for some of the participating models changed over the course of this project.

Fixed Operations and Maintenance (FOM) Costs

FOM costs are key factors in projections of future operation, which makes it important to review the sources of these costs. These costs include all labor, materials, contracted services, general and administration (G&A), and maintenance capital costs.

As shown in Table 5-1, there are a range of FOM cost assumptions across the four models:

- **IPM:** IPM adopts the NEMS assumption for all non-capital costs and applies an age-based equation to estimate capital costs associated with the investments required to operate existing nuclear plants beyond 40 years.
- **NEMS:** The NEMS model updated its FOM cost assumptions for AEO2018 based on a 2016 INL report, which is based on a review of public and proprietary data (INL, 2016). The costs for each unit are a function of the number of units located at each facility, and for single-unit facilities, the size of that unit. G&A costs are an additional percentage adder. At 30 years, a capital cost related to plant aging is added to each unit.
- **ReEDS:** ReEDS also starts with the NEMS assumptions based on the year 2020, and increases that cost by $1.25/kW-yr (in 2017$) each year through 2030 and by $1.81/kW-yr each year after 2030 (Sargent & Lundy, 2018).
- **REGEN:** REGEN adopts FOM cost assumptions from two different sources. Capital costs are based on data from the Electric Utility Cost Group, and non-maintenance FOM are based on reported FERC Form 1 data.

Nuclear FOM cost assumptions vary widely by plant, over time, and across different models.

Figure 5-1 shows the range of cost assumptions employed by each model. Cost assumptions vary by plant and over time. These costs vary widely across plants within each model, as well as across different models. Within each model, there is a range of cost assumptions that can span up to roughly $200/kW-yr. Across models, the difference between the highest costs can reach roughly $150/kW-yr. Note that the 2020 average FOM across the U.S. fleet was about $190/kW (NEI, 2021). Costs have decreased steadily by a total of 20% across the fleet between 2014 and 2020, which is consistent with the industry's "Delivering the Nuclear Promise" initiative (NEI, 2021).

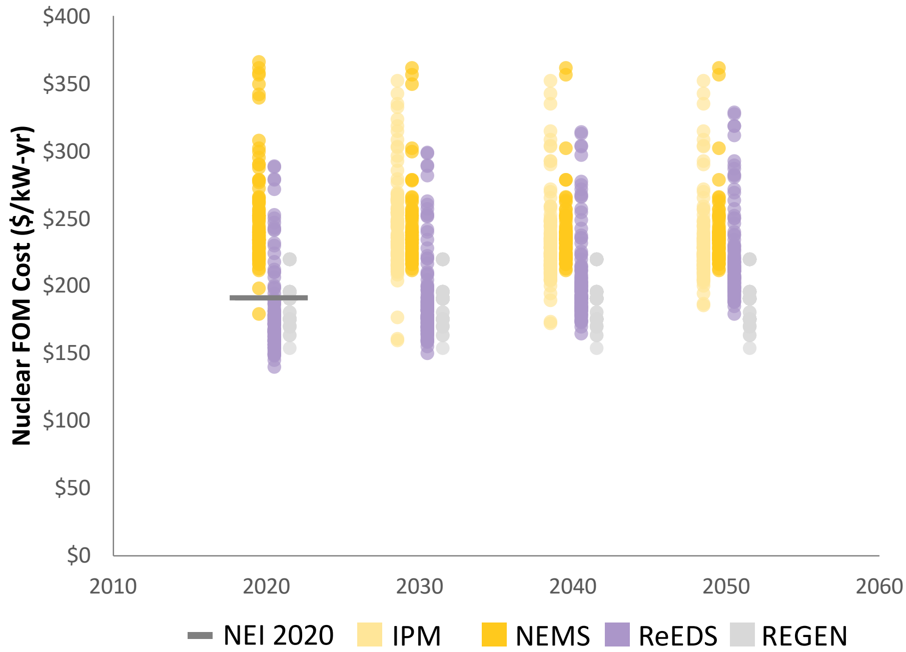

Figure 5-1
Nuclear fixed operations and maintenance (FOM) costs in 2020$ over time across models. FOM costs include all labor, materials and contracted services, general and administration, and maintenance capital costs. Points represent individual nuclear unit costs. The line shows 2020 average FOM across the U.S. fleet from NEI (2021).

Both IPM and NEMS employ different age-based algorithms to represent the capital expenditures for continued operation into first and second relicensing periods. In IPM, capital costs are assumed to increase until age 50, at which point they remain flat. In NEMS, an annual adder is applied beginning at age 30. In the ReEDS model, an annual 1.5% escalation is applied. REGEN assumes static costs across the model horizon.

The primary reason for the differences in cost assumption across the models is data availability. A comprehensive public data source for current FOM costs does not exist. Additionally, limited data are available on the magnitude and timing of unit-level capital investments over time. Each of the models has a different approach to estimate future costs based on the limited available data.

The intra-model comparison later in this section illustrates how FOM cost assumptions can impact existing nuclear retirement projections. However, retirement projections are due to a range of model-specific factors, as illustrated in Section 2, where REGEN has the second highest nuclear retirements in the reference scenario with native cost assumptions (Figure 2-3) despite having the lowest FOM costs (Figure 5-1).

Dispatchability and Flexibility

Assumptions about the dispatchability and flexibility of existing nuclear plants can impact projections for their operations and retirements. Existing boiling water reactor (BWR) and pressurized water reactor (PWR) plants in the U.S. can lower output down to 70% of their nameplate capacity within an hour (Ziebell, et al., 2021). There are no licensing requirements that would limit the flexibility of the existing nuclear fleet, though economic and technical considerations may influence such operating modes. In contrast, many existing energy models represent nuclear plants as inflexible "must-run" capacity (Jenkins, et al., 2018b).

The projected dispatch of existing nuclear capacity and assumptions about its flexibility vary across the four models:

- **IPM:** In IPM, projected dispatch is flexible in each time segment up to a maximum assumed availability for each unit. That availability is a function of an age-based capacity factor algorithm (where capacity factors increase for the first 30 years and then remain flat) and seasonal planned outage assumptions (which are assumed to occur in the winter and shoulder segments). Given the low variable cost of existing nuclear, the model typically dispatches these units up to the availability.
- **NEMS:** NEMS assigns multiple operating modes for each unit by season to allow for projected contribution to load or spinning reserves. The maximum capacity factor is a function of age (where capacity factors increase for the first 30 years and then remain flat), and each unit can operate down to a 50% capacity factor if chosen to maximize the spinning reserve contribution.
- **ReEDS:** In ReEDS, existing nuclear plants are assigned a maximum capacity factor of 91.2%, and the model typically operates these units at that maximum value. However, ReEDS enables seasonal decommitment of nuclear capacity in scenarios where the value of doing so exceeds the variable cost, subject to a minimum annual capacity factor of 40%. ReEDS also allows nuclear plants to turn down to 70% of their rated capacity if it is optimal to do so.
- **REGEN:** In REGEN, the maximum level of generation at each existing nuclear unit is a function of monthly availability factors, which account for seasonal variation in outages and are based on historical data. Unlike IPM and NEMS, these availability factors are static over time, though hourly capacity factors are endogenous and can vary over time. Minimum generation is limited to 70% of nameplate capacity.

Section 6 provides an intra-model comparison that illustrates how flexibility and dispatchability assumptions can impact model outputs related to new and existing nuclear.

Other Considerations

As shown in Table 5-1, fuel cost assumptions across all four models are based on the values adopted in EIA's AEO. Similarly, uprates are exogenously determined across each of the models. The NEMS team reviews announced updates and requests submitted to the U.S. Nuclear Regulatory Commission (NRC), and the other models either rely on this review or perform similar reviews of the available information. The NEMS model assumes that 2.1 GW of uprates for existing nuclear plants occur through 2050. This assumption is implemented regionally, and informed by EIA analysis of the remaining uprate potential by reactor, based on the reactor design and previously implemented uprates.

The final points of comparison between the four models relate to various policies that directly affect the existing nuclear fleet. IPM, NEMS, ReEDS, and REGEN all enable endogenous nuclear retirements and lifetimes up to 80 years (recall, however, that each model has a different approach for estimating future FOM costs). All four models represent ZEC programs by preventing endogenous retirements of existing nuclear capacity in states where these programs are in effect. In NEMS, the value of the ZEC is calculated and passed through to retail prices (subject to any applicable cap). Similarly, in all four models the existing nuclear fleet's zero-emitting generation is able to contribute toward CES programs.

Intra-Model Comparison: FOM Cost Assumptions and Nuclear Retirements

Nuclear FOM cost assumptions are first-order drivers of model projections of nuclear plant retirements.

FOM cost assumptions are key drivers in future projections of existing nuclear capacity. As shown in Figure 5-1, unit-level FOM assumptions vary widely across the participating models. The differences between the native IPM and REGEN assumption is notable: In 2030, unit-level differences can be up to $160/kW-yr (in 2020$).

To assess the sensitivity of the modeling results to FOM assumptions, we evaluate the impacts of applying two sets of FOM costs using IPM, holding all else constant and assuming a "current policies" reference scenario. The first scenario assumes the native IPM FOM cost assumptions. The second scenario assumes REGEN assumptions, which are generally much lower. The near-term retirement constraints and uncertainty adjustments, summarized above, were removed from IPM for these scenarios.

The impact on projected retirements is significant (Figure 5-2): IPM projects a 46 GW decrease in retirements by 2050 as the result of applying the lower FOM cost assumptions from REGEN (out of an existing fleet of approximately 90 GW). The results are similar in the near- and mid-term, where applying the lower costs increased operable nuclear capacity by roughly 40 GW.

Unsurprisingly, these notable changes in projected nuclear retirements have large impacts on related model projections. For example, the increase in nuclear generation resulting from the lower nuclear FOM cost assumptions leads to significant decreases in fossil generation (about 20% and 5% decrease in coal and gas, respectively, in 2030), as well as decreases in new renewable construction. Overall, decreases in nuclear retirements result in lower CO_2, SO_2, and NO_X emissions.

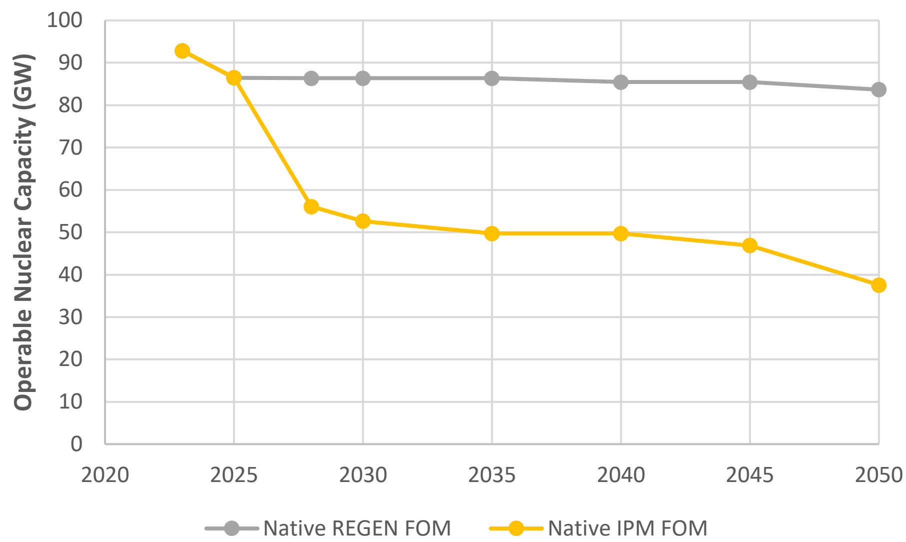

Figure 5-2
Projected changes in operable capacity resulting from two different sets of FOM assumptions in IPM.

Recommendations for Future Modeling RD&D

Given its size, implications for dispatch, and potential to affect emissions, accurately representing the existing nuclear fleet is key for reliable projections of power sector investments and operations. As we see above, changes to a single input assumption can have large impacts on power sector projections. The following three areas are of particular importance for future modeling research and development regarding representation of the existing nuclear fleet in capacity expansion modeling:

- *Improve data and methods for estimating retirements:* Retirements represent a significant driver for new capacity needs, but these dynamics are challenging to represent in models. Understanding drivers of retirements across models would be valuable, especially accounting for uncertainty (e.g., policy, FOM and future capital costs) and foresight (as discussed in Section 7). Option theory combined with policy uncertainty may suggest postponing nuclear plant retirements, especially since such decisions are essentially irreversible. However, most models are deterministic and do not explicitly account for such uncertainty.[28]
- *Provide public data for nuclear costs:* Given the notable impact that different FOM cost assumptions can have on the modeling, it is important to reflect those costs as accurately as possible. To that end, public data for current FOM costs by plant and guidance on projected changes (both the magnitude and timing) would be useful for modeling teams. Such cost data would be valuable for understanding projections for nuclear generation and estimates for other resources. In addition to input assumptions, it is important to compare model algorithms and heuristics for power plant retirement, cost, and operational decisions against actual data and to update these model features as appropriate.
- *Understand possible nuclear plant license renewals to 80 years and beyond:* It is important to consider the possibility of license renewals beyond 80 years, especially as models begin to expand projections beyond 2050.

[28] It is important to note, however, that IPM includes an FOM adjustment through 2030 that reflects the potential impact of clean energy and/or carbon regulation optionality that nuclear units may consider while making retirement decisions.

Section 6: Representation of New Nuclear

Summary

- New nuclear deployment varies considerably based on scenario definitions—the most impactful of which are future cost trajectories and policy assumptions. Default model input assumptions and structures have more limited impacts on new nuclear deployment.
- As with all resources, it is important for models to capture different nuclear technologies and their anticipated characteristics. The scope of many models, including the four participating ones in this study, mean that cost assumptions are key drivers of deployment. Outputs can be highly sensitive to inputs about the cost and performance assumptions for different nuclear reactor technologies and to assumptions about the costs of other resources. However, there is considerable uncertainty about the projected costs of new nuclear designs and appropriate methods for capturing technological change.
- Model representations of changes in technological performance and costs are critical determinants of model outputs, as the intra-model comparison in this section illustrates. Technological change can either be exogenous (i.e., based on pre-defined input assumptions about changes over time) or endogenous (i.e., based on model-driven changes in deployment given input assumptions about learning rates). Endogenous technical change raises several challenging conceptual and practical considerations, including attribution, parameter selection, spillovers, and computation. The appropriateness of different approaches to representing technological change varies by model and context.
- Nuclear power is a high-capital-cost but low-variable-cost resource, which makes assumptions about project finance and discounting critical for evaluating its economic competitiveness.
- The section concludes with a list of modeling and analysis needs related to new nuclear.

Overview of Considerations and Approaches

The advanced[29] nuclear reactor technology landscape has evolved over the last several years in the U.S. and globally, with plans for a range of demonstration projects and commercial construction over the next decade. These designs offer new features, attributes, capabilities, and deployment models that differ from those of the operating fleet and mature commercial offerings (Sowder, 2021; Marciulescu, et al., 2019). With many drivers of decarbonization at federal and subnational levels, deployment of zero-emitting technologies like new nuclear may play important roles, so long-term energy system models should reflect salient features of these new nuclear technologies.

[29] Advanced nuclear is used here to refer to reactor concepts beyond Generation III/III+ technologies, including non-light-water designs, light-water SMRs, and microreactors.

Table 6-1
Comparison of the representation of new nuclear across models

Model	New Nuclear Technology Options	Cost Assumptions and Source(s)	Flexibility Assumptions	Financing Assumptions	Cooling Technologies	Deployment Constraints	Fuel Cost Assumptions
IPM	Light Water Reactor (based on AEO2020 assumptions)	AEO2020; exogenous technical change	Dispatchable up to 90% capacity factor	Approximately 8% capital charge rate, 40-year book life	N/A	6-year lead time	Based on EIA's AEO
NEMS	Advanced Nuclear and Small Modular Reactor disaggregation are represented as nuclear technologies in NEMS	AEO2020 based on Sargent & Lundy report; endogenous technical change	For capacity planning, new nuclear is assumed to dispatch at max generation, but once built is allowed to vary	Same financing for all technologies; 30-year economic life; cost of capital from macro model projections, AEO2021 discount rate ~6% nominal	N/A	SMR first online date is 2028; no nuclear builds allowed in NYC or California	Exogenous input assumption (same value for existing and new)
ReEDS	AP1000 and SMR	AEO2020 for new nuclear (based on brownfield AP1000 development); exogenous technical change	Linear optimization allows complete dispatchability	20-year economic life, 6-year construction, 15-year MACRS depreciation schedule	Once through, recirculating, and cooling pond technologies (dry cooling is not allowed)	New nuclear generation cannot be available for generation before 2028	Based on EIA's AEO
REGEN	Gen III+ (based on AP1000); generic advanced nuclear technology (parametrized based on SMR)	EPRI "Generation Options" report; regional variation in labor costs; exogenous technical change	Fully dispatchable; no ramping constraints; output limited by monthly availability factors	Technology-specific physical/economic lifetimes; discount rate of 7% typically assumed	Water withdrawal and consumption calculated ex post; REGEN does not endogenously determine cooling for existing/new capacity	Constraints on "brownfield" sites; advanced nuclear not available until 2030; state-based moratoria	Based on EIA's AEO

Table 6-1 compares the representation of new nuclear across the four participating models.

Technological Availability, Cost, and Performance Assumptions

A fundamental consideration for modeling new nuclear is the choice set of available technologies and their parameterizations. Long-term system models incorporate the operations of existing nuclear plants (Section 5) as well as new investments over time, including Generation III/III+ designs (e.g., Westinghouse AP1000), small modular reactors (SMRs), and Generation IV designs, which are often distinguished by their primary system coolant (e.g., liquid metal, molten salt, gas-cooled). As shown in Table 6-1, models generally capture the ability to invest in AP1000 designs and SMRs.[30]

Model outputs can be highly sensitive to input assumptions about the cost and performance for nuclear and other system resources.

Each technology includes associated parameters related to cost (e.g., capital costs, FOM costs) and performance (e.g., fuel use, flexibility).[31] Outputs can be highly sensitive to inputs about the cost and performance assumptions for nuclear and other system resources.

Capital cost projections for new nuclear and other generation options over time are shown in Figure 6-1. Note that ReEDS assumptions are used for the harmonized cost scenarios in Section 2. Sources for cost projections of new nuclear over time vary by organization. There is considerable uncertainty about the projected costs of new nuclear designs over time, which reflects questions about initial all-in costs for emerging technologies, extent of learning and cost reductions over time and with greater deployment, country- and region-specific factors,[32] indirect costs,[33] and impacts of policy support. It is important not only to specify reference costs over time but also reasonable low- and high-cost sensitivities for additional scenario analysis.

[30] Some models have generic characterizations of new nuclear options with unspecified reactor types. Differentiating could have implications for cost and the fuel cycle.

[31] Note that ReEDS explicitly represents cooling technologies for thermal generating assets. Water use is constrained using technology-specific withdrawal and consumption rates alongside water availability and cost data.

[32] Historical construction costs for new nuclear have varied substantially by country (Lovering, et al., 2016), though past performance is not necessarily indicative of potential future costs.

[33] The rise in U.S. nuclear plant construction costs in recent decades have largely been due to "indirect" expenses, primarily soft costs (Eash-Gates, et al., 2020).

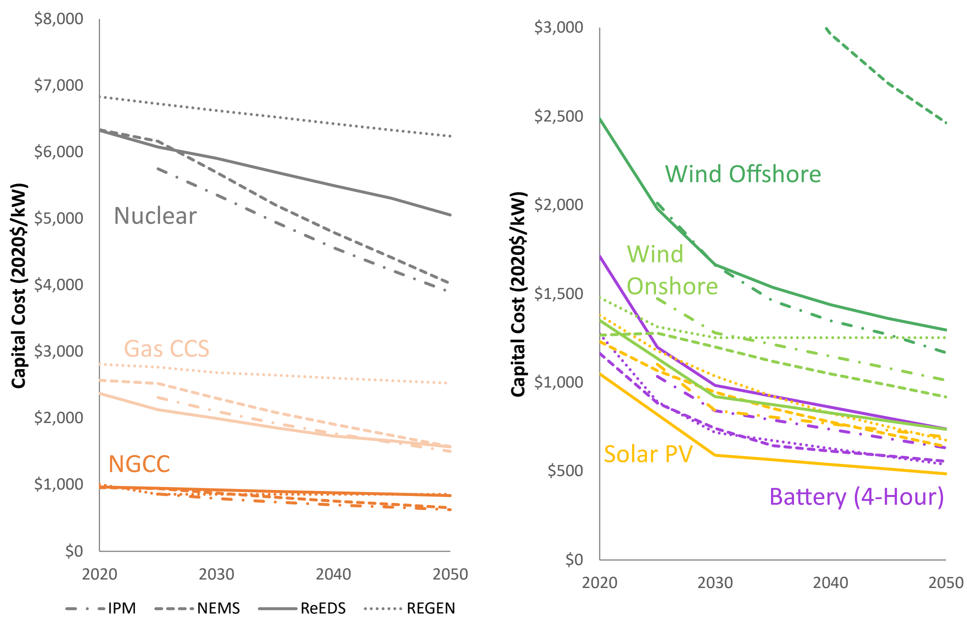

Figure 6-1
Comparison of native capital cost assumptions by technology and model over time. Note that the ReEDS costs are used for the harmonized cost sensitivities in Section 2.

Technological Change

Model representations of changes in technological performance and costs are critical determinants of model outputs. Technological change can either be exogenous (i.e., based on input assumptions about changes over time) or endogenous (i.e., based on model-driven changes related to deployment and other factors).[34] Although the most widespread treatment of technological change in energy models is to consider it exogenously, endogenous technological learning has also been widespread in the energy systems and climate policy modeling literatures (Gillingham, Newell, and Pizer, 2008).

[34] For the models in this comparison, IPM, ReEDS, and REGEN assume exogenous technological change, while NEMS often assumes endogenous technological change, but can be run with exogenous cost trajectories.

Endogenous technical change raises practical and conceptual issues, including attribution, parameter selection, spillovers, computation.

There are several key conceptual and practical considerations raised by endogenous technological learning:

- **Attribution:** Traditional one-factor learning curves assume that changes in cost are solely a function of cumulative experience. However, technological change is a complex process, and the empirical literature on historical determinants of technological change suggests that a broader range of factors (e.g., economies-of-scale, learning-by-doing, RD&D, forgetting effects,[35] materials costs) contributes to these changes (Grubb, et al., 2021; Kavlak, McNerney, and Trancik, 2018; Gillingham, Newell, and Pizer, 2008; Nemet, 2006).
- **Parametrization:** Although there is extensive literature documenting historical learning rates (Grubb, et al., 2021; EPRI, 2020b; Isoard and Soria, 2001), selecting forward-looking parameters across different technologies is challenging for prospective modeling.[36] This difficulty is especially prominent for nascent technologies, where there is no empirical basis for parametrizing technological relationships, but also can present problems for existing technologies, as learning rates may change across different stages of deployment. Cost estimates can be highly sensitive to the choice of learning rates and other parameters, which can bias optimization model outputs (Nordhaus, 2014).
- **Spillovers:** Spillover effects across countries, firms, and technologies may be important for technological change in practice, but these dynamics are often simplified in prospective models (Grubb, et al., 2021).
- **Computation:** Endogenous technical learning leads to several computational challenges, including increasing the size and solve time of the optimization problem, creating path dependencies (which can lead to many distinct local optima), and adding nonlinearities to the problem formulation (Gritsevskyi and Nakićenovi, 2000).

Different approaches to modeling technological change are appropriate in different contexts.

The appropriateness of different approaches to representing technological change varies by model and context, as exogenous technological change may be more appropriate in settings while endogenous is preferred in others.[37] A range of studies examines strengths, limitations, and policy implications of different approaches to modeling technological change (Grubb, et al., 2021; Nordhaus, 2014; Gillingham, Newell, and Pizer, 2008). In all cases, emissions policies and technical change interact with one another (Acemoglu, et al., 2012).

[35] Depreciation of the knowledge stock and potential cost increases when deployments and RD&D decline over time.

[36] This is a pervasive challenge for multi-decadal models not only for technological costs but also for assumptions about fuel costs, demand, policies, and many other areas.

[37] It is unclear ex ante whether adopting exogenous technological change vis-à-vis endogenous change impacts the deployment of nuclear energy, as a range of context-specific considerations likely influence how model representations of technical change interact with other model decisions and outputs.

Technological change is important for considering new nuclear, due both to the impact of cost assumptions on model outputs and to the expectation that costs of new nuclear will fall as the technology moves down the learning curve. Factory-fabrication of modular technologies can reduce costs over successive builds, and several recent studies (Sweerts, Detz, and van der Zwaan, 2020; Wilson, et al., 2020) indicate higher learning with smaller units (i.e., learning rates depend more on size than on technology). Newer nuclear plants such as SMRs are designed to be standardized and mass-produced in factories rather than being built onsite, which has the potential to lower costs. First-of-a-kind technology additions may be characterized by higher costs, but at moderate learning rates, costs may come down considerably, especially for SMRs where the cost trajectory may be more dependent on learning rate assumptions than on first-of-a-kind costs (Lovering, 2020).

Refer to the intra-model comparison in the subsequent section for an illustration of how technological change assumptions can impact the deployment of new nuclear.

Discounting and Financing

Nuclear is a high-capital-cost but low-variable-cost resource, which means that financing and discounting are key assumptions for assessing its competitiveness.

Nuclear power—like renewables, transmission, and energy storage—is a high-capital-cost but low-variable-cost resource, which means that assumptions about project finance and time preference (i.e., comparing current costs and revenues vis-à-vis future ones) are important for evaluating its economic competitiveness. The potential for longer asset lifetimes also makes discounting and financing assumptions central to assessing the competitiveness of new and existing nuclear plants. Nuclear and all other generating technologies entail intertemporal tradeoffs between upfront capital costs and ongoing operating costs.

There are many considerations at play in the selection of parameters and model representations, which are discussed in detail in Section 7 (including an intra-model comparison to illustrate how these parameters can materially impact nuclear-related model outputs). Differences in discounting and financing vary across models (Figure 7-2).

Deployment Barriers

As potential scenarios are considered with significant and sometimes rapid deployment of new nuclear, it is important to understand potential challenges that might arise and could dampen the pace or extent of nuclear deployment. Issues that could arise during a rapid nuclear build-out in the U.S. include:

- Limited supply chain, including labor and parts, for developing many new nuclear projects simultaneously;
- Fuel processing and supply capabilities for new reactors;

- State-level restrictions[38] that might limit the siting options for new nuclear technologies;
- Public acceptance of nuclear technologies, especially as they could be deployed to locations where nuclear plants have not existed in the past;
- Securing sufficient financing to support the development of many plants simultaneously;
- Insufficient means for dealing with the waste produced by nuclear plants; and
- Availability and regulatory approval of new nuclear designs in the timeframe for the deployments envisioned by the models.

Most of these potential barriers are not explicitly captured in the four participating models with the exception of state-level restrictions. Integrated assessment models can impose ad hoc constraints on deployment to capture “reactor safety and cost, uranium availability, nuclear waste disposal, proliferation, public acceptance, and others” (Kim, et al., 2014).

Intra-Model Comparison: Technological Change

Given the importance of investment cost assumptions over time for nuclear deployment, an intra-model comparison is conducted in NEMS to compare impacts of different representations of technological change. In NEMS, the EMM solves sequentially and can provide annual feedback from other modules during the model solution, as well as use one year’s solution to update decisions in future years. In the typical model process, EIA assumes that new power plant costs change over time dynamically based on several factors, although it can also take fixed cost paths as inputs. The dynamic factors include a commodity cost index[39] that is calculated based on macroeconomic projections for metals and metal products, a technological optimism factor,[40] and a learning factor.

Of the four models in this study, NEMS is the only one that represents endogenous technological change (Table 6-1). NEMS models endogenous learning through a log-linear function that projects costs to fall at a fixed percentage for every doubling of capacity. For the newest technologies, the learning rate changes over time, with three distinct steps in the calculation. Learning is implemented at a component level for many technologies to allow sharing of learning between technologies, and to reflect that different

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[38] Though states that have previously restricted new nuclear builds have recently passed legislation to reverse such bans: https://www.ncsl.org/research/environment-and-natural-resources/states-restrictions-on-new-nuclear-power-facility.aspx

[39] The commodity cost index was added to NEMS to account for cost escalation for critical commodity materials and labor in the power sector such as was seen in the mid 2000s and appears to be occurring in the early 2020’s.

[40] Technological optimism reflects the tendency to underestimate costs for new technologies. EIA currently applies this factor to a few technologies which are considered complex designs or in early stages of development. The SMR design assumes that initial costs will be 10% above the base cost estimate due to this technological optimism factor. This adjustment declines linearly over the first four builds of the new design.

components are in different stages of development. In general, standardized learning rates of 20% on the revolutionary step, 10% on the evolutionary step and 1% on the conventional step are used. However, for both nuclear SMRs and AP1000, aggregated learning rates are used to reflect a mix of experience with the design without explicitly breaking down the components. For both nuclear technologies, cost declines of 5% are assumed for the first three doublings of capacity, cost declines of 3% occur for the next five doublings, and cost declines of 1% occur for any future doublings (Figure 6-2). Builds of AP1000 and SMR do not currently contribute to the learning rate of the other design.

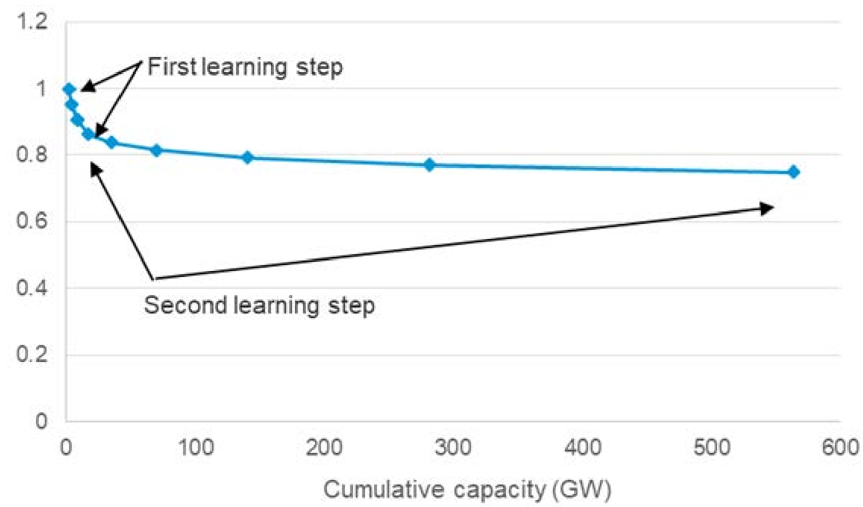

Figure 6-2
Learning factor as a function of cumulative system capacity.

Costs declines are most rapid for early builds, as experience is gained in developing a new technology (or component), which slows as more capacity is built. EIA also assumes a minimum level of learning to reflect ongoing research and development that may affect future costs even absent new builds, which results in an exogenous, time-dependent component to the learning function as well as the capacity-driven portion.

To observe the impact of the learning algorithm as applied to a nuclear SMR, EIA developed sensitivities with a carbon fee on power sector emissions. An initial cost for the nuclear technology is chosen that results in new builds (roughly $5,400/kW initially), so that the learning algorithm can be observed. As an alternative to EIA's learning algorithm, a separate case is run with a fixed cost path, declining linearly by roughly 32% by 2050. In both cases, a $15 per ton carbon fee is applied in 2030, rising at 5% per year to reach $40 per ton in 2050, to further stimulate demand for low-carbon generation. These assumptions are for illustrative purposes only and do not necessarily reflect current technology assessments or policy expectations of EIA or other modelers.

Endogenous technical learning can lead to greater market penetration after the first few builds as costs decline more rapidly.

The EMM projects new nuclear builds to occur starting after 2035, as shown in Figure 6-3. In both cases, nuclear costs follow similar trajectories through 2035, dominated by changes in the commodity price index and scheduled cost reductions. Once builds begin, the case with endogenous learning experiences greater cost declines (as the first step of the learning curve results in relatively large drops in cost for the initial builds), which then leads to higher future builds of new capacity as the cost becomes even more competitive (Figure 6-3). In the fixed cost path, the builds occur more slowly, and the rate does not significantly change over time as the builds had no impact on the cost trajectory.

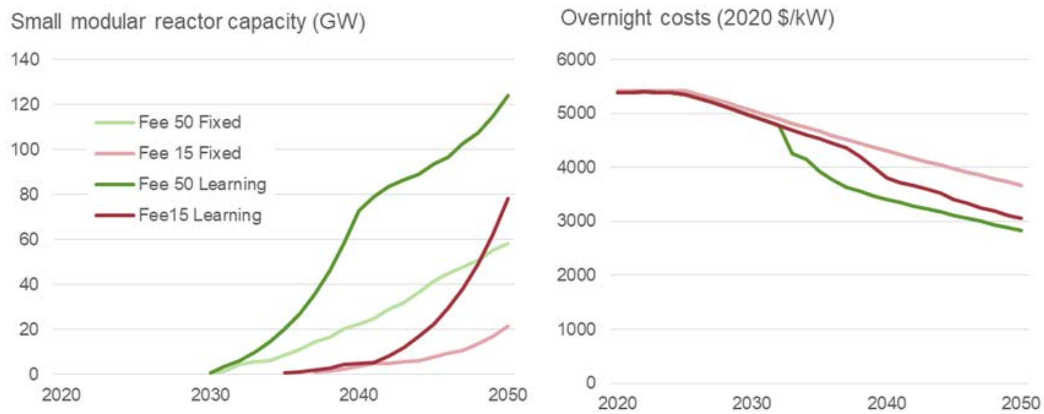

Figure 6-3
Cumulative capacity additions and overnight costs under two carbon fee scenarios and with fixed costs versus endogenous learning in NEMS.

An additional pair of scenarios is run with higher carbon fees, starting at $50 per ton in 2030 and rising at 5% per year, reaching $133 per ton in 2050. In these cases, the new nuclear technology is competitive earlier (by 2030), and additional builds are seen relative to the $15 fee case. The endogenous learning case responds with an earlier drop in cost and with a larger drop in costs as a result of higher builds. Learning leads to higher additions of new nuclear (124 GW versus 78 GW with a fixed cost path). When using endogenous learning, the costs in 2050 are 7% lower in the $50 fee case compared to the $15 case as a result of additional capacity investments (Figure 6-3, right panel). Costs in 2050 are between 17% and 23% lower than the fixed cost path, and builds are 57 and 66 GW higher. As a result of the higher nuclear capacity, the cases with endogenous learning have fewer natural gas-fired and renewable capacity additions and slightly lower electricity prices.

In the scenarios analyzed, the inclusion of endogenous learning cost reductions has a greater impact on deployment of SMR technology than the carbon fee level. There is an additional 20 GW of nuclear capacity built in the $15 fee case with endogenous learning compared to the $50 fee case with fixed costs, indicating the decline in the cost of the technology is a larger driver of new builds than the increased level of carbon fee.

These intra-model comparisons illustrate how representations of technological learning can impact long-term expansion model results, especially for new or less commercially mature technologies. As described in the earlier subsection on "Technological Change," implementing endogenous learning requires careful review of the current status of different technologies to determine where each is on the current learning curve and what the appropriate parameters should be. But the ability to have endogenous feedback across scenarios can help identify potential interactions that result in a technology breakthrough.

Intra-Model Comparison: Flexibility

CEMs often include a representation of operating reserves and ancillary services, which can be provided by flexible and dispatchable resources. The goal of this intra-model comparison is to evaluate how impactful the nuclear flexibility definitions and access to operating reserves and ancillary service revenues in a model framework are to projected nuclear power plant retirement and investment decisions.

Using the ReEDS model, we explore scenarios with varying levels of flexibility for both conventional and advanced (SMR) nuclear technologies (Table 6-2). Under our "low flexibility" assumptions, conventional nuclear power plants are assumed to be inflexible (such that they could not provide operating reserves or ancillary services), and we adopt relatively conservative flexibility assumptions for SMRs with minimum loads of 70% (Table 6-2). Under our "high flexibility" assumptions, conventional nuclear power plants are allowed to operate flexibly and, in turn, provide operating reserves. For SMRs, we adopt "high flexibility" assumptions based on operating characteristics for a NuScale SMR.

Table 6-2
Flexibility parameterization for conventional and advanced (SMR) nuclear technologies under our low-flexibility and high-sensitivity assumptions

Characteristic	Conventional Nuclear		SMR	
	Low Flex	High Flex	Low Flex	High Flex
Minimum Load	100%	70%	70%	40%
Minimum Load for Op. Characteristics	100%	70%	70%	20%
Ramp Rate (per minute)	0%	0.32%	0.32%	0.67%
Regulation Reserve Cost ($/MWh)	-	$13.71	$13.71	$13.71
Flexible Reserve Cost ($/MWh)	-	$0	$0	$0
Spinning Reserve Cost ($/MWh)	-	$0	$0	$0

These two different levels of flexibility are then layered with two policy scenario definitions: one with current policies (only) and the other with a hypothetical power sector carbon policy that forces a linear reduction towards a 100% decarbonized electricity supply in 2050 ("100% by 2050"). We further explore these scenario combinations with low-cost assumptions for new SMR capacity.

Flexibility assumptions about existing and new nuclear are smaller determinants of the economics of these resources relative to other factors.

Scenario outcomes indicate that modifying flexibility assumptions has no impact on installed nuclear capacity under either the Current Policies or 100% by 2050 policy. In particular, the ReEDS model does not retire any existing nuclear capacity (beyond announced retirements) in any of the scenarios explored for this intra-model comparison; in addition, the magnitude of new SMR capacity is insensitive to the assumed level of flexibility (although it did vary based on policy and technology cost assumptions). In other words, the flexibility assumptions on their own are not found to be a principal determinant in the economics of existing or new nuclear capacity on the bulk power system.

Additional insights can be gained from the reduced-form dispatch results from ReEDS, which take the form of total generation (or capacity) factor by representative time slice. When examining these results for new and existing nuclear power plants, the only visible changes occur in the 100% by 2050 scenarios (Figure 6-4). Under our "high flexibility" assumptions, the model shows an increase in generation from nuclear power plants during the Spring, which is a period of significant VRE curtailment. In the model, an inflexible nuclear plant must operate at a lower seasonal capacity factor, because it cannot vary output to balance (or avoid the curtailment of) VRE generation. By contrast, our high flexibility assumptions allow the nuclear power plants to operate more flexibly, resulting in a greater degree of load following and the ability to increase total generation in that representative season.

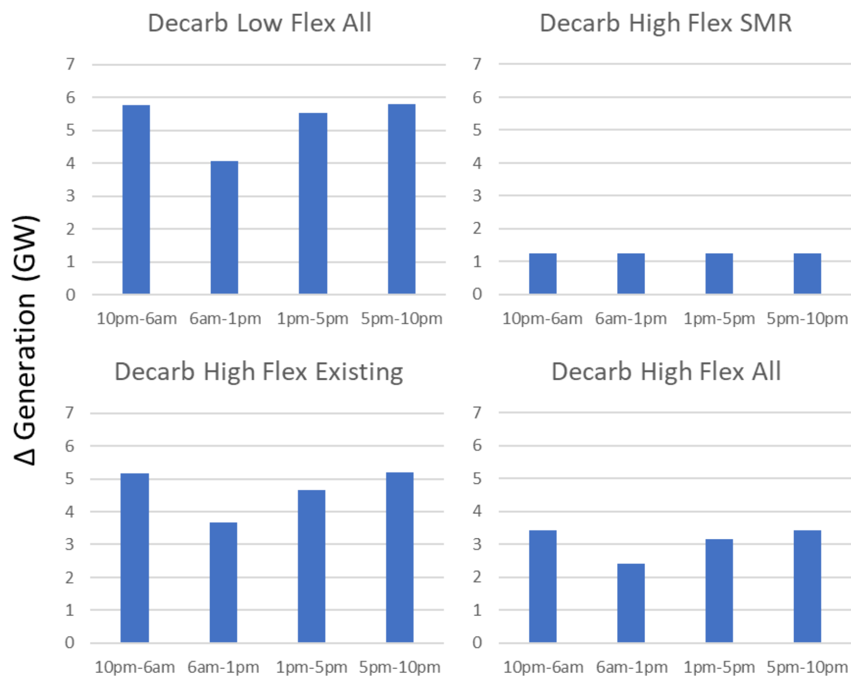

Figure 6-4
ReEDS Spring season dispatch of existing and new nuclear capacity across the four scenarios explored for this model intra-comparison.

Finally, the operating reserves results from ReEDS indicate that modifying nuclear flexibility assumptions has a modest effect on operating reserve prices (Figure 6-5). Providing energy and operating reserves are mutually exclusive decisions within the ReEDS model, and for nuclear power plants, opting to provide energy typically leads to the greatest system cost (and revenue) benefits.

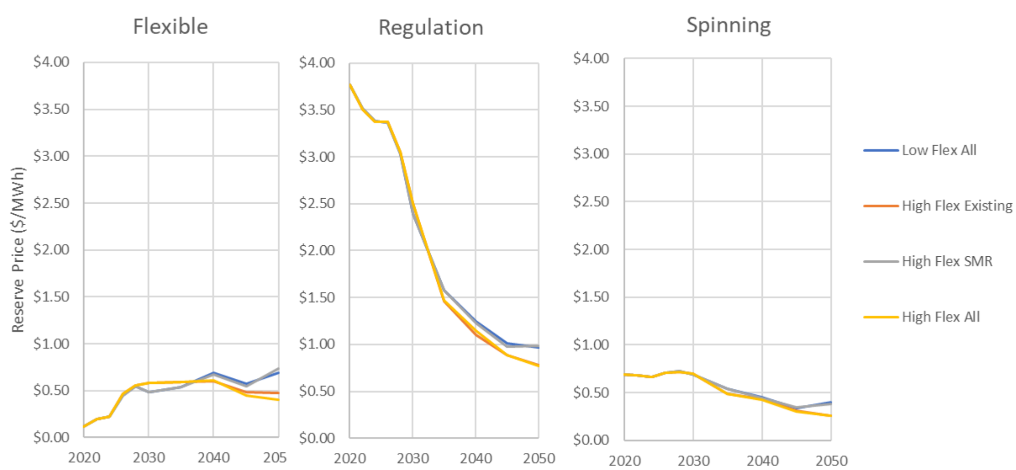

Figure 6-5
ReEDS model outputs for operating reserve prices across a subset of the intra-model comparisons for nuclear power plant flexibility.

Intra-Model Comparison: Deployment Barriers

EIA includes short-term supply cost adjustment factors for the installation of new electricity generating technologies in the capacity planning module of NEMS, which is unique among the four participating models. The factors reflect the expectation that rapid expansions in the supply of installations using new technologies may induce shortages of critical manufacturing and project development resources as discussed earlier. Shortages could reflect manufacturing bottlenecks; delays in regulation, licensing, and public approval; and resource constraints resulting from shortages of trained construction and operations personnel and equipment.

EIA uses supply steps for new builds to reflect the potential for cost increases when new capacity is built faster than recent experience.

EIA assumes generating capacities can increase in a given year by a pre-specified amount without incurring cost increases, but costs are assumed to increase above a threshold rate of increase. The threshold is based on previous builds of the technology, so that as a specific industry is built up and proven to be able to bring significant capacity online in a single year, this annual limit will grow and no longer become binding. Capacity builds in a given year can be up to 25% above a base amount in a given year without a cost adjustment (that is, 125% of the base capacity). This increment is based on the greatest amount of capacity brought online in a single year during the past 10 years, but with recent experience more heavily weighted. The capacity amounts are specific to the individual designs, with overlap assumed only for the solar PV and solar PV with battery storage technology. For other designs, such as the SMR and AP1000 nuclear plants, the constraints are applied on each individual design. If no existing capacity is online, then an exogenous assumption is used for the initial base amount. For SMRs, an initial 3 gigawatts (GW) of capacity can be built without incurring these costs.

The short-term cost adjustment factors are based on the percentage change of national installed capacity of a technology, using an exponential cost function relating an increase in capacity to a cost multiplier.[41] These adjustment factors are endogenous to the EMM and are only affected by the rate of increase in specific technology builds and would not represent external economy-wide disruptions in supply chains. In reference case modeling, these supply constraints are generally binding in relatively few years for the newest technologies, as the model tends to follow recent trends in capacity expansion and new technologies become economic gradually over time. However, in sensitivity cases which require a large shift in the generation mix or when new technologies are assumed to have a breakthrough in cost, these constraints can have a larger impact on model results.

[41] Because the linear program cannot model a continuous upwardly sloping function, the formulation creates a three-step supply curve. The capacity assumed for the steps is 125% of the base amount for the first step (with no cost factor), 75% of the base amount for the second step, and 100% of the base amount for the third step. The midpoint capacities on steps 2 and 3 are used to calculate the cost multiplier, using the assumption that a 1% increase in capacity will lead to a 1% increase in costs.

To illustrate the impact of this feature, EIA compares two sensitivity cases around the low-cost decarbonization scenario presented in Section 2.[42] EIA models the decarbonization scenario through a carbon fee to the power sector of $50 per ton in 2030, growing at 5% per year to $133 per ton in 2050. The sensitivity cases assume a different threshold for the first supply step, one with a lower value of 115% and another with a higher value of 135%. These assumptions alter how quickly nuclear capacity could grow without an additional cost factor. Typically, EIA uses the same elasticity parameters for all technologies, but for this sensitivity, the value is changed just for nuclear to isolate the impact on the SMR builds.

Limiting the pace of expansion of new nuclear through the supply-step constraint affects the overall generation mix and cost of producing power.

In the case with the reference elasticity threshold, the capacity builds hit the annual constraint on the first supply step for the first 12 years of builds before the threshold grows enough to become non-binding. With a lower elasticity, this constraint is binding in all projection years, and cumulative builds are under 100 GW by 2050, while the case with the reference elasticity builds 173 GW in the same time frame. In the case with the higher elasticity, builds increase more quickly in the early years and the constraint was no longer binding after nine years; however, builds in later years are not significantly different, ending around 187 GW in 2050 (Figure 6-6). Under this scenario, the choice of the initial elasticity parameter affects how quickly new nuclear can be brought online and has an impact on the overall cost to the system, as shown in the electricity prices (Figure 6-6) as well as the generation mix (Figure 6-7).

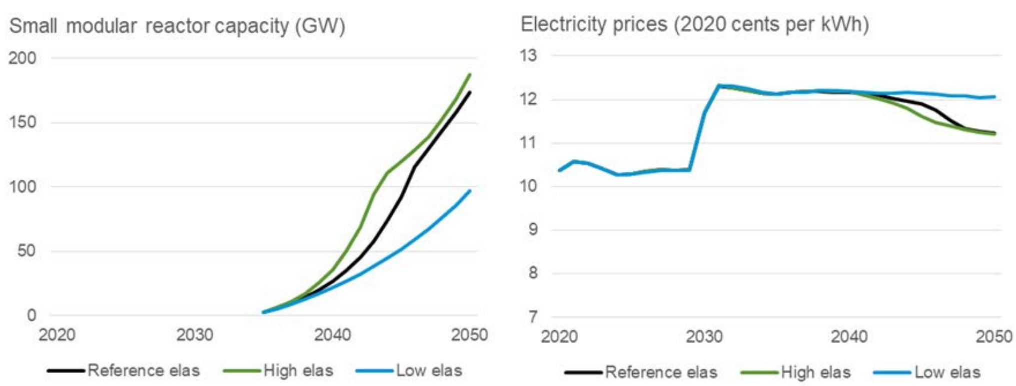

Figure 6-6
Cumulative small modular reactor capacity and electricity prices in three short-term elasticity ("elas") scenarios in NEMS.

[42] In these scenarios, the cost of the new nuclear technology is assumed to be lower than the reference case, and is an economic choice for capacity expansion in the NEMS projections, particularly in the cases that include a carbon fee.

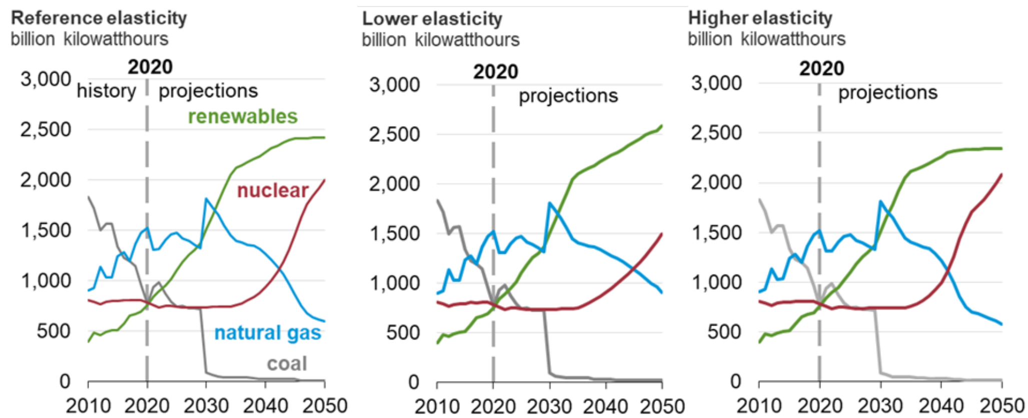

Figure 6-7
Electricity power sector generation from select fuels across three short-term elasticity scenarios in NEMS.

In these cases, electricity prices rise significantly in 2030 when the carbon price is imposed, but prices fall slightly when the low-cost nuclear capacity is added in later years. If industry expansion bottlenecks are more constraining and SMR growth occurs more slowly, electricity prices remain high. More natural gas-fired generation is used, incurring higher costs through the carbon fees, and additional renewable capacity is built and operated.

The results of this analysis indicate that, under transformational scenarios where new technologies are brought online quickly, the inclusion of a short-term elasticity constraint will have an impact on the overall results of the program or policy being evaluated. Without a constraint on near-term expansion, models may tend to overstate the ability to stand-up new supply chains; train engineers, construction managers, and operators; and develop smoothly functioning regulatory and permitting processes for complex new technologies. However, such impacts are transient in nature, and structures that are too constraining may understate the longer-term potential impact of policies or market developments that result in breakthrough technologies.

Recommendations for Future Modeling RD&D

Based on the comparisons in this section and discussions from workshops, there are several modeling needs related to new nuclear:

- *Develop methods and data for characterizing advanced nuclear designs:* These comparisons illustrated how existing models tend to focus on AP1000 and SMRs for new nuclear deployment decisions (Table 6-1). Additional advanced or “Gen IV” reactor designs could be incorporated into models if costs and performance projections were made available, though most public datasets on electric sector technologies do not include such options. Potential differences in fuel supply for advanced reactor designs could entail model development and data needs to appropriately characterize these differences.

- *Incorporate more robust representations of hybrid systems:* There has been an increasing focus on policy and planning for hybrid systems for nuclear energy that provide heat and electricity to non-grid applications (e.g., hydrogen production, steam delivery to industrial processes, heat to support direct air capture) and other technologies (e.g., solar and batteries). Such systems can utilize multiple feedstocks and provide multiple products/services. However, the dynamic optimization of these resources is complex owing to their diverse configurations, multiscale interactions, and markets, which makes modeling such resources challenging (Arent, et al., 2021).[43]
- *Develop and apply methods for quantifying and incorporating climate impacts and resource adequacy:* For the future role of nuclear and other technologies, questions related to climate impacts and resource adequacy (including extreme events) have been prominent for many stakeholders, especially as deeper decarbonization is targeted. Approaches for quantifying and incorporating climate impacts and resource adequacy are under development, including endogenous changes in capacity contributions of different resources as the supply-side mix changes and demand-side loads evolve (e.g., shifts toward winter peaking), cooling water availability, and planning for different weather years.

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[43] Dedicated models for optimizing configurations of hybrid resources have been developed and continue to be enhanced such as the Framework for Optimization of ResourCes and Economics ecosystem (FORCE) and the Institute for the Design of Advanced Energy Systems (IDAES) framework. These detailed hybrid system models could be integrated with broader energy systems and capacity expansion models to capture integration across multiple sectors.

Section 7: Cross-Cutting Issues

Summary

- Several cross-cutting modeling issues influence not only projections for nuclear energy but also model outputs related to other technologies. Model development decisions depend on the questions being asked, analysis type, system characteristics, and available resources for development and analysis.
- Choices about a model's temporal and spatial resolutions can be key factors in influencing model outcomes. Common approaches to simplify temporal resolution in energy models may not reproduce fundamental relationships for power sector decarbonization, as the intra-model comparisons in this section demonstrate. Higher temporal resolution is critically important for policy analysis, electric sector planning, and technology valuation in a range of scenarios, including under deeper decarbonization and higher variable renewables deployment. Simplified approaches understate nuclear deployment.
- Assumptions about discount rates and economic lifetimes can materially impact power sector generation and capacity outcomes, especially for nuclear energy given that it is a capital-intensive and long-lived resource. Discount rates have countervailing effects on existing and new nuclear—lower rates increase new nuclear capacity but decrease shares from existing nuclear.
- These comparisons also identify several other cross-cutting areas where future work would be valuable, including impacts of foresight, end effects, and uncertainty.

Temporal and Spatial Resolution

Overview

Temporal resolution—the number of time segments within a year[44]—is widely viewed as an important model dimension for capturing the joint variability of time-series variables (e.g., load, potential wind/solar output), system operations, and economics of system resources (Cole, et al., 2017; Merrick, 2016; Bistline, et al., 2021). Intra-annual temporal variability is aggregated in energy systems models and CEMs to reduce solve times. The number of time segments is typically on the order of 10-100 within the optimization and 100-10,000 outside

[44] Temporal resolution is distinct from temporal coverage, which can refer to the length of the time horizon and length of timesteps.

of the optimization. This is an active area of research, with significant learnings and improvements over the last several years (Bistline, 2021a; Blanford, et al., 2018). Those who are building, updating, and applying models generally attempt to select a level of temporal resolution that is sufficient to capture the declining value of generation, storage, and transmission but insufficient to capture specific challenges in operating regimes, which more detailed models (e.g., production cost models) are often more appropriate to investigate.[45] Lower temporal resolution can dampen price volatility and thus understate the value of dispatchable resources including nuclear power (Bistline, 2021a; Bistline, et al., 2020; Diaz, Inzunza, and Moreno, 2019). A key takeaway from earlier analysis is that the selection method for temporal and spatial resolution can matter as much as the resolution itself.

The spatial resolution of models can range from individual projects to nations, with tradeoffs between model detail and tractability. Spatial resolution is typically measured by the number of model regions. Plant siting and very local issues are generally not captured by CEMs, and more specialized tools are used to investigate more highly spatially resolved questions. Similar to temporal resolution, spatial resolution is a key consideration for data and model structure, which is customizable in some models but also influenced by available data.

Temporal and spatial resolution of models are important dimensions for properly capturing the economics of investment and operations.

Temporal and spatial resolutions of the four participating models used in this study are summarized in Table 3-2.

Decisions about temporal and spatial resolution can have substantial impacts on model outputs, including the level of nuclear deployment. However, appropriate levels of resolution for those building and developing models depend on the questions being asked, analysis type, system characteristics, data availability, and available resources for development and analysis. For those looking to apply existing models to answer specific questions, model selection can be a complex function of the nature of these research questions, available alternatives, model resolution, and considerations discussed in other sections of this report.

[45] Some modeling platforms have customizable temporal resolution, which means that the model user rather than the developer makes decisions about temporal resolution and the methods for selecting these periods.

Intra-Model Comparison

To test the impact of temporal resolution on nuclear deployment, an intra-model comparison was conducted using REGEN.[46] A full hourly investment and dispatch model is compared against three common approaches[47] to simplify temporal resolution:

- **Representative Day (RD):** Where 24 days per year are represented, each with hourly resolution.
- **Seasonal Average (SA):** Where daily load periods (peak, shoulder, off-peak) are represented across separate seasons (summer, winter, shoulder). These intra-annual periods are often referred to as "time slices."
- **Levelized-Cost (LCOE):** Where load and renewable resource availability are averaged across the year for a given region, which is implicit in LCOE comparisons.[48]

These approaches are run under a reference scenario (with current policies) and CO_2 caps of 90% and 100% electric sector reductions from 2005 levels.

Common approaches to simplify temporal resolution in energy models may not reproduce fundamental relationships for power sector decarbonization.

Detailed scenario descriptions and discussions of the results are provided in Bistline (2021a).

The results demonstrate how common approaches to simplify temporal resolution in integrated assessment and energy system models may not reproduce fundamental relationships for power sector decarbonization or may exhibit large differences from more detailed hourly modeling. Key features missed in simplified approaches include nonlinear increases in abatement costs at higher levels, diminishing marginal returns for high penetrations of variable renewables, and the value of broader technological portfolios and carbon removal.

[46] These experiments use a different version of REGEN than the experiments in other sections of the report, including the intercomparison in Section 2, which means that capacity and generation mixes may not align. In particular, these scenarios use a single-year version of the model with greenfield investment (i.e., adding new capacity for most of the system, inheriting only endowments of existing hydropower, nuclear, and interregional transmission).

[47] Many models employ side constraints, costs, and out-of-optimization calculations to account for temporal aggregation simplifications, which are not accounted for in these experiments.

[48] Note that this implementation is more sophisticated than typical LCOE approaches, including the value to generators of reserve margin contributions and policies.

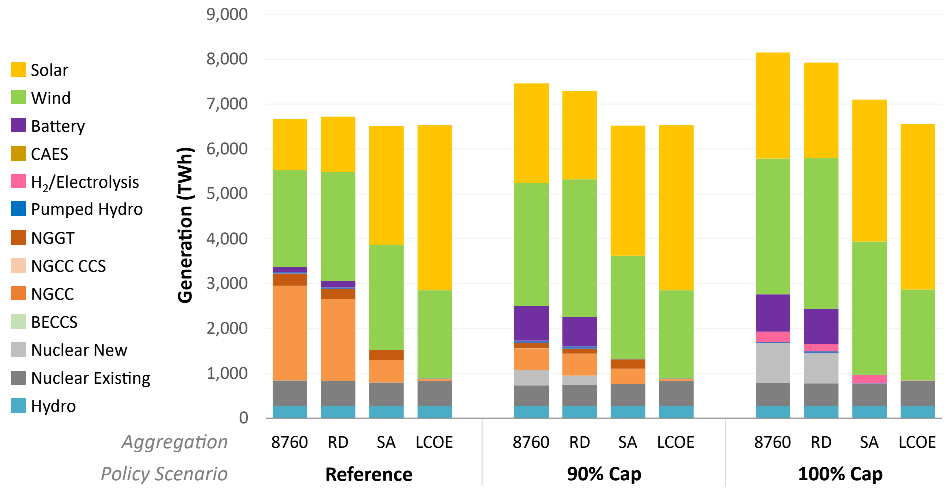

Figure 7-1
National generation by technology and policy scenario across temporal aggregation approaches in REGEN.

Simplified temporal aggregation approaches understate nuclear, natural gas, and storage deployment.

Simplified temporal aggregation approaches tend to understate the value of broader technological portfolios, firm low emitting technologies, wind generation, and energy storage resources and can overstate the value of solar generation (Figure 7-1). The need for dispatchable, firm capacity is clearer with higher temporal resolution across all policy scenarios. In particular, new nuclear increases as decarbonization approaches 100% in the full hourly model, but the SA and LCOE simplifications do not capture the value of these resources. Under the 100% CO_2 cap, new nuclear additions are 117 GW with hourly resolution, but 0 GW with the SA and LCOE approaches. Simplified temporal aggregation approaches underestimate variability and can distort costs by missing periods that are important to the valuation of low-carbon technologies as emissions decline and the deployment of renewables increases.

Errors from simplified temporal aggregation approaches increase with tighter CO_2 targets, understating abatement costs by an order of magnitude in many instances, which are discussed in detail in Bistline (2021a). Approximation accuracy also depends on assumptions about technological cost and availability: Differences across approaches are smaller when carbon removal is available and when wind, solar, and storage costs are lower (Bistline, 2021a). Additionally, using the capacity mixes from simplified approaches in detailed operational simulation models would illustrate reliability shortcomings of lower temporal resolution models, as there would likely be a significant number of hours where system resources could not meet load.

Overall, the analysis suggests that higher temporal resolution is critically important for policy analysis, electric sector planning, and technology valuation in a range of scenarios, including under deeper decarbonization and higher variable renewables deployment.

Discounting and Financing

Overview

Nuclear power—like renewables, transmission, and energy storage—is a high-capital-cost but low-variable-cost resource, which means that assumptions about project finance and time preference (i.e., comparing current costs and revenues vis-à-vis future ones) are important for evaluating their economic competitiveness.

There is a wide range of financing treatments across models, but the most important differences likely stem from differences in the assumed **discount rate** and **economic life**.[49] In energy systems models, effective discount rates may aggregate many effects like the pure rate of time preference (i.e., social discount rate[50]), opportunity cost of capital, risk, and/or financing (e.g., costs of equity and debt), and could differ by sector and decision-maker. For power sector technologies, this rate is typically based on a utility's weighted average cost of capital (WACC).[51] All else equal, lower rates improve the economics of capital-intensive technologies and decrease the relative importance of nearer-term cash flows. The economic lifetime of an asset (also referred to as the "book life") is the asset recovery time or the lifetime assumed in economic investment decisions, which could differ from the asset's physical lifetime (i.e., the maximum length of operation when economic) or service lifetime (i.e., time online before retirement, which is less than or equal to the physical lifetime).

Discount rates, economic lifetimes, and methods for selecting these parameters differ across models.

The average discount rate across the four models is 4.5% (real), as shown in Figure 7-2. REGEN assumptions fall on the higher end of the range (with values that reflect electric sector and end-use decisions), while other models use similar values between 3-4%. These assumptions fall within the broader literature reviewed. The harmonized scenarios in the model intercomparison analysis (Section 2) assume a 3% discount rate.

[49] Other factors (e.g., debt fraction, debt rate, tax rate, inflation) could be compared across models in future work. This section compares long-run parameters, but these values may change over time and across decision-makers (e.g., NEMS models changing discount rates over time, IPM differentiates between merchant and utility investors, NEMS and ReEDS model the changing debt fraction as a function of tax credits).

[50] This rate is the weight applied to cash flows or utility occurring at different times.

[51] The cost of capital may be technology-specific and include a risk premium that varies by technology (Donovan and Corbishley, 2016).

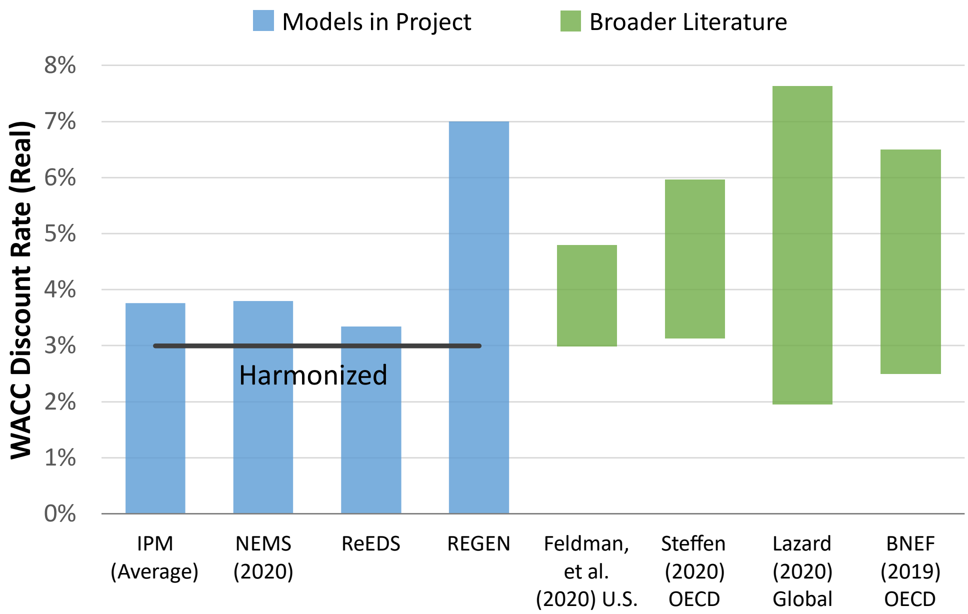

Figure 7-2
Comparison of native discount rate assumptions across models and the broader literature. "Harmonized" indicates the value used for the model intercomparison analysis in Section 2.

A wide range of economic lifetimes are assumed due to technology-specific variations (Figure 7-3). The high end of the range is typically for hydropower and nuclear to capture residual value for these long-lived assets. Assumptions for wind and solar fall within a narrower range (20-30 years) consistent with the broader literature. Models vary in terms of whether they reflect separate economic (i.e., asset recovery time) and physical lifetimes. NEMS assumes no fixed physical lifetimes, ReEDS assumes longer physical lifetimes than the economic lifetimes from Figure 7-3, and REGEN assumes that economic and physical lifetimes are equal. All four models assume endogenous service lifetimes (i.e., model-driven retirements) for many assets, including endogenous retirements for existing nuclear power plants with lifetimes up to 80 years (Table 5-1).

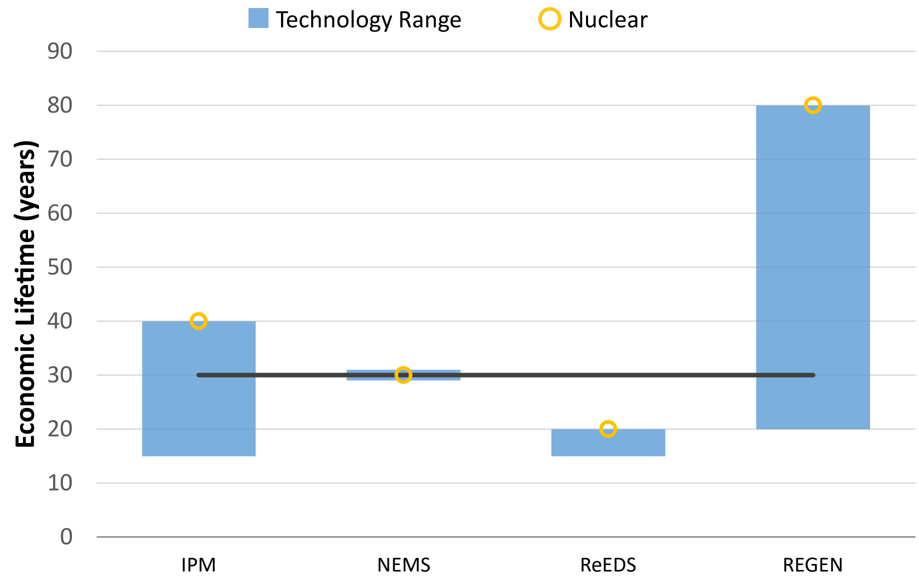

Figure 7-3
Comparison of native economic lifetime (i.e., asset recovery time) assumptions across models. "Harmonized" indicates the value used for the intercomparison in Section 2.

There are many questions about discounting and financing that analysts must contend with in building and applying models (Lind, et al., 1982). What should the long-term discount rate be? How should this rate be chosen (and does it reflect a descriptive or normative basis)? Should this rate change over time? Do models reflect separate economic and physical lifetimes? These dilemmas do not have clear answers, and solutions are likely to vary across different modeling contexts, which increases the importance of transparency in documenting what was assumed and why (Bistline, Budolfson, and Francis, 2021; DeCarolis, et al., 2017).

Intra-Model Comparison

To test the impact of assumed discount rates and economic lifetimes on nuclear generation, an intra-model comparison was conducted using REGEN. There are three dimensions explored in these sensitivities:

- **Discount rate:** The effective discount rate was varied from 3% (the harmonized assumption in the model comparison in Section 2), 5%, 7% (the native assumption in REGEN), and 9%.
- **Economic lifetime:** Economic lifetimes for new investments are assumed to be either uniform at 30 years (the harmonized assumption in the model comparison in Section 2) or heterogenous lifetimes across different generation options (the native assumption in REGEN).
- **Policy:** Each discount rate and economic lifetime assumption is varied across the three policy scenarios from Section 2: A "current policies" Reference (Ref), Deep Decarbonization with an 80% reduction in 2050 relative to 2005 (DD80), and Deep Decarbonization with a 100% target in 2050 (DD100).

Figure 7-4 illustrates how discount rate assumptions alter new build and retirement decisions across different policy environments. New nuclear is built only in the 100% decarbonization scenario, and much like other capital-intensive technologies like renewables and storage, nuclear deployment is highest with lower discount rates. New nuclear spans 18 GW (with a 9% discount rate) to 45 GW (with a 3% discount rate).

Discount rates have countervailing effects on existing and new nuclear—lower rates increase new nuclear but decrease shares from existing nuclear.

On the other hand, existing assets (including the current nuclear fleet) benefit from higher discount rates. Early nuclear retirements are especially common when low discount rates occur in a Reference policy scenario. Nuclear retirements are lower for all discount rates under the 80% and 100% decarbonization scenarios, since the shadow price on CO_2 increases electricity prices, which in turn increases revenues for inframarginal units like nuclear. Ultimately, the discount rate response has countervailing effects on existing and new nuclear—lower rates increase new nuclear generation but decrease shares from existing nuclear. Under the 100% decarbonization scenario, these opposing effects mean that overall nuclear shares are similar across discount rates.

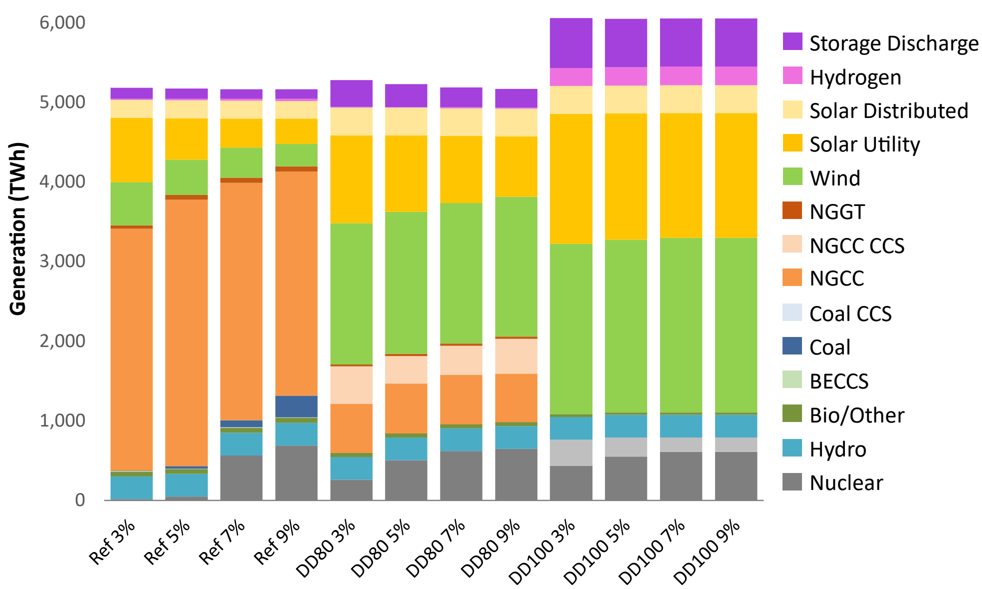

Figure 7-4

National generation in 2050 by technology across policy and discount rate sensitivities in REGEN.

Assumptions about discount rates and economic lifetimes can materially impact power sector generation and capacity outcomes, especially for nuclear.

Figure 7-5 suggests that economic lifetime assumptions have more limited impacts on the generation mix relative to discount rates. A large fraction of revenues (in net-present-value terms) occurs in the first couple decades of operation, which lowers impacts of revenues and costs beyond a 30-year horizon. However, due to its longer anticipated lifetime, new nuclear power generation has a larger sensitivity to assumed lifetimes, especially in the 100% decarbonization policy. New nuclear additions are 23.7 GW in the 100% decarbonization case with heterogenous lifetimes and only 5.3 GW with uniform

(30-year) lifetimes.[52] Note that impacts of discount rates and economic lifetimes may depend on the model's time horizon and treatment of end effects, which are discussed in the last portion of this section.

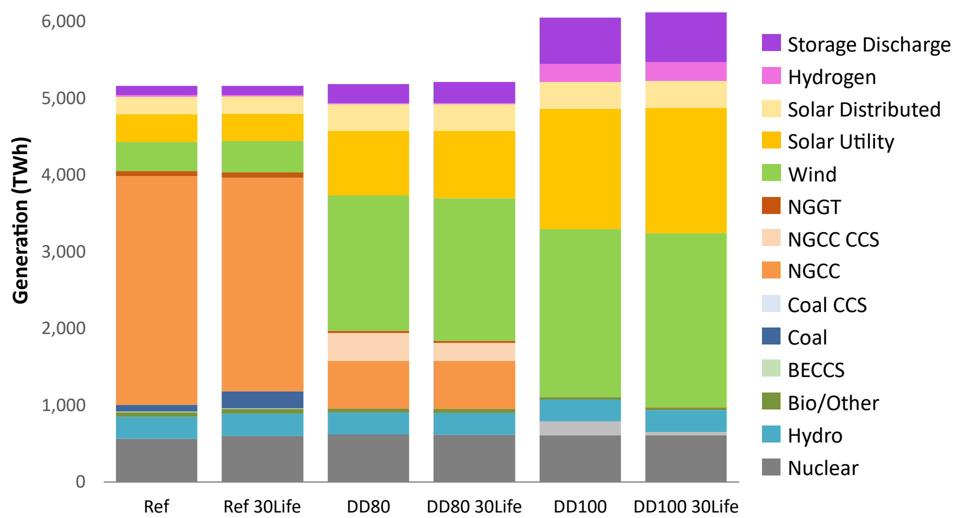

Figure 7-5

National generation in 2050 by technology across policy and economic lifetime sensitivities in REGEN.

Overall, these sensitivities illustrate how assumptions about discount rates and economic lifetimes can materially impact generator entry and exit decisions.[53] For these scenarios and assumptions, discount rates have larger impacts on the generation and capacity mix for most technologies, though lifetime effects are larger for nuclear relative to other resource classes. For the model intercomparison in Section 2, the larger difference between native and harmonized results in REGEN reflect differences in these input assumptions, especially the discount rate.

[52] Note that discount rate assumptions can interact with lifetime assumptions. A 7% discount rate is used for these comparisons.

[53] This finding is consistent with other studies in the literature that find that financing assumptions can impact power sector investment decisions (Polzin, et al., 2021; Emmerling, et al., 2019).

Other Considerations

Although the workshops and analysis focused on the aforementioned issues, a number of important ancillary topics were also discussed, which deserve consideration for long-term planning RD&D:

- **Foresight:** Assumptions about foresight are central to long-term CEMs and energy system models and shape generator investment and retirement decisions. A model with foresight will adjust investment activity in response to anticipated future policies and technological change, especially for long-lived low-carbon resources such as nuclear. Intertemporal perfect foresight and sequential myopic approaches are common in the literature (Merrick, Bistline, Blanford, 2021) and across models in this report (Table 3-1).
- **End effects:** The time horizon considered for planning can create distortions in final model periods. Approaches for correcting these end effects can impact technology-specific outputs, including for nuclear energy in light of its long physical lifetime (Figure 7-3).
- **Uncertainty:** Modeling uncertainty is a perennial challenge in prospective analysis. Parametric uncertainty is often addressed by conducting sensitivity and scenario analysis, though explicit uncertainty can be considered with several stochastic methods (Kann and Weyant, 2000; Bistline, 2015). Addressing structural uncertainty can be more difficult, but modelers can experiment by changing adding, removing, or modifying model constraints or features to observe the impact on outputs (e.g., the temporal resolution sensitivities from earlier in this section) or can participate in model intercomparison projects like this one. There are several indirect methods of accounting for uncertainty. An example is the inclusion in NEMS of a three-percentage-point adder applied to the costs of debt and equity for new coal capacity that represents "the implicit costs being added to GHG-intensive projects to account for the possibility that, eventually, they may have to purchase allowances or invest in other projects that offset their emissions" (EIA, 2020b), which is a proxy for market behavior around uncertainty.

Section 8: Summary and Conclusions

Capacity expansion and energy system models can generate useful insights for understanding nuclear energy and broader energy systems under a variety of future policy, technology, and market conditions. The insights in this report on developing and interpreting the results of such models can help stakeholders improve their tools and their understanding of the role of nuclear energy in future energy systems. Although not an exhaustive list of considerations, this report highlights progress to date and identifies opportunities to improve the representation of nuclear energy in long-term models.

Implications for Policy and Planning

This report highlights how models vary in their treatment of key considerations related to nuclear energy and that better understanding key features and tradeoffs can provide context for interpreting outputs used for resource planning, policymaking, and global analysis. Central issues for those using and interpreting model outputs include:

- *Model representations of nuclear energy (and features that affect nuclear's role) can vary considerably:* Sections 4 through 7 discuss a range of model considerations and dimensions that impact nuclear energy, including capturing different value streams and market participation, representing new and existing nuclear capacity, and cross-cutting issues such as temporal resolution and financing. These areas suggest questions that consumers of modeled scenarios can ask to help evaluate results when nuclear-focused or decarbonization analyses are released.
- *New nuclear deployment depends on combinations of policies and cost reductions:* Model results across organizations indicate the pronounced impact that stringent power sector CO_2 policies could have on the future U.S. electricity supply mix. Decarbonization targets generally help to retain existing nuclear capacity but may not be enough to bring new capacity online unless nuclear experiences significant cost declines. In scenarios that layer a deep decarbonization policy with low capital cost assumptions for new nuclear, models show significant nuclear capacity additions.
- Ample scenarios should be conducted, given the sensitivity of model outputs to uncertainties related to input assumptions and model structures, especially with deep decarbonization: Model outputs should not be viewed as forecasts for how the world will unfold, but are conditional projections that are sensitive to model structures and assumptions about technologies, markets, behaviors, and policies. Consumers of model outputs are increasingly

expecting analysts to conduct a wide range of sensitivities to test the robustness of conclusions, especially under deeper decarbonization targets, including a decarbonized electric sector and economy-wide net-zero emissions. This report summarizes how normative and descriptive disagreements exist about appropriate parameter values (e.g., discount rates) and how models navigate tradeoffs between parsimony and accuracy (e.g., temporal resolution), which can materially impact model outputs related to nuclear energy and other technologies.

- *Model resolution and parametrization decisions influence projections of nuclear energy deployment:* The intra-model and inter-model comparisons in this report highlight how model development decisions can alter the projected role of nuclear energy. For instance, lower temporal resolution tends to understate the value of nuclear (Section 7). On the other hand, the intra-model comparisons also suggest areas that have more limited impacts on the competitiveness of new and existing nuclear in these models, including flexibility assumptions.
- Nuclear can complement other low-emitting technologies but such interactions require detailed capacity expansion and energy systems models to evaluate: Nuclear generation provides firm, zero-emissions electricity, which can complement other clean electricity resources that are subject to weather fluctuations. Evaluating these interactions require systems models—like capacity expansion and energy systems models that are the focus of this report. Linking these models with other tools can provide more detailed insights depending on the questions being asked. Levelized-cost metrics are incomplete metrics for evaluating the relative competitiveness of system resources, which requires detailed energy modeling to assess.

Implications for Modelers

This report stresses tradeoffs between a range of model considerations, which are necessary to make models tractable. Appropriate levels of detail for nuclear energy and other model dimensions depend on the type of analysis being performed, motivating questions, available data and resources, system characteristics, and analysis timeframe (Section 3) and may merit using multiple tools to capture all relevant interactions. Key implications for modelers include:

- *Transparency about model decisions and analysis assumptions are important for communicating with stakeholders:* There are many transparency-related practices that can help to encourage better modeling and move dialogues in more productive directions, including making code and data available, participating in model intercomparison studies, and providing a range of outputs across scenarios (Bistline, Budolfson, and Francis, 2021; DeCarolis, et al., 2017). In particular, given the sensitivity of outputs to model decisions and assumptions, it is important to make these model decisions and analysis assumptions as clear as possible. For instance, the model intercomparison in Section 2 illustrated how installed nuclear capacity ranges 2–329 GW in

2050 depending on assumptions about nuclear costs and policy. Such transparency is valuable not only to understand the strengths, limitations, and implications of chosen modeling approaches but also to convey these compromises and caveats to different audiences.

- *Encouraging collaborations across models at different scales:* Increased collaborations between energy-economic models and more detailed operational models are needed for integrating and linking perspectives. Intra-model comparisons on value streams (Section 4), endogenous technological change (Section 6), and temporal resolution (Section 7) suggest that linking with more detailed models can provide additional insights.
- *Stress test models with a range of assumptions:* The sensitivity of nuclear-related outputs to input assumptions and model structures suggest that modelers should be sensitive to possible parametric and structural uncertainties and should conduct a wide range of stress tests to understand the robustness of insights.

Future Work

Sections 4 through 7 identified many specific model and data needs related to the representation of nuclear energy and other electric sector and energy system resources:

- *Understand future changes in value streams and demand for grid services:* Potential changes in planning reserve margins and operating reserves should be studied in futures with higher renewables penetration, electrification, and deep decarbonization (EPRI, 2018).
- *Characterize a range of low-emitting technologies:* Because nuclear technologies see much greater deployment in scenarios that require significant decarbonization, properly capturing the value of nuclear technologies requires that other low- and zero-carbon technology options are adequately modeled. Not adequately representing the portfolio of candidate technologies and pathways that are being considered to meet such power sector and economy-wide targets could incompletely characterize the competitiveness of nuclear relative to these other technologies.
- *Select appropriate levels of model resolution:* Modeling zero- or very-low-emitting energy systems might require additional temporal or spatial resolution to properly capture the value of the different generator types. Additional work is needed to understand the importance of model resolution on outcomes for these zero and low-carbon solutions.
- *Improve time-series data:* Models often use a single year of historical meteorological data. Given that many low-carbon futures depend heavily on variable renewable technologies, multi-year variability in wind resources, solar resources, and load are particularly important (Diaz, et al., 2021). Improved understandings of the impact of multi-year variability (of load and renewables) can inform resource adequacy estimates and contributions of different resources. If infrequent but impactful wind lulls or cloudy periods are not captured in the model, then firm capacity resources such as nuclear

could be undervalued. Similarly, capturing the extreme events that seem to be increasingly common can ensure that power sector solutions are more robust no matter the composition of the resulting generation fleet produced by the model. Future work to understand the importance of representing compensation for currently uncaptured attributes in markets (e.g., inertia) would also be valuable.

- *Incorporate more robust representations of hybrid systems and sectoral integration:* Pathways towards achieving a net-zero energy system in the United States typically involve growing interactions among electricity supply, energy supply, and energy demand (including electricity, direct fuel use, and heat). There has been an increasing focus on policy and planning for hybrid systems for nuclear energy that provide heat and electricity to non-grid applications (e.g., hydrogen production, steam delivery to industrial processes, heat to support direct air capture) and other technologies (e.g., solar and batteries). These hybrid energy systems have been proposed as candidates for flexibly contributing to the full spectrum of demands across the energy system (Arent, et al., 2021). However, the dynamic optimization of these resources is complex owing to their diverse configurations, multiscale interactions, and markets, which makes modeling such resources challenging. Planned demonstration projects will help to evaluate the operational capabilities of such hybrid energy systems, but their ultimate competitiveness will depend on the incremental costs and benefits of their ability to contribute products and services across different parts of the U.S. energy sector. A better understanding of the future demand for, and value of, hydrogen is a key component of evaluating the incremental value of hybridization, particularly for models that represent interactions across different segments of the U.S. energy sector.

- *Improve data and methods for estimating retirements:* Retirements represent a significant driver for new capacity needs, but these dynamics are challenging to represent in models. Understanding drivers of retirements across models would be valuable, especially accounting for uncertainty (e.g., policy, FOM and future capital costs) and foresight (as discussed in Section 7).

- *Provide public data for nuclear costs:* Given the notable impact that different FOM cost assumptions can have on the modeling, it is important to reflect those costs as accurately as possible. To that end, public data for current FOM costs by plant and guidance on projected changes (both the magnitude and timing) would be useful for modeling teams. Such cost data would be valuable for understanding projections for nuclear generation and estimates for other resources. In addition to input assumptions, it is important to compare model algorithms and heuristics for power plant retirement, cost, and operational decisions against actual data and to update these model features as appropriate.

- *Understand possible nuclear plant license renewals to 80 years and beyond:* It is important to consider the possibility of license renewals beyond 80 years, especially as models begin to expand projections beyond 2050.

- *Develop methods and data for characterizing advanced nuclear designs:* These comparisons illustrated how existing models tend to focus on AP1000 and SMRs for new nuclear deployment decisions (Table 6-1). Additional "Gen IV" reactor designs could be incorporated into models if costs and performance projections were made available, though most public datasets on electric sector technologies do not include such options. Potential differences in fuel supply for advanced reactor designs could entail model development and data needs to appropriately characterize these differences.
- *Develop and apply methods for quantifying and incorporating climate impacts and resource adequacy:* For the future role of nuclear and other technologies, questions related to climate impacts and resource adequacy (including extreme events) have been prominent for many stakeholders, especially as deeper decarbonization is targeted. Approaches for quantifying and incorporating climate impacts and resource adequacy are under development, including endogenous changes in capacity contributions of different resources as the supply-side mix changes and demand-side loads evolve (e.g., shifts toward winter peaking), cooling water availability, and planning for different weather years.

A broader model need is to determine appropriate levels of model complexity for given applications. Model development decisions depend on the analysis type, motivating questions, system characteristics, and available resources for development and analysis (Merrick and Weyant, 2019; Saltelli, 2019). The temporal resolution sensitivities in Section 7 illustrate an area where model complexity has first-order impacts on the deployment of nuclear energy and other low-emitting technologies, but there is currently limited guidance about the conditions under which higher fidelity modeling is needed.

Another general model challenge and need is to assess suitable levels of model endogeneity. The report touches on several areas of model-driven decisions related to existing and new nuclear—retirements, operations, load shapes, technological change—where there is variation in model treatments. Much like model complexity, there is a need to understand the conditions under which endogenous decisions are most important.

Finally, future work should investigate net-zero emissions energy systems and modeling dimensions to appropriately characterize these systems given interest from policy-makers, companies, and other stakeholders (Bistline, 2021c). Electric sector capacity expansion models can be linked to other fuels, end use, and economy models to represent these cross-sectoral interactions. REGEN has recently added a range of additional supply-side technologies, fuel conversion pathways, and end-use options to characterize economy-wide net-zero emissions scenarios, which will be released in its forthcoming Low-Carbon Resources Initiative (LCRI) report later in 2022. ReEDS has recently added similar capabilities—in the form of hydrogen, negative emissions technologies, and demand-side trajectories consistent with an economy-side decarbonization pathway—which were implemented in recent analyses (Cole, et al., 2021b; DOE, 2021) and also will be highlighted in a forthcoming study on rapid decarbonization of the U.S. energy sector.

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Appendix A: Summary of Model Enhancements

An objective of the workshops and project was to stimulate model improvements, especially in areas related to nuclear energy. Each modeling team identified and/or incorporated improvements across the course of the two-year project, and a summary of these changes is provided here.

Integrated Planning Model (IPM) from the U.S. Environmental Protection Agency (EPA)

EPA has recently incorporated several model improvements relevant to this project:

- The operational costs of existing nuclear capacity were updated to reflect the AEO2020 assumptions.
- Inclusion of small modular reactors as a new generation technology option.
- Updated RPS and CES assumptions for OR, IL, DE, NC, and MA.

National Energy Modeling System (NEMS) from the U.S. Energy Information Administration (EIA)

EIA has implemented several model enhancements for AEO2022. EIA revised the operating modes available for baseload technologies so that they can operate more flexibly within a season, responding to changes in net load based on intermittent generation in the region. The addition of the RESTORE submodule to the NEMS electricity market module during AEO2019 has helped improve the overall accuracy of EMM's long-term capacity planning and dispatch modeling capability with an increasingly high renewable penetration level. However, operation modes for nuclear and fossil plants have been determined without feedback from the captured dispatch solution from RESTORE. As projections have incorporated more intermittent generation with distinct seasonal and daily resource profiles, the net load by time slice has a different pattern than total load in many regions and will affect how baseload dispatch will need to change to load follow. For the AEO2022, the RESTORE average dispatch information for the nuclear and fossil plants is passed to EMM as an additional operating mode which will allow more flexible dispatch within a season for coal, natural gas-fired combined cycle, and nuclear electric generating technologies. This will allow nuclear capacity to operate more flexibly to supply additional spinning reserves if that is more valuable to the system than generation due to excess renewables in certain time slices.

EIA also has improved the market sharing algorithm which adjusts build decisions among competitive technologies to allow options for sharing across all technologies, or within subsets (i.e., dispatchable versus non-dispatchable). There are a few minor improvements made for the renewables modeling representation during AEO2022 such as devising a new declining capacity credit algorithm for standalone energy storage, allowing endogenous wind retirements, updating the solar inverter loading ratio for standalone solar PV from 1.2 to 1.3, improving biomass supply curves, and representing the Civil Nuclear Credit Program as included in the Bipartisan Infrastructure Law.

Regional Energy Deployment System (ReEDS) from the National Renewable Energy Laboratory (NREL)

The following changes were made to ReEDS as part of this project:

- Added a SMR technology. Previously, ReEDS only represented AP1000 nuclear power plants.
- Added the nuclear demonstration projects to the ReEDS plant database. This enables the demonstration projects to come online in the locations and at the dates specified by the companies developing them.
- Changed existing nuclear power plants to be able to ramp down to 70% of their rated capacity. Plants are assumed to ramp up to 2% per minute and are allowed to use this ramping capacity to contribute toward operating reserves.
- Changed the default lifetime of existing nuclear plants to 80 years. Previously, ReEDS used a mix of 60- and 80-year lifetimes for existing plants. The shorter 60-year plant lifetime was used for nuclear plants in restructured power market regions, with all other nuclear plants using the 80-year lifetime. The model can still choose to retire plants before they reach their 80-year lifetime if they become uneconomic.
- Adjusted capacity in the model to be represented using summer *and* winter capacity ratings. Previously ReEDS only used the summer capacity rating. Because nuclear power plants typically have a higher winter capacity rating than summer capacity rating, this change increased the output of the nuclear power plants during the winter, which in turn led to slightly higher (~1%) annual capacity factors.

Regional Economy, Greenhouse Gas, and Energy (REGEN) from the Electric Power Research Institute (EPRI)

The REGEN model made several nuclear-related model improvements during the course of this project. These changes and their timeline for inclusion in the model are summarized in Table A-1.

Table A-1
REGEN model improvements under the nuclear comparison project

Feature	Change	Timeline
Flexibility of existing and new nuclear	Updating flexibility-related parameters based on EPRI research	In current production code
Lifetimes of existing nuclear plants	Updated to allow all existing capacity to extend operations to 80 years when economic	In current production code
New nuclear options	Adding small modular reactors	In current production code
Temporal resolution	Routinely running configurations of REGEN with 8,760 hourly resolution for expansion decisions	In current production code (inclusion varies by application)
Hydrogen production	Adding more pathways for creating/using hydrogen	Early 2022

Appendix B: Policies and Incentives in Model Current Policies (Reference) Scenarios

The four participating models in this study reflect a range of on-the-books state and federal policies and incentives that impact the electric sector and energy system.[54]

U.S. state and regional policies generally include:

- State-level renewable portfolio standards, including technology-specific carveouts for solar
- State-level clean electricity standards with state-specific definitions of qualifying resources
- State-level offshore wind mandates
- State-level energy storage mandates
- State-level Zero-Emissions Credit (ZEC) policies for existing nuclear power plants
- California AB32, represented as a carbon tax based on projections by the California Air Resources Board
- Regional Greenhouse Gas Initiative (RGGI) cap-and-trade system
- Other state-level CO_2 caps in the electric sector and economy-wide
- State-level constraints on new nuclear capacity

[54] Modeling for this study was completed in 2021 before the Bipartisan Infrastructure Law was passed, which means that the Civil Nuclear Credit Program and incentives for other electric sector resources (e.g., carbon capture, long-duration energy storage, transmission, hydrogen, advanced nuclear) were not included in these scenarios. Scenarios also do not include economy-wide or electric sector targets from the updated U.S. Nationally Determined Contribution.

Federal policies and regulations generally include:

- Current Clean Air Act Section 111(b) new source performance standards for power plants
- Production tax credits for wind
- Investment tax credits for solar
- 45Q tax credits for CO_2 capture

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