The Role of Natural Gas in Future Low-carbon Energy Systems

by

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Abstract

Concerns over climate change along with rapidly falling costs of clean energy technologies have led to increased scrutiny over the role of fossil-fuels in a low-carbon energy future. This thesis evaluates the role of natural gas-fired power plants (NG) in future electrical grids using an advanced, multi-period capacity expansion modeling framework with perfect foresight. We model cost-optimal grid operations, investments, and retirements through 2050 using a detailed representation of the American Southeast's electrical grid which includes inter-region transmission, variable renewable energy resource characteristics, brownfield capacity, and lifetime and economic retirements. We examine several pathways to a highly decarbonized grid, assuming rapid growth in energy demand through mid-century. Sensitivities include CO2 emissions limits, technology costs, nuclear plant lifetime extensions, and NG deployment and financing schemes which aim to minimize stranded costs.

We find that investments in NG are made across all scenarios evaluated, as well as unprecedented deployments of variable renewable energy resources and battery storage. Results highlight the substantial emissions contributions of the existing coal fleet, and the potential for emissions reductions if lower-carbon generation resources, including new NG with and without carbon capture and storage, can replace this capacity. Furthermore, emissions limits which require the lowest mid-century CO2 emissions do not necessarily lead to the greatest cumulative emissions reductions over the planning horizon. These results support a nuanced approach to resource planning for future low-carbon grids which considers both short-term and long-term emissions reductions.

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List of Acronyms	
Units	
Gt	Gigatonnes
GW	Gigawatt
GWh	Gigawatt-hour
kV	Kilovolts
kW	Kilowatt
kWh	Killowatt-hour
MMBtu	Million metric British thermal units
Mt	Megatonnes / Million tonnes
Resources	
NG	Natural gas
NGCC	Natural gas-fired combined cycle power plant
NGCT	Natural gas-fired combustion turbine power plant
NGST	Natural gas-fired steam turbine power plant
PHS	Pumped hydroelectric storage
Solar PV	Solar Photovoltaic
Entities	
DEC	Duke Energy Carolinas
EIA	United State Energy Information Agency
EPA	Environmental Protection Agency
IEA	International Energy Agency
NREL	National Renewable Energy Laboratory
Additional Acronyms	
AEO	EIA Annual Energy Outlook
ATB	NREL Annual Technology Baseline
CCS	Carbon capture and stroage
CF	Capacity factor
CRF	Capital recovery factor
BA	Balancing area
EFS	NREL Electrification Futures Study
FOM	Fixed O&M costs
GHG	Greenhouse gas
IOU	Investor owned utility
IPM	Integrated Planning Model
LCOE	Levelized Cost of Energy
ReEDs	Regional Energy System Deployment model
RPS	Renewable Portfolio Standard
SLTE	Second lifetime extension
VOM	Variable O&M costs
VRE	Variable Renewable Energy

0 Introduction

Climate change driven by anthropogenic greenhouse gas (GHG) emissions threatens to bring rising sea levels, more extreme weather events, and severe human and economic losses. Governments and private sector interests alike are recognizing the need for rapid decarbonization of the global economy to limit temperature rise. In 2015, nearly all nations entered the Paris Climate Accord, where they pledged to keep global warming well below 2ºC, and pursue efforts to keep warming below 1.5ºC. In order to meet a 1.5ºC temperature rise ceiling, the Intergovernmental Panel on Climate Change has suggested that CO_2 emissions will need to reach "net-zero" by around 2050. Under net-zero emissions, no more anthropogenic CO_2 would be emitted into the atmosphere than removed from it. Although achieving such as goal is physically possible, it would require "rapid, far-reaching and unprecedented" changes across the global economy (IPCC, 2018).

At 25% of global emissions, electricity and heat production are responsible for the largest share of GHG emissions across economic sectors, based on 2010 emissions data (Edenhofer et al., 2014). In the United States, electricity production alone accounted for 25% of the nation's GHG emissions in 2019 (US EPA). America's electricity sector must undergo rapid decarbonization if mid-century net-zero targets are to be achieved.

In the United States, nearly three-quarters of electricity customers received their power from "investor-owned utilities," or IOUs, in 2017, which are "large electric distributors that issue stock owned by shareholders." (U.S. EIA, 2019) Most IOUs are publicly traded companies and include some of America's largest companies by market capitalization – a number of electric and multi-utilities are listed on the S&P 500 index. Many of these utilities have already announced mid-century net-zero goals. As of July 2020, 13 of America's 30 largest publicly traded electric and gas utilities by market capitalization have set net-zero or 100% clean energy goals for 2050 (Whieldon & Ryser, 2020).

A recent report by Deloitte states that IOUs "are expected to have the greatest impact on driving a full transition" to net-zero across the electric power sector due to their high percentage of customers and nationwide electricity sales (Porter et al., 2020, p. 4). It is encouraging, then, that every year more public utilities are announcing corporate net-zero targets. However, announcing a net-zero goal decades in the future does not mean that utilities will successfully reach those targets, or that they are necessarily serious about achieving them. Indeed, the Deloitte report notes "there are significant gaps between decarbonization targets and the scheduled fossil-fuel plant retirements, renewable additions, and flexibility requirements needed to achieve full decarbonization." (p. 8) Other commentators have questioned public utilities' commitment to their net-zero pledges, noting a "lack of urgency" among a "growing" number of public utilities with ambitious net-zero goals (Gearino, 2019).

The American Southeast – which I define here to include Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee – is home to many of the country's largest IOUs by market capitalization. The three largest IOUs by market cap to announce net-zero by 2050 goals – Dominion Energy Corp. (Dominion Energy), Duke Energy Corp. (Duke Energy), and Southern Company – operate there predominantly as vertically-integrated public utilities which own their generation, transmission, and distribution assets. These utilities operate as natural monopolies and are shielded from competition by state regulators. Unlike utilities operating in wholesale competitive power markets, most utilities operating in the Southeast generate power from their own power plants, and therefore have a higher degree of control over their resource mixes. According to Energy Innovation, a nonpartisan energy and climate policy firm, this has led them to be “among the slowest to embrace clean electricity resources,” and for them to continue operating coal-fired power plants even when nearly all of them are uneconomic compared to new local wind and solar power (Eric Gimon and Mike O’Boyle et al., 2020).

There is active debate over the role of natural gas (NG) on pathways towards deep decarbonization, with recent research suggesting a limited role for NG and industry plans for continued NG development coming into conflict. A widely cited 2019 study by the Rocky Mountain Institute projects that by 2035, new clean-energy portfolios consisting of wind, solar, battery storage and demand flexibility will be cheaper to build than continued operation of 90% of proposed new natural gas combined cycle (NGCC) power plants (Teplin et al., 2019). Southeastern IOUs, however, are standing by their plans to develop new NG plants. Duke Energy’s 2018 resource plan, for example, “lean[s] heavily on natural gas-fired generation” (Walton, 2018) and proposed adding nearly 10 gigawatts (GW) of new NG capacity by 2033, compared to less than 4 GW of new solar resources. According to Grubert et al. (2020), historic trends suggest a retirement age of approximately 30 years for NGCC and natural gas combustion turbine (NGCT) power plants, which supports concerns that new NG facilities such as these may become “stranded assets,” or plants which retire before the end of their economic life, in a rapidly decarbonizing grid with low-cost variable renewable energy resources (VREs) and storage. This outcome risks leaving ratepayers, or in some cases, corporate shareholders, to continue paying off the cost of power plants that are no longer in use.

In this thesis, I investigate how technological, regulatory, and financial assumptions affect the role of NG in future low-carbon grids, using the American Southeast as a case study, and motivated by the recent net-zero announcements of major IOUs in the region. I use GenX (Jenkins et al., 2021), an advanced capacity expansion model, to model cost-optimal grid operations, investments, and retirements through 2050 using a detailed representation of the American Southeast which includes inter-region transmission, VRE characteristics, brownfield capacity, and lifetime and economic retirements.

In Part I, I lay out the motivation behind my investigation into the role of NG under deep decarbonization pathways. I begin with a high-level overview of the challenges that electric utilities nationwide will face as they work to achieve mid-century net-zero goals, followed by a more in-depth examination of the challenges specific to planning for new investments in NG capacity in low-carbon grids. Then, I provide an overview of exiting literature which discusses the role of NG in future low-carbon energy systems. I include academic studies which aim to better understand optimal investments under low-carbon scenarios broadly, as well as those which focus on the role of NG as their central research question. Additionally, I include a specific example of how one Southeastern IOU is incorporating uncertainty over the future role of NG into its resource planning.

In Part II, I provide a detailed overview of the present-day electric power sector in the American Southeast, including the net-zero plans of the regions' largest IOUs and relevant state clean energy and emissions policies. In addition, I discuss current and historic trends in the regions' capacity mix, annual generation, and CO_2 emissions.

In Part III, I lay out the experimental setup. I introduce the GenX capacity expansion model and the multi-period modeling framework which was adopted for this experiment. I then outline the policy, technology, and financial sensitivities that I'll be evaluating. Finally, I describe the model representation of the Southeastern grid that I use in the experimental analysis, detailing key data sources, data processing and aggregation methodologies, and modeling assumptions.

In Part IV, I present modeling results and discuss key findings for both constrained and unconstrained CO_2 emissions scenarios.

Finally, in Part V, I conclude with a discussion of experimental limitations and possibilities for future research, followed by policy recommendations for lawmakers, regulators, and utility decision makers based on key findings from this work.

1 Part I: Motivation

1.1 The Challenge of Net-Zero

Utilities will need to radically transform their businesses if they are to achieve their net-zero goals. Fossil fuels accounted for over 60% of the annual generation mix in the United States in 2020. Meanwhile, carbon-free wind and solar only accounted for only 8.4% and 2.3% of nation-wide electricity generation, respectively (U.S. EIA, 2021a). Utilities will need to transition to produce or procure exclusively low- or no-carbon electricity and ensure system reliability, while simultaneously meeting a demand for electricity which is projected to grow substantially over the coming decades with increasing electrification of transport and other end-uses. What's more, utilities face tremendous uncertainty about future energy technologies, commodity prices, and state and federal policies which may have unforeseen implications for how they implement their plans.

1.1.1 Meeting an Increased Demand for Electricity

Electric utilities will need to decarbonize their generating mixes while simultaneously meeting a greater demand for electricity. Sector-wide shifts towards "beneficial electrification," or electrification of traditionally fossil-fuel heavy sectors of the economy, such as transportation and industry, could lead to far greater increases in electricity demand in the coming decades. A 2018 study by the National Renewable Energy Laboratory (NREL) suggests that economy-wide electrification of transportation, residential and commercial buildings, and industry could result in an increase in electricity consumption by nearly 40% by 2050 compared to a business-as-usual reference case (Mai et al., 2018). If such a high-electrification scenario materializes, utilities must be prepared to meet what the study describes an "unprecedented" sustained annual growth in demand.

1.1.2 Technological and Policy Uncertainty

Utilities face a number of exogenous policy, regulatory, and market factors that are sure to impact their investment and operational decisions over the coming decades. Changes in the federal administration may lead to abrupt changes in climate policy; for example, the final version of the Clean Power Plan, which established CO_2 emissions limits on American power plants, was unveiled by President Obama in 2015, with the Trump Administration announcing its repeal only two years later. Federal climate policy is supplemented with a patchwork of state-level regulations, such as renewable portfolio standards (RPS) or cap and trade programs. Like federal policy, state climate policy is subject to shifts – for example, New Jersey withdrew from the Regional Greenhouse Gas Initiative, a multi-state cap and trade program, in 2012, only to rejoin in 2020 (C2ES, 2021b). Market forces, such as variations in fuel prices or new technological innovations in the oil and gas sector, can lead to unforeseen shifts in energy economics, as has been observed in declining NG prices over the past decade because of the shale gas boom.

The emergence of innovative new energy technologies may also have a substantial impact on how utilities achieve their net-zero ambitions. The International Energy Agency (IEA) projects that by 2050, nearly half of emission reductions will be attributed to technologies currently in the demonstration or prototype phase, although the technologies needed to drive most emissions reductions through 2030 are already on the market (IEA, 2021). These new technologies include small modular nuclear reactors, long-duration energy storage resources, electrolysis-based hydrogen, and more. If such technologies become commercially viable, they may help to provide dispatchable power supply and reduce concerns about the variability of solar and wind resources, although the rate at which they can be deployed at scale remains uncertain.

1.1.3 Addressing the "Net" in Net-Zero

Net-zero emissions targets are distinct from no-carbon emissions targets in that they allow emitters to produce some carbon dioxide, which they intend to offset through negative emissions technologies. Although this gives utilities greater flexibility and allows for a broader range of feasible decarbonization pathways, this same flexibility presents a challenge for how they plan to achieve their goals. While forestry and enhanced agricultural practices offer natural methods of sequestering carbon, these methods require credible carbon accounting to be effective and can realistically remove only a fraction of annual emissions; for example, a 2019 report published the National Academies Press estimates that the United States has capacity for only 0.5 gigatonnes (Gt) of annual CO_2 removal via these methods using current technologies (Committee on Developing a Research Agenda for Carbon Dioxide Removal and Reliable Sequestration et al., 2019, p. 112), a fraction of the 5.13 Gt of energy-related CO_2 emissions produced by the U.S. in 2019 (U.S. EIA, 2020f). Other nascent negative carbon technologies, such as Direct Air Capture and Bioenergy with Carbon Capture and Sequestration are costly and still in early stages of development. It is unclear whether a cost-effective portfolio of negative emissions technologies will be available by 2050 to offset utilities' remaining CO_2 emissions.

1.2 Why Consider Natural Gas as Part of a Decarbonization Pathway?

Natural gas-fired power plants accounted for 38% of America's utility-scale electricity generation in 2019, and the percent share of total generation produced by NG has been trending steadily upwards over the past two decades (see Figure 1). NG produces around 45-50% fewer CO_2 emissions per million metric British thermal units (MMBtu) than coal, and 65% of the decline in U.S. power sector emissions between 2005 and 2019 is attributable to the shift away from coal to NG (U.S. EIA, 2021a).

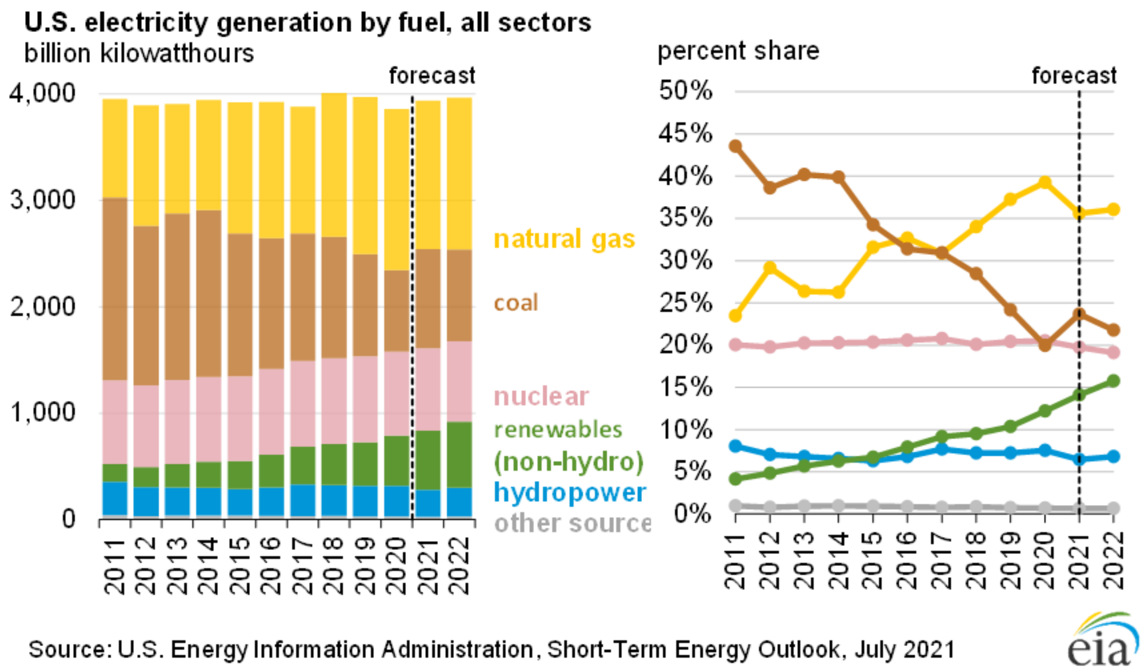

Figure 1: U.S. electricity generation by fuel, all sectors. Total generation (billion kilowatthours) (left) and percent share of total generation (right). Source: U.S. Energy Information Administration, Short-Term Energy Outlook, June 2021.

In 2010, NGCC power plants had the lowest average levelized cost of energy (LCOE) of all major generator resources, including solar photovoltaic (solar PV), wind, and coal. However, rapid cost declines of VREs means that the average LCOE of both solar PV and wind has fallen below that of NG (Lazard, 2020). Nonetheless, natural gas-fired power plants offer grid services which VREs, while perhaps cheaper on an LCOE basis, may not be able to provide. First, natural gas-fired power plants are dispatchable, which means that they can be turned on or off to produce power on demand. Some NG peaker plants, for example, have start up times of less than ten minutes (U.S. EIA, 2020e), which means that they can be used to ensure system reliability during periods of low VRE penetration. Although grid-scale battery storage coupled with VREs may be able to provide these services, less than a GW of large-scale battery storage was operational in the United States at the end of 2018, representing only 1.2 megawatt hours (MWh) of storage capacity (U.S. EIA, 2020d, p. 5). Second, the power density of natural gas-fired power plants, that is, the electric power produced per unit of land area by a power source, is three orders of magnitude greater than that of VREs like solar PV and wind (van Zalk & Behrens, 2018). This means that NG power plants can reliably serve an increasing load without widespread land-use impacts.

Despite the reliability and land use benefits of natural gas-fired power plants compared to VREs, NG remains a fossil fuel, and if NG plants continue to emit CO_2, they may only be able to play a limited role, if any, under deep decarbonization pathways[1]. However, new technologies offer the potential to retrofit NG plants for hydrogen firing or carbon capture and storage (CCS) so that they produce low- to zero-emissions, which could allow them to retain their economic value even in a low-carbon grid. If such technologies become commercially viable, it would help to mitigate the risk of NG plants becoming "stranded assets."

1.3 Literature Review

There is a growing body of academic literature focusing on low-carbon power grid scenarios using various capacity expansion models, many of which suggest possibilities for the role of NG in future low-carbon energy systems. Sepulveda et al. (2018) use the GenX capacity expansion model to generate optimal resource portfolios across nearly 1,000 emissions, geographic, and technology uncertainties. They explore several low emissions intensity scenarios, including fully-decarbonized cases, and find that the availability of firm, low-carbon generation resources, such as NGCC with CCS and nuclear power, reduce costs 10-62% across fully-

[1] NG production and transportation is also a major source of methane, a greenhouse gas with substantially greater global warming potential than CO_2. Grubert et al. (2020) estimate that methane emissions associated with the NG system add about 30% to the emissions intensity of natural gas-fired electricity in the United States. However, methane emissions are not considered in this analysis.

decarbonized scenarios. When firm, low-carbon resources are not included, NG capacity without CCS is built across scenarios with emissions intensities as low as 1 gCO_2 per kilowatt-hour (kWh). MacDonald et al. (2016) use the National Electricity with Weather System (NEWS) model to generate a cost-optimized U.S.-wide power system that includes new generation and HVDC transmission, and focus on solar PV, wind, and NGCC power plants. They suggest that an optimal system under low NG and high VRE costs assumptions would lead to a 33% decrease in grid-wide CO_2 emissions compared to a 1990 emissions baseline, while high NG prices and low VRE costs would lead a 78% reduction in emissions. In both cases, these emissions reductions would be achieved without an increase in the LCOE compared to a reference case. Mileva et al. (2016) use the SWITCH capacity expansion model to explore how various economic, environmental, and technology sensitivities influence resource deployment in the Western Electricity Coordinating Council region through 2050 under a CO_2 emissions reduction pathway. They find that across most scenarios, the "substitution of coal with gas [was] a main carbon-reduction strategy through 2030" except in the "Methane Leakage" scenario, which includes assumed methane CO_2-equivalent emissions from NG use. Doubling the price of NG led to more wind and geothermal resource deployment before 2030 but had a limited effect on system composition after 2030. Jayadev et al. (2020) develop an optimization model for U.S.-wide electric sector capacity planning and explore four scenarios: a no-policy baseline, a no new transmission sensitivity, a pessimistic VRE and storage cost sensitivity, and a carbon tax sensitivity. Their results suggest five key policy insights, one of which is that "natural gas capacity growth is strong and robust, but utilization of gas capacity declines steadily and significantly."

Although each of the aforenoted studies describes a role for new NG capacity in future low-carbon grids, NG is not the central focus. Only a handful of papers have centrally evaluated the role of NG under varying regulatory, policy, and financial assumptions. Mignone et al. (2017) use the National Energy Modeling System (NEMS) U.S. energy system model with foresight to evaluate the effect of a rising future price of CO_2 on investments in new NG capacity before 2030. They find no material effect on new NG deployment before 2030 under varying carbon pricing cases. However, their modeling excludes new storage resources, which are expected to be an important part of a renewables-dominant grid. Babaee and Loughlin (2018) use the MARKet ALocation (MARKAL) U.S.-wide energy systems optimization model to explore the role of NGCC power plants with CCS in a low-carbon energy future from 2005 to 2055. They evaluate three emissions reductions scenarios, representing 50%, 40%, and 30% reductions in GHG emissions compared to a business-as-usual scenario, in addition to several sensitivities related to CCS costs and operational characteristics, and other energy system parameters. They find that NGCC provides substantial generation along emissions reductions pathways in the short-term and mid-term with the exception of runs with high NG prices, and that a substantial portion of this capacity is retrofit with CCS in the long-term. Additionally, they find the methane leakage rate to be the strongest factor in contributing to optimal deployment of NGCC with CCS. Riesz et al. (2015) use a Monte-Carlo based generation portfolio modeling tool to evaluate the role of NG in low-carbon energy pathways in Australia's National Energy Market region. Their findings suggest a decreasing role of NG through 2050, and that portfolios with high amounts of NG capacity are costlier and riskier compared than those with high levels of renewables. In addition, they find that dispatchable, firm generation would be best provided by transitioning existing coal-fired plants into peaker plants rather than building new NG capacity under the lowest cost and lowest risk portfolios.

In response to concerns about continued reliance on NG, utilities, in some cases, have performed their own analyses to explore system outcomes without new NG generation. For example, in its 2020 Integrated Resource Plan, Duke Energy Carolinas (DEC) evaluates a "No New Gas Generation Sensitivity" in its sensitivity analysis of potential resource planning pathways, citing the "growing interest from environmental advocates and Environmental, Social, and Corporate Governance (ESG) investors to understand the impacts of no longer relying on natural gas as a bridge fuel to a net-zero carbon future." (p. 181) In evaluating this sensitivity, DEC assumes that coal plants would remain in operation through their "most economic" retirement dates to "provide the needed capacity until the nascent technologies needed in the mix can be implemented throughout the systems at scale." (p. 182) DEP finds that they are able to provide reliable power without building new NG through the 15-year IRP window, however, plant retirements soon after the planning horizon mean that reliably meeting demand will be challenging without new NG capacity "until more zero-emitting, load following resources can be deployed." (p. 182) Likely in response to concerns about potential stranding of NG assets, DEC also tested the sensitivity of reducing the book life of NGCC and NGCT power plants from the 35 years assumed in their base case to 25 years and found "little change in the expansion plan." (p. 172)

1.4 Research Contribution

This thesis will provide several novel contributions to the growing body of knowledge surrounding the role of NG in future low-carbon energy systems. First, it is unclear the extent to which the aforementioned studies evaluate the role of NG in a highly electrified future; our analysis will assume high electrification in order to better understand how the capacity mix responds to a growing electrical load, as would likely occur if we are to achieve a highly decarbonized economy. Second, in addition to contributing further insight into commonly tested technology and policy sensitivities such as low VRE and storage costs, we will explore several novel scenarios, including the effect of nuclear plant lifetimes, salvage-value assumptions for NG plants, and restrictions on new NG construction. Third, there is a gap in research investigating the role for NG specifically under deep decarbonization, as opposed to low-carbon, pathways. While studies such as Sepulveda et al. (2018) include deep decarbonization scenarios including 1 gCO_2/kWh emissions intensity and no-emissions cases, they take a "greenfield" approach which lacks inter-annual trends or existing "brownfield" capacity. Existing studies which take a multi-period approach, such as Babaee and Loughlin (2018), fail to evaluate NG deployment under extremely low emissions scenarios. By combining a multi-period approach with multiple deep decarbonization pathways which increase in stringency over the planning horizon, this thesis will shed light on how the capacity mix will evolve over time in a transition to a deeply decarbonized grid. Furthermore, by focusing on a specific region and including existing capacity, our analysis will be granular enough to help inform regional resource planning.

2 Part II: Electric Power in the American Southeast – An Overview

2.1 Introduction to the American Southeast

The American Southeast (see Figure 2, states in dark red) is home to about 62.7 million people as of April, 2020 (US Census Bureau, 2021). In 2019, a total of 31.5 million retail electricity customers were served by the Southeast's full-service electricity providers, which include investor-owned utilities (IOUs), public entities such as municipal utilities, federal utility providers such as the Tennessee Valley Authority (TVA), electricity cooperatives (co-ops), and non-utility providers. IOUs serve the majority (57%) of retail electricity customers in the region, although this varies dramatically by state – 75% of retail customers in Florida are served by one of the state's 12 IOUs, while only 1% of retail customers in Tennessee are (U.S. EIA, 2021e).

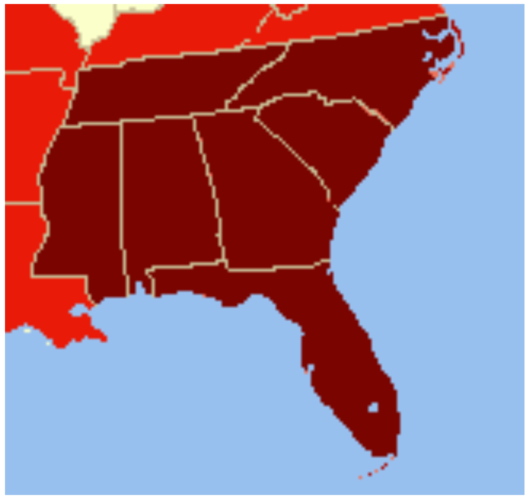

Figure 2: Map of the American Southeast (in dark red), which includes the states of Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee.

The majority of the Southeast is served by vertically-integrated utilities, with a few exceptions – the northeastern corner of North Carolina, in the service area served by Dominion Energy, and a small portion of northeastern Tennessee, served by Appalachian Power, are part of the PJM regional transmission organization, where utilities bid for power on competitive wholesale power markets; the western half of Mississippi, served by Entergy Mississippi, participates in MISO-operated wholesale power markets. South Carolina, Georgia, Alabama, and Florida are fully served by vertically-integrated utilities.

2.2 Public Utility Net-Zero Plans

The three largest public utilities in the American Southeast – Duke Energy, Dominion Energy, and Southern Company – have all set goals of achieving net-zero emissions from electricity generation by 2050, and which include 2030 interim targets (see Table 1). Each company has announced early-stage plans for how they will achieve these goals. Notably, all three companies plan to rely on NG generation to varying degrees and plan to leverage early-stage no-and low-carbon technologies as central elements in achieving their emissions reductions goals. For example, Southern Company "expect[s] that natural gas will remain a fuel source it [its] 2050 operations" due to its "domestic abundance, affordability, and relatively low GHG emissions profile," (Southern Company, 2020, p. 16) and analysis performed by Duke Energy in its "Achieving a Net Zero Carbon Future" report, "makes it clear" that Zero-Emitting Load-Following Resources like advanced nuclear reactors; carbon capture, sequestration and utilization (CCUS); hydrogen; renewable natural gas; and long-duration energy storage technologies will be "needed" for it to achieve its net-zero goals (Duke Energy, 2020, p. 5). While they vary in their details, the companies' plans additionally call for expanding VREs like wind and solar PV, increased investments in storage resources, increased energy efficiency and demand-side management, and phasing out coal-fired power plants.

Company	Base Year	Interim Target	2050 Target
Duke Energy	2005	50% reduction by 2030	Net-zero
Dominion Energy	2005	55% reduction by 2030	Net-zero
Southern Company	2007	50% reduction by 2030	Net-zero

Table 1: Emissions reductions goals for major investor-owned utilities which operate in the American Southeast, at the time of writing.

2.3 State Climate Policies

Most states in the American Southeast lack state-wide climate, clean energy, or GHG emissions reductions policies. As of March 2021, only North Carolina has a statewide emissions reduction target (C2ES, 2021a). North Carolina Executive Order 80, signed by Governor Roy Cooper in October 2018, establishes a statewide target of a 40% reduction in GHG emissions by 2030, and ordered the Department of Environmental Quality (DEQ) to develop a Clean Energy Plan (Cooper, 2018). This plan, published in October 2019, calls for a 70% reduction in GHG emissions below a 2005 baseline by 2030, and for the state to become net-zero by 2050 (NC DEQ, 2019). While this plan is aligned with Duke Energy's and Dominion Energy's mid-century net-zero goals (both utilities operate in North Carolina), it is more ambitious than both companies' 2030 goals. Furthermore, North Carolina is the only state with a renewable portfolio standard (RPS) requirement, requiring IOUs to obtain renewable energy certificates accounting for least 12.5% of retail electricity sales, although South Carolina has a 2% voluntary RPS goal for its IOUs (NCLS, 2021).

2.4 Electric Sector Overview

2.4.1 Generation and Capacity

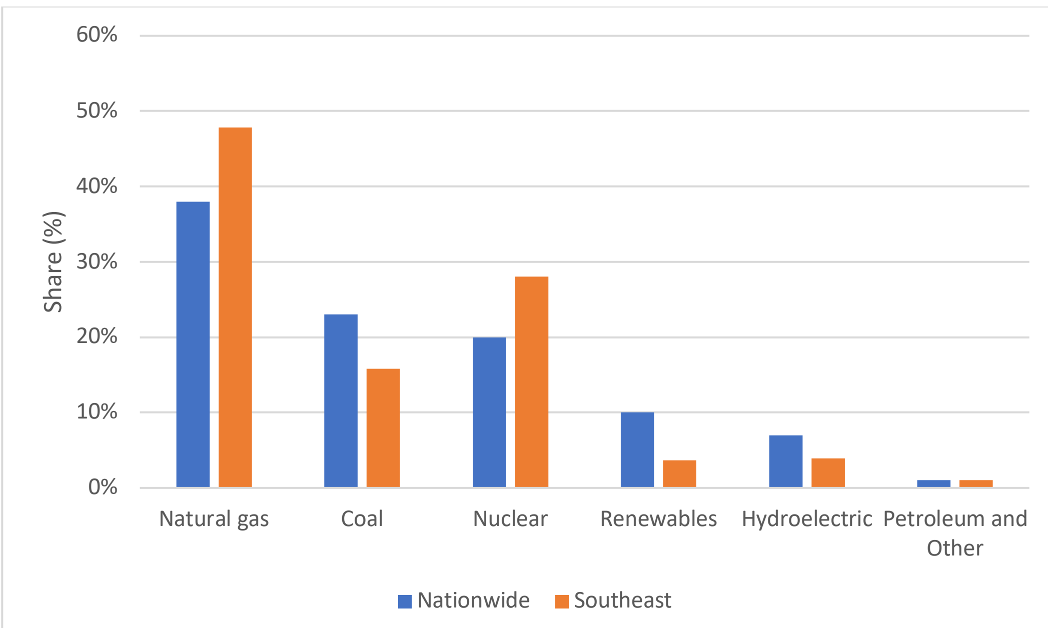

Figure 3: Share of utility-scale electricity generation by primary energy source in 2019. Source: EIA-923 and EIA, Monthly Energy Review (March 2020), Table 7.2a.

In 2019, utility-scale electricity generation in the seven states in the American Southeast produced 897 TWh of energy, about 22% of the nation's total. NG was the predominant source of electricity, accounting for 48% of the region's electrical energy, followed by nuclear at 28%, coal at 16%, hydroelectric power at 4.9%, renewables at 3.7%, and petroleum and other sources at around 1% (see Figure 3). The share of electric generation from NG and nuclear in the Southeast were notably higher than the national average (at 38% and 20% respectively), and the share of electric generation from coal and hydroelectric power notably lower than the national average (at 23% and 7% respectively). The 3.7% share of generation attributed to renewable energy sources was especially low in the Southeast compared to the national average of 10%.

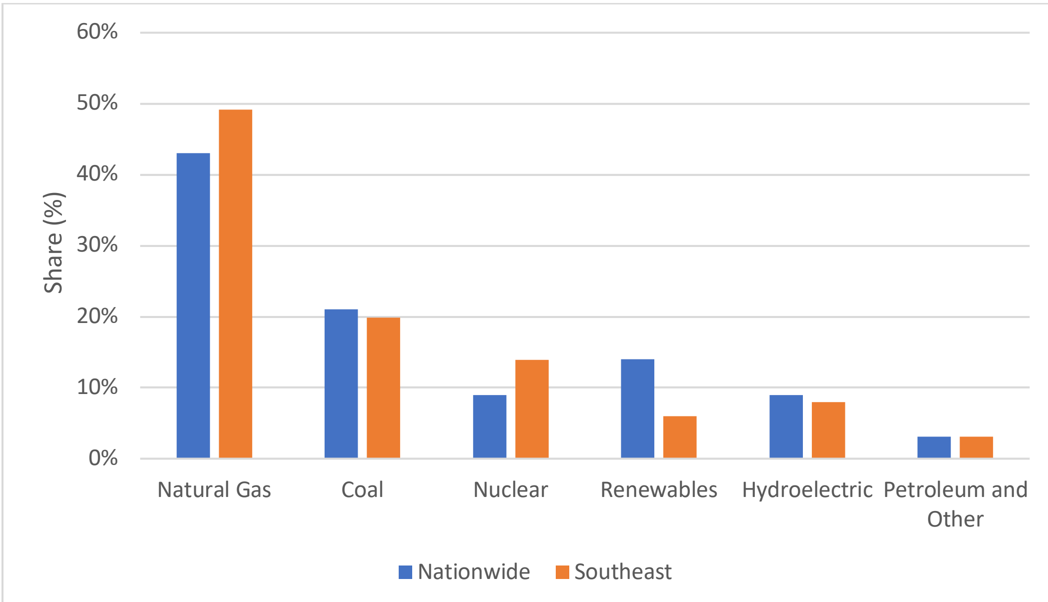

Figure 4: Share of utility-scale electricity generating capacity by primary energy source in 2019. Source: EIA-860 and EIA, Electric Power Monthly (February 2020), Table 6.1.

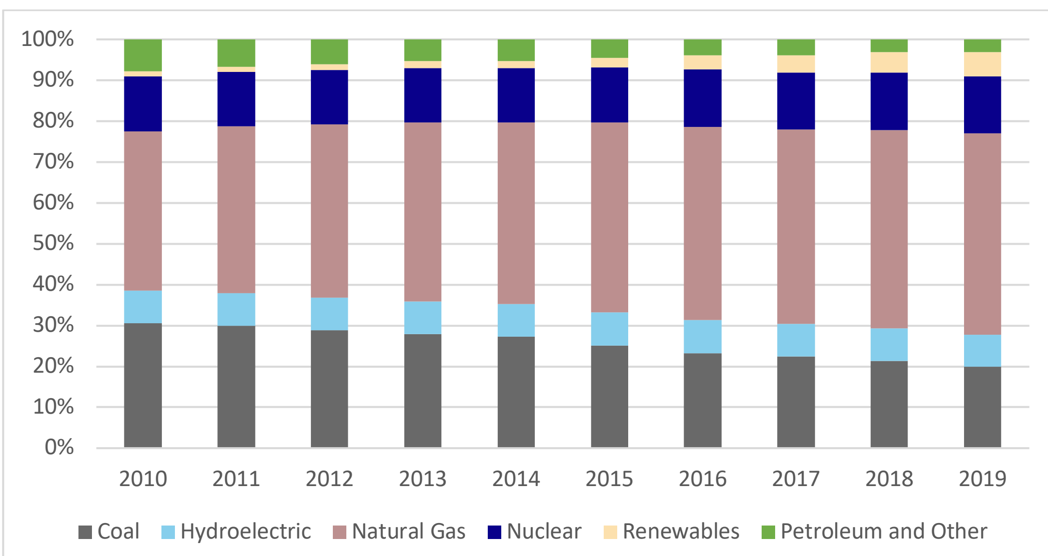

Figure 5: Share of utility-scale generating capacity in the American Southeast by resource type from 2010 – 2019. Source: EIA-860.

Utility-scale generation capacity in the Southeast totaled approximately 221 GW in 2019, accounting for about 20% of the nation's total. Compared to generation, capacity by resource type in the Southeast is more closely aligned with the national average share of capacity (see Figure 4). Over time, changes in the capacity mix in the Southeast has been predominately characterized by the steady increase in NG capacity and decline in coal capacity (see Figure 5). In 2010, coal accounted for 30.5% and NG for 38% of total electric industry capacity, respectively; by 2019, coal accounted for less than 20% of total capacity, and NG for over 49%. Although renewable energy sources, at 6% of total capacity, constitute only a small percentage of the 2019 capacity mix, renewable capacity has been growing rapidly – total renewable capacity increased over 4.5-fold since 2010. NG, the second-fastest growing capacity resource over the same period, increased only 1.3-fold.

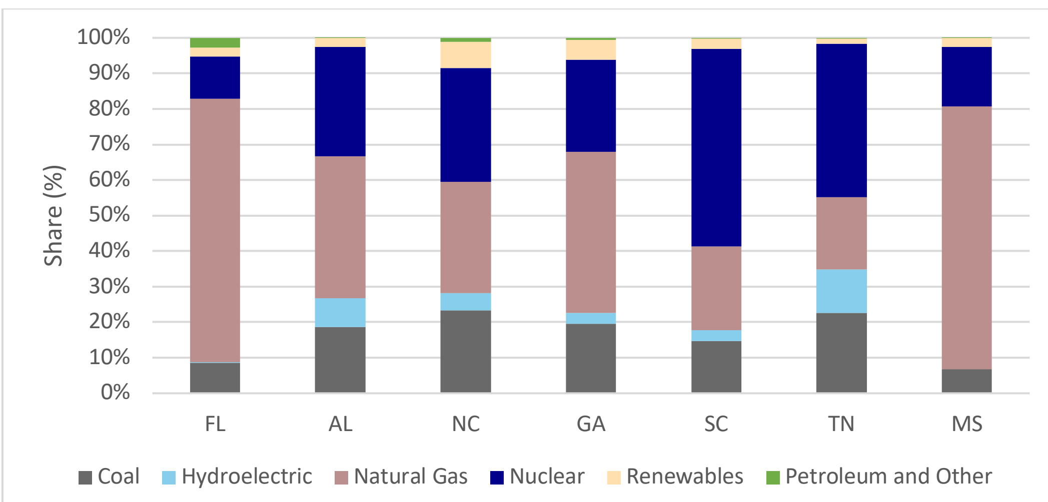

Figure 6: Share of utility-scale electricity generation in the American Southeast by resource type. Source: EIA-923.

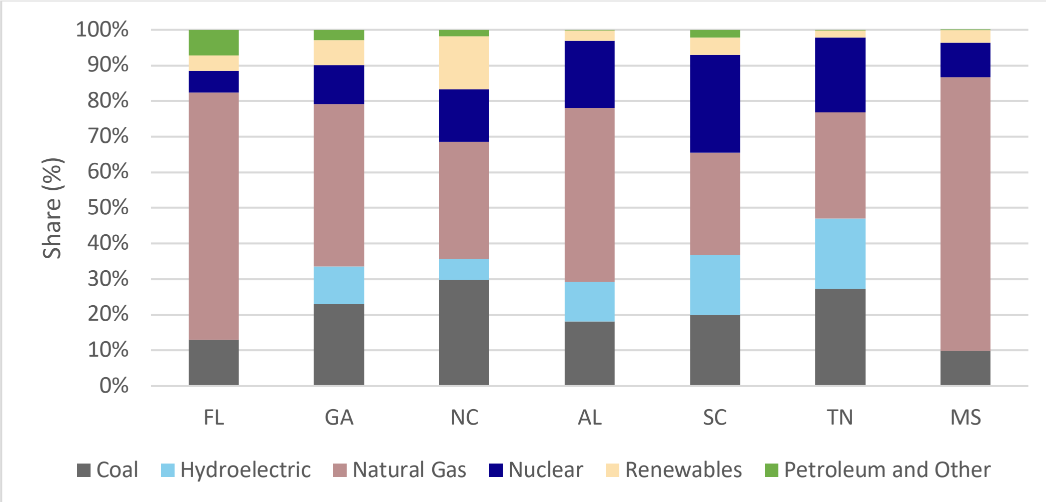

Figure 7: Share of utility-scale electricity generating capacity in the American Southeast by resource type. Source: EIA-860.

Across the states of the Southeast, there is a substantial variation in the breakdown of the generation and capacity mix by resource type (see Figure 6 and Figure 7). Containing 27% of the Southeast's total generation capacity and generating 27% of total utility-scale electricity, Florida constitutes a substantially larger capacity mix and share of total generation than the other Southeastern states; total generation in Florida is about the same as the total generation of the smallest three Southeastern states by total generation and capacity – South Carolina, Tennessee, and Mississippi – combined. Florida and Mississippi have little to no hydroelectric capacity, while hydroelectric power constitutes nearly 20% of the capacity mix in Tennessee. Nuclear power accounts 56% of the electricity generated in South Carolina each year, but less than 12% of electricity generated in Florida. Figure 8 and Figure 9 show statewide total generation (TWh) and capacity (GW) by resource type.

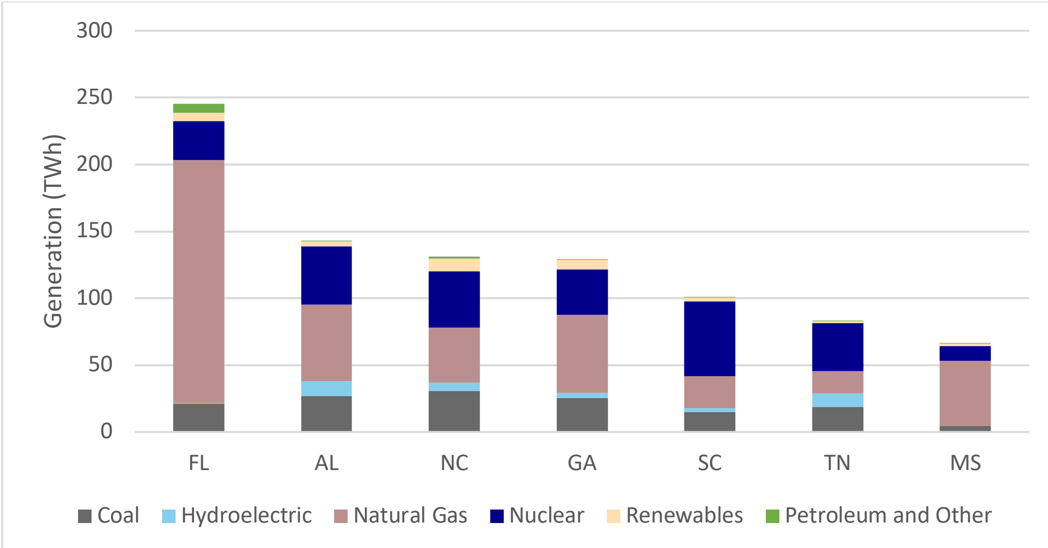

Figure 8: Total utility-scale electricity generation in the American Southeast by resource type. Source: EIA-923.

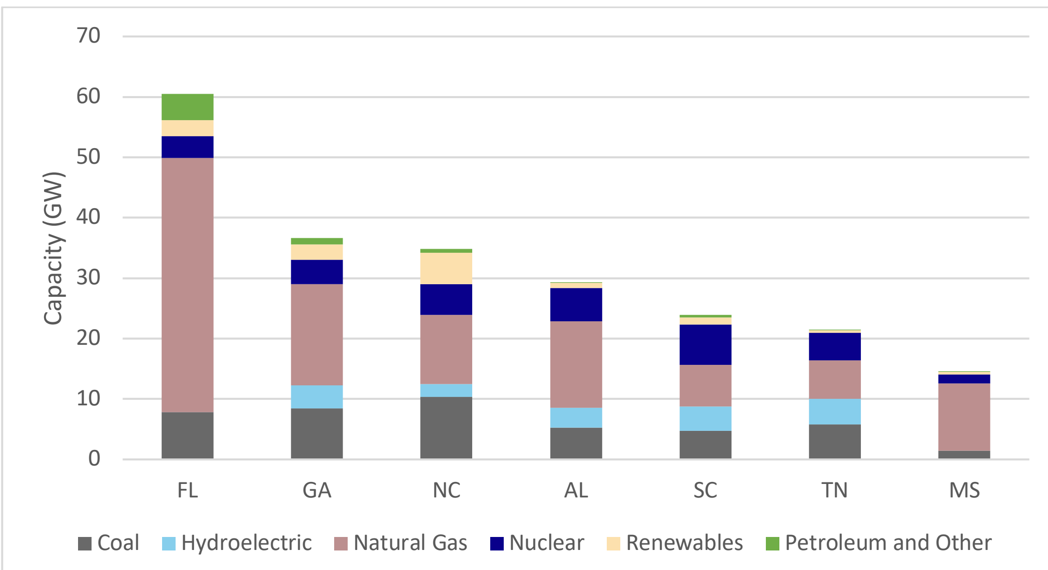

Figure 9: Total utility-scale electricity generating capacity in the American Southeast by resource type. Source: EIA-860.

2.4.2 Emissions

In 2019, the Southeast emitted 325 Mt of CO_2 into the atmosphere, accounting for about 20% of electric power sector emissions in the United States (U.S. EIA, 2021b). Emissions have been trending downward since 2007, when emissions peaked at 525 Mt of CO_2, a 38% reduction, no doubt driven, as discussed earlier, by the transition away from coal and towards NG (see Figure 10).

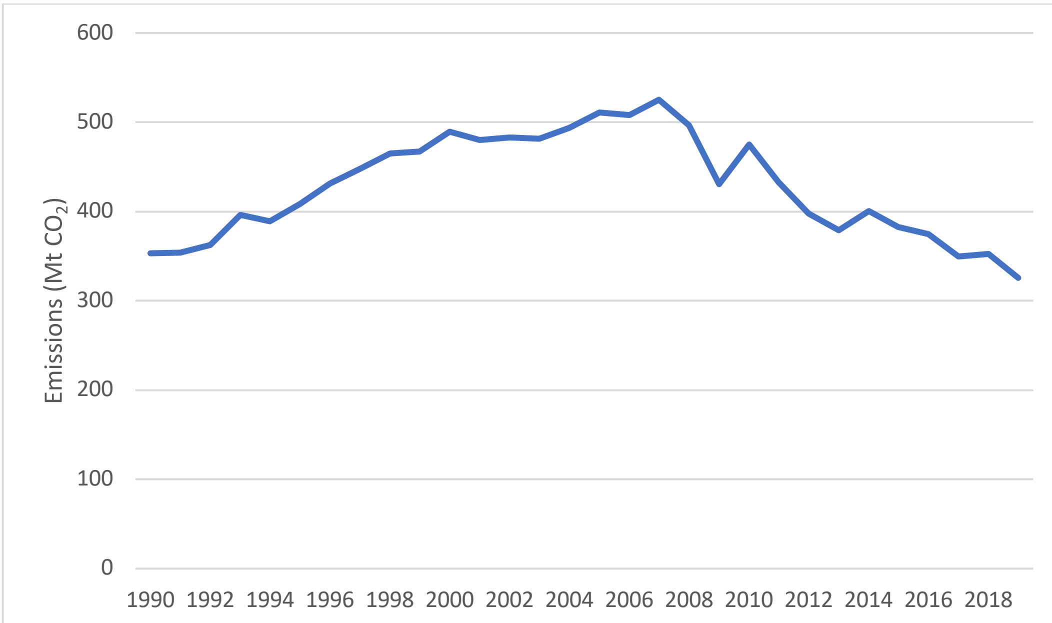

Figure 10: Total electric power industry CO_2 emissions in the American Southeast from 1990 to 2019. Source: Source: EIA.

3 Part III: Experimental Setup

3.1 The GenX Capacity Expansion Model

3.1.1 Introduction to GenX

GenX (Jenkins et al., 2021) is a high resolution, least-cost capacity expansion model which features high temporal granularity, operational detail, and integrated transmission network planning (see Figure 11). GenX is open-source and available for public use, and at the time of writing, has been used in over a half-dozen peer-reviewed publications.

GenX can model supply-side generation and storage resources, including long duration energy resources, and demand-side flexibility. It is highly customizable and can represent a range of new and existing technology types, making it suitable for modeling low-carbon electricity systems. In addition to economic dispatch with ramping and storage constraints, GenX can model unit commitment of thermal resources, and spinning and operating reserve requirements. GenX is compatible with downscaled representations of timeseries data via representative and extreme period selection, which allows it to capture inter- and intra-annual operational variability while maintaining computational feasibility. It also supports advanced representation of VREs with a range of capacity limits and resource availability profiles to support computational efficiency.

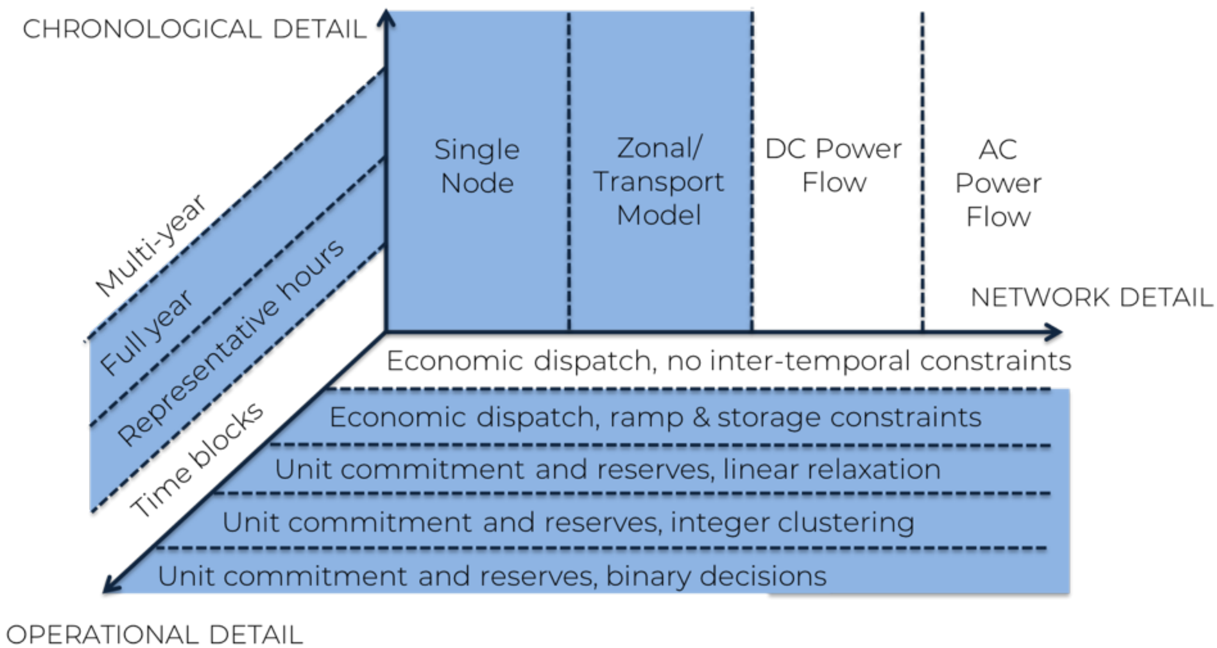

Figure 11: Key features of the open-source GenX capacity expansion model, highlighted in blue. Although "multi-year" chronological detail is not available in the open-source GenX software at the time of writing, a custom-built software extension was developed to permit multi-year modeling. Source: https://genxproject.github.io/.

GenX has traditionally been used to model a single year of grid operations, including a single investment period. However, planning for future grids with high levels of VREs and evolving carbon policies requires detailed modeling of grid operations over multiple planning periods. In addition, a multi-period model allows us to incorporate dynamic cost information and lifetime retirements for new and existing capacity.

The dual dynamic program (DDP) algorithm is a well-known approach for solving multi-period optimization problems in a computationally efficient manner, first proposed by Pereira and

Pinto (1991). This algorithm splits up a multi-period investment planning problem into multiple, single-period sub-problems. Each period is solved iteratively as a separate linear program (LP) ("forward pass"), and information from future periods is shared with past periods ("backwards pass") so that investment decisions made in subsequent iterations reflect the contributions of present-day investments to future costs.

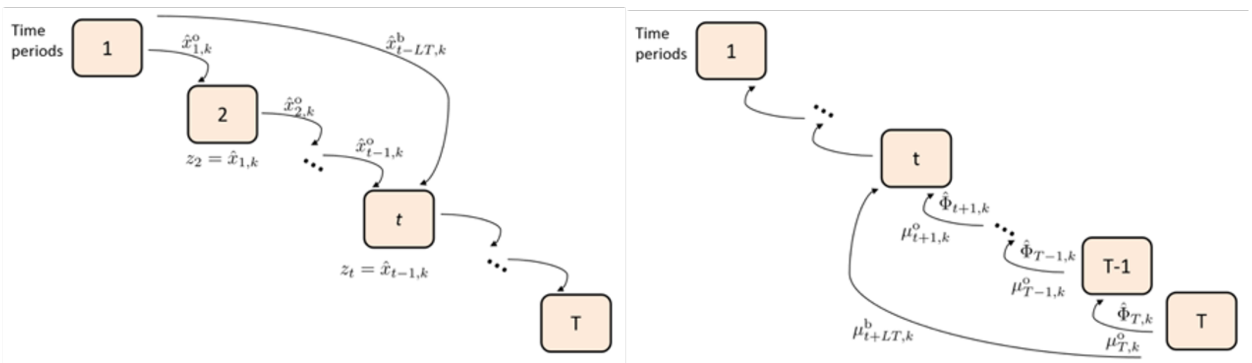

Figure 12: Representation of the forward pass (left) and backwards pass (right) of the dual dynamic programing (DDP) algorithm. $\hat{x}_{t,k}$ represents the optimal value of the linking variable from period t, iteration k; $\hat{\Phi}_{t,k}$ represents the objective function value (total costs) of the optimal solution at period t, iteration k; and $\mu_{t,k}$ represents the dual variable (shadow price) of the linking constraint $z_t = \hat{x}_{t-1,k}$ at period t, iteration k. Source: Lara et al. (2018).

3.1.2 Multi-Period GenX Model Setup

The DDP algorithm was used to link single-period GenX LPs into a multi-year, least-cost optimization problem with perfect foresight. We use 6 periods, each five years in length, beginning in 2020 and extending up to 2050. Capacity additions and retirements are made at the start of each model period, and no capacity additions are allowed in 2020, although retirements are permitted. Although each model period simulates a single year of operational behavior, operational costs, non-served energy costs, and emissions are scaled up so that each period represents 5 years of each. Beginning with the 2025 model period, investment cost assumptions and fixed O&M (FOM) cost assumptions from 5 years prior were used, to capture the fact that project financing typically occurs years before plants become operational. For example, in the 2025 model period, investment cost and FOM cost assumptions for the year 2020 were used. Annual fuel prices, variable O&M

(VOM) costs, and hourly load profiles match their corresponding model year; that is, the 2025 model period uses 2025 fuel prices, VOM costs, and load profiles, for example (see Table 2).

Model Period	Investment Cost Year	FOM Cost Year	VOM Cost Year	Fuel Cost Year	Load Profile Year
2020	2020	2020	2020	2020	2020
2025	2020	2020	2025	2025	2025
2030	2025	2025	2030	2030	2030
2035	2030	2030	2035	2035	2035
2040	2035	2035	2040	2040	2040
2045	2040	2040	2045	2045	2045

Table 2: Assumed years used for representing investment costs, FOM costs, VOM costs, fuel costs, and hourly load projections for each model period.

GenX was configured to model unit commitment of thermal power plants under a linear relaxation assumption, which has been shown to be a reasonable approximation when considering capacity expansion under decarbonization constraints. Network expansion of existing transmission was also enabled. However, operating reserves were not modeled due to the substantial increase in memory and computational time that this would require.

3.2 Experimental Sensitivities

Scenario Name	Scenario Number	CO2 Emissions Reduction Policy	VRE Technology Costs	Nuclear Second Lifetime Extentions (SLTEs)	Salvage Value for NG w/o CCS After 2050	No New NG w/o CCS After 2025 Constraint
Reference Case	*0*	*None*	*Moderate*	*Yes*	*Yes*	*No*
NoCO2Limit_LowVRECosts	1	None	Low	Yes	Yes	No
NoCO2Limit_NoSLTE	2	None	Moderate	No	Yes	No
HighCO2Limit	3	High	Moderate	Yes	Yes	No
MedCO2Limit	4	Medium	Moderate	Yes	Yes	No
LowCO2Limit	5	Low	Moderate	Yes	Yes	No
HighCO2Limit_LowVRECosts	6	High	Low	Yes	Yes	No
MedCO2Limit_LowVRECosts	7	Medium	Low	Yes	Yes	No
LowCO2Limit_LowVRECosts	8	Low	Low	Yes	Yes	No
HighCO2Limit_NoSLTE	9	High	Moderate	No	Yes	No
MedCO2Limit_NoSLTE	10	Medium	Moderate	No	Yes	No
LowCO2Limit_NoSLTE	11	Low	Moderate	No	Yes	No
HighCO2Limit_NG2025	12	High	Moderate	Yes	No	No
MedCO2Limit_NG2025	13	Medium	Moderate	Yes	No	No
LowCO2Limit_NG2025	14	Low	Moderate	Yes	No	No
HighCO2Limit_NGFullCost	15	High	Moderate	Yes	Yes	Yes
MedCO2Limit_NGFullCost	16	Medium	Moderate	Yes	Yes	Yes
LowCO2Limit_NGFullCost	17	Low	Moderate	Yes	Yes	Yes

Table 3: List of scenarios. Cells in grey indicate parameters in each scenario which differ from the Reference Case. Note that SLTE stands for "second lifetime extension."

3.2.1 Emissions Reductions Policies

We consider the effects of three emissions reduction policies with varying limits on annual CO_2 emissions, in addition to a fourth, "no emissions policy" scenario, in which there are no limits on annual CO_2 emissions. All emissions reductions policies were computed relative to a regional 2007 baseline level of CO_2 emissions. This baseline was computed as approximately 500 million tonnes (Mt) of CO_2 per year over the entire the Southeast model region[2], and was used as the 2020 emissions cap. All three policies require 50% emissions reductions by 2030 compared to this

[2] To compute this value, annual CO_2 emissions for each of the seven Southeastern states were taken from 2019 EIA state-level summary tables. Then, these state totals were scaled according to state-level contributions to each Southeast model region according to Table 28, and summed together to get an approximate model region-wide annual emissions value. Based on this calculation, 2007 was the year with the greatest historic region-wide emissions of 508 Mt of CO_2, which we approximate as a 500 Mt emissions baseline for the purpose of this analysis.

baseline, or a model region-wide annual emissions limit of 250 Mt CO_2 (see Figure 13 and Table 4). In 2045, the "high" emissions policy requires a 90% emissions reduction (50 Mt annual CO_2 limit), the "medium" emissions policy requires a 95% reduction (25 Mt annual CO2 limit), and the "low" emissions policy requires a 99% reduction compared to this baseline. These three scenarios were chosen to represent various mid-century emissions targets that a net-zero strategy may aim for, with varying levels of expected emissions offsets.

In addition to the limits imposed in the 2020, 2030, and 2045 model periods, emissions caps were imposed on interim periods. These limits were computed via linear interpolation of emissions caps from 2020 to 2030, and from 2030 to 2045. This resulted in an annual emissions limit of 375Mt in 2025 under all three policies, and policy-dependent limits for 2035 and 2040.

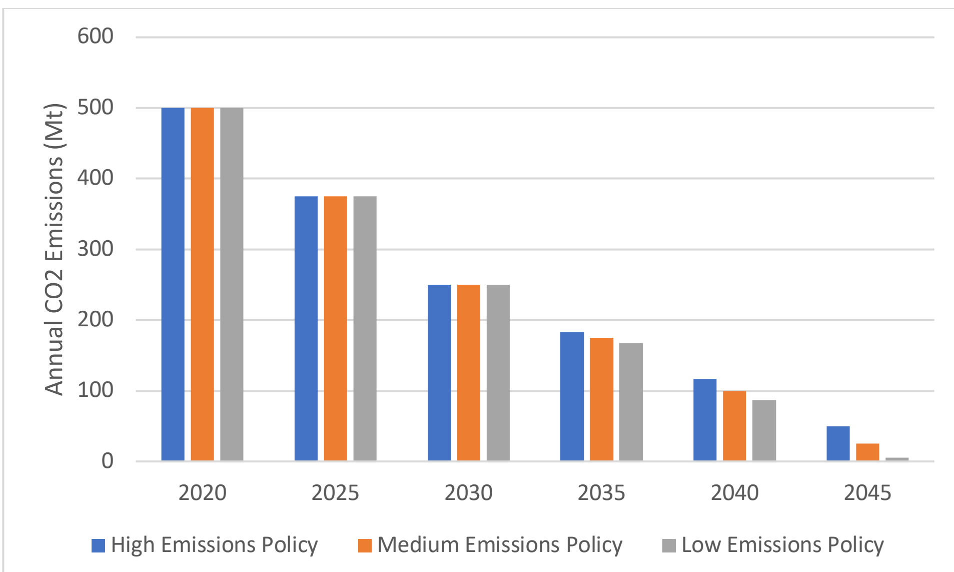

Figure 13: Annual model region-wide CO_2 emissions limits (Mt) by emissions reduction policy.

	Annual CO2 Emissions (Mt)					
Emissions Policy	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
High Emissions	500	375	250	183	117	50
Medium Emissions	500	375	250	175	100	25
Low Emissions	500	375	250	168	870	5

Table 4: Annual model region-wide CO_2 emissions limits (Mt) by emissions reduction policy.

3.2.2 Technology Advancement

We evaluate two technology advancement scenarios, as specified in the National Renewable Energy Laboratory's (NREL's) 2020 Annual Technology Baseline (ATB) (Akar et al., 2020) – "moderate" and "advanced" technology advancement. These assumptions are reflected in technology costs trajectories, with "moderate" representing mid-level future cost projections and "advanced" representing low-level future cost projections. While capital costs and FOM costs for thermal generation remain the same under both scenarios, these costs decline more steeply for solar PV, wind, and battery storage under the "advanced" technology advancement scenario (see Figure 14 and Figure 15). VOM costs do not change for any technologies between the two scenarios.

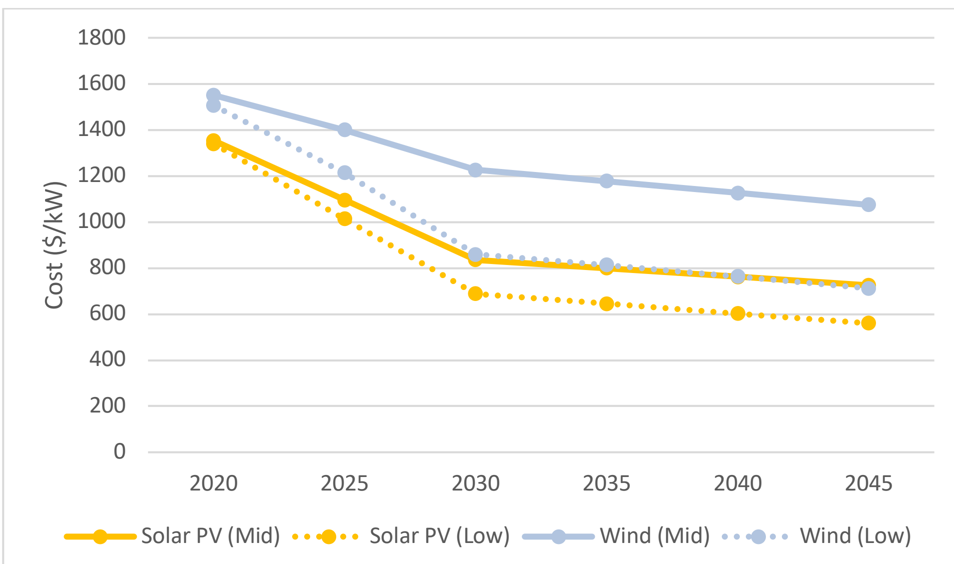

Figure 14: Cost projections ($/kW) for solar PV and onshore wind resources. Source: 2020 NREL ATB, with "Mid" cost projections corresponding to "Moderate" technology advancement, and "Low" cost projections corresponding to "Advanced" technology advancement.

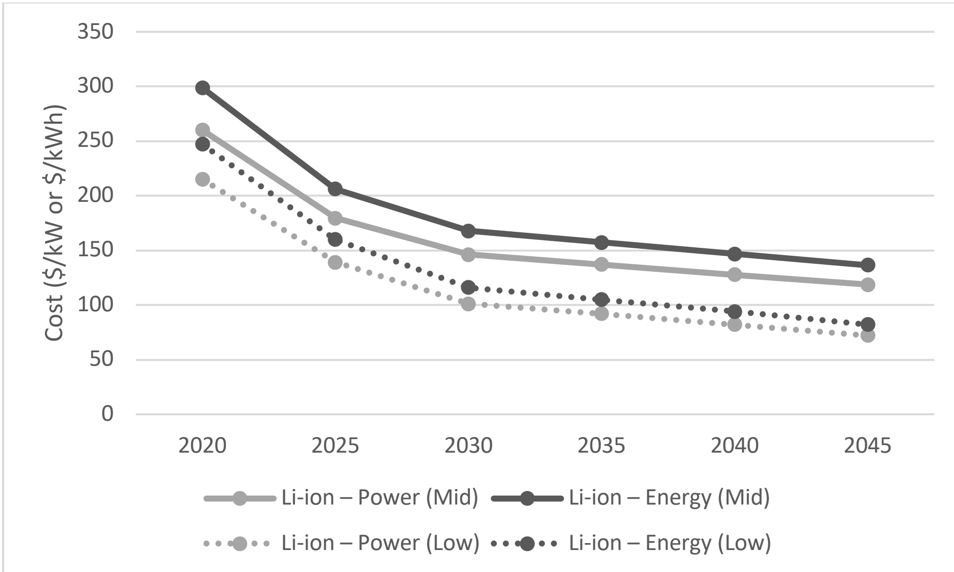

Figure 15: Cost projections for Li-ion battery storage resources, in $/kW for power capacity and $/kWh for energy capacity. Source: 2020 NREL ATB, with "Mid" cost projections corresponding to "Moderate" technology advancement, and "Low" cost projections corresponding to "Advanced" technology advancement.

3.2.3 Second Lifetime Extensions for Existing Nuclear Power Plants

Our default assumption is that all existing nuclear plants in the Southeast receive a second lifetime extension (SLTE), which would lead to an 80-year assumed operational lifetime for existing nuclear capacity. Under this assumption, there would be no retirements in the existing nuclear fleet before 2050 (see Table 5). We assume that there are no re-licensing or refurbishing costs associated with SLTEs, and plants continue to operate under the same cost and performance assumptions.

We test the impact of nuclear SLTEs by including scenarios where none are granted. This results in a 60-year operational lifetime assumption for all existing nuclear power plants in the Southeast region, and for assumed operational capacity to decline from 32.9 GW in the 2020 model period to 23.6 GW, 18.6 GW, and 9.5 GW in the 2035, 2040, and 2045 model periods, respectively.

Plant Name	Generator ID	Model Region	Nameplate Capacity (MW)	Start Date	Assumed Retirement Date Without SLTE	Assumed Retirement Date With SLTE
Browns Ferry	*1*	TVA	1,152	8/1/1974	8/1/2034	8/1/2054
Browns Ferry	*2*	TVA	1,152	3/1/1975	3/1/2035	3/1/2055
Browns Ferry	*3*	TVA	1,190	3/1/1977	3/1/2037	3/1/2057
Sequoyah	*1*	TVA	1,221	7/1/1981	7/1/2041	7/1/2061
Sequoyah	*2*	TVA	1,221	6/1/1982	6/1/2042	6/1/2062
Watts Bar Nuclear Plant	*1*	TVA	1,270	5/1/1996	5/1/2056	5/1/2076
Watts Bar Nuclear Plant	*2*	TVA	1,270	6/1/2016	6/1/2076	6/1/2096
Brunswick Nuclear	*1*	Carolinas	1,002	3/1/1977	3/1/2037	3/1/2057
Brunswick Nuclear	*2*	Carolinas	1,002	11/1/1975	11/1/2035	11/1/2055
Catawba	*1*	Carolinas	1,205	6/1/1985	6/1/2045	6/1/2065
Catawba	*2*	Carolinas	1,205	8/1/1986	8/1/2046	8/1/2066
H B Robinson	*2*	Carolinas	769	3/1/1971	3/1/2031	3/1/2051
Harris	*1*	Carolinas	951	5/1/1987	5/1/2047	5/1/2067
McGuire	*1*	Carolinas	1,220	9/1/1981	9/1/2041	9/1/2061
McGuire	*2*	Carolinas	1,220	3/1/1984	3/1/2044	3/1/2064
Oconee	*1*	Carolinas	887	7/1/1973	7/1/2033	7/1/2053
Oconee	*2*	Carolinas	887	9/1/1974	9/1/2034	9/1/2054
Oconee	*3*	Carolinas	893	12/1/1974	12/1/2034	12/1/2054
V C Summer	*1*	Carolinas	1,030	1/1/1984	1/1/2044	1/1/2064
Edwin I Hatch	*1*	SoCo	857	12/1/1975	12/1/2035	12/1/2055
Edwin I Hatch	*2*	SoCo	865	9/1/1979	9/1/2039	9/1/2059
Joseph M Farley	*1*	SoCo	888	12/1/1977	12/1/2037	12/1/2057
Joseph M Farley	*2*	SoCo	888	7/1/1981	7/1/2041	7/1/2061
Vogtle	*1*	SoCo	1,160	5/1/1987	5/1/2047	5/1/2067
Vogtle	*2*	SoCo	1,160	5/1/1989	5/1/2049	5/1/2069
Vogtle	*3*	SoCo	1,250	-	-	-
Vogtle	*4*	SoCo	1,250	-	-	-
St Lucie	*1*	Florida	1,080	5/1/1976	5/1/2036	5/1/2056
St Lucie	*2*	Florida	1,080	6/1/1983	6/1/2043	6/1/2063
Turkey Point	*3*	Florida	877	12/1/1972	12/1/2032	12/1/2052
Turkey Point	*4*	Florida	760	9/1/1973	9/1/2033	9/1/2053
Total Assumed Existing Nuclear Capacity: 32.9 GW						

Table 5: Existing nuclear capacity included in the Southeast model, including the month and year the plant entered into operation, and assumed retirement dates if the plant does and does not receive a second lifetime extension (SLTE) (note that Vogtle Units 3 and 4 are included even though they have not yet entered into operation, and therefore an operational start date and expected retirement dates under the two assumptions are not included). Total existing nuclear capacity in 2020, plus Vogtle Units 3 and 4, is included for reference. Source: EIA-860.

3.2.4 Salvage Value for Natural Gas without CCS after 2050

We explore the effect of financial assumptions related to the salvage value of new NGCT and NGCC power plants without CCS. We consider two financial models – one which assumes that undepreciated costs post-model horizon of these plants are fully recoverable, and one which requires that all capital costs be paid in full before the end of the model horizon. We call the first the "rental" financial model, and the second the "full-cost" financial model.

3.2.4.1 Rental Financial Model

In the rental financial model, annualized investment costs are modeled as rental payments for each year's use of a capital asset. We only pay for the years in which the capital asset is able to be used – that is, the model does not consider annualized investment costs which would occur after the model horizon.

The annualized investment cost (AIC) of an asset in period p with weighted cost of capital $WACC$ and overnight capital cost $C^{Overnight}$ is computed using the following formula:

$$AIC_p = \frac{WACC * C^{Overnight}}{1-(1+WACC)^{-L}}$$

where L is the economic lifetime of the asset. The adjusted total capital cost under the "rental" financial model, C^{Rental}, which equals the discounted sum of the annual "rents" paid for within the model horizon, is computed as follows:

$$C_p^{Rental} = \sum_{i=1}^{\min(L,Y_p)} \frac{AIC_p}{(1+WACC)^i}$$

where Y_p is the number of years remaining between the start of period p and the end of the planning horizon. Note that when $L \leq Y_p$, $C_p^{Rental} = C^{Overnight}$ that is, the sum of rental payments is equal to the overnight capital cost. When $Y_p < L$, however, $C_p^{Rental} < C^{Overnight}$, that is, the sum of rental payments is less than the overnight capital cost.

For example, suppose we build a capital asset in 2030 with an overnight capital cost of \$1,000,000, and an economic lifetime of 30 years. With a WAAC of 4.5%, this translates to an annualized investment cost of about \$67,000. If the model horizon only extends through 2050, however, we would only pay this amount annually for 20 years, not the full 30 years of the assets' economic life. This means that from the model's perspective, the adjusted total capital cost equals the discounted sum of these rents over this 20-year period, which is about $800,000.

3.2.4.2 Full-cost Financial Model

In the "full-cost" financial model, we assume that there is no salvage value for NG assets without CCS beyond the model horizon; that is, they become "stranded assets" without any useful economic value after 2050. Therefore, the full-cost financial model requires that all capital costs of new NG plants without CCS be paid in full within the model horizon. This means that $C_p^{Full-cost} = C^{Overnight}$ for all periods p.

3.2.5 CCS Requirement for New Natural Gas Beginning in 2030

We consider the effects of limiting all deployment of new NG capacity beginning in 2030 to include CCS. This constraint means that all NG power plants without CCS may only be built in the 2025 model period.

3.2.6 Reference Case

A reference case is established as a baseline against which to compare how the sensitivities described above impact relative costs, emissions, and capacity mixes. The reference case does not include a CO_2 emissions policy (i.e., emissions are unconstrained), uses "moderate" technology advancement assumptions (i.e., baseline costs for VREs and battery storage), assumes that SLTEs are granted for all existing nuclear power plants (i.e., all existing nuclear capacity remains online through the 2050 planning horizon), assumes full salvage value for all resources post-planning horizon (i.e., "rental" financial model for all assets), and imposes no constraints on when new NG capacity may be deployed (i.e., new NG capacity may be built any model period besides the first, when no new investments of any kind are allowed) (see Table 3, Scenario Number 0).

3.3 Southeast Power Sector Model

3.3.1 Model Regions

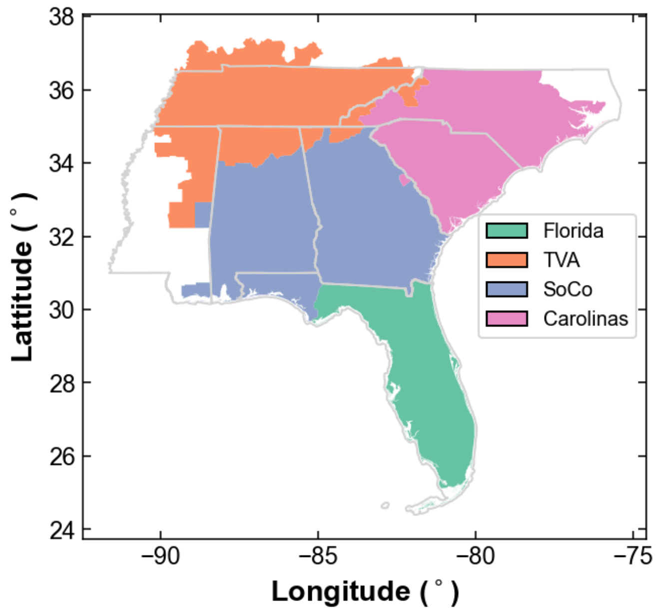

Figure 16: Geographic boundaries of the Southeast model, by model region.

Four model regions from the United States Environmental Protection Agency's (EPA's) Power Sector Modeling Platform v6 Integrated Planning Model (IPM) (EPA, 2018, p. 40) were used to define the boundaries of the Southeast model (see Figure 16). These regions are S_C_TVA, S_VACA, S_SOU, and FRCC, which will be referred to here as "TVA," "Carolinas," "SoCo," and "Florida" respectively (see Table 6). These four model regions include parts of the seven Southeastern states outside of wholesale power markets (see section 2.1).

IPM Region	Name in Southeast Model
S_C_TVA	TVA
S_VACA	Carolinas
S_SOU	SoCo
FRCC	Florida

Table 6: IPM regions from EPA's Integrated Planning Model and their corresponding representations in the Southeast model.

3.3.2 Resource Types

Resource Label	Full Resource Name	Includes Brownfield Capacity?	Eligible for Capacity Expansion?
Coal_bf	Conventional Steam Coal	Yes	No
Hydro_Res_bf	Reservoir Hydroelectric	Yes	No
Hydro_RoR_bf	Run-of-River Hydroelectric	Yes	No
NGCC_bf	Natural Gas Fired Combined Cycle	Yes	No
NGCT_bf	Natural Gas Fired Combustion Turbine	Yes	No
NGST_bf	Natural Gas Steam Turbine	Yes	No
Nuclear_bf	Nuclear	Yes	No
PHS	Hydroelectric Pumped Storage	Yes	Yes
Solar_PV	Solar Photovoltaic	Yes	Yes
Wind_1	Onshore Wind Turbine	Yes	Yes
Wind_2	Onshore Wind Turbine	Yes	Yes
Wind_3	Onshore Wind Turbine	Yes	Yes
Li-ion	Lithium-ion Battery Storage	No	Yes
NGCC	Natural Gas Fired Combined Cycle	No	Yes
NGCC_CCS	Natural Gas Fired Combined Cycle w/ CCS	No	Yes
NGCT	Natural Gas Fired Combustion Turbine	No	Yes
Nuclear	Nuclear	No	Yes

Table 7: List of resources included in the Southeast model, including whether each resource type includes representations of brownfield capacity and whether it is eligible for capacity additions.

The Southeast model is configured to represent 17 unique resources in each model region. Seven of these resource types exclusively represent existing, or "brownfield" capacity, and are not eligible for new capacity additions, but may be retired owing to lifetime of economic considerations (see Table 7). Brownfield thermal resource types not eligible for new capacity additions include existing NGCC plants (NGCC_bf), existing NGCT plants (NGCT_bf), existing NG steam turbine plants (NGST_bf), existing coal plants (Coal_bf), and existing nuclear plants (Nuclear_bf). Brownfield hydroelectric resources not eligible for new capacity additions include run-of-river hydroelectric plants (Hydro_RoR_bf) and reservoir hydroelectric plants (Hydro_Res_bf). Other resource types are used to exclusively represent new, or "greenfield," capacity additions. These resources include new combined cycle NG plants (NGCC), new combined cycle NG plants with CCS (NGCC-CCS), new combustion turbine NG plants (NGCT), new nuclear plants (Nuclear), and new utility-scale Li-ion battery storage facilities (Li-ion). Finally, some resource types are used to represent both existing capacity and new capacity additions. These include utility-scale solar photovoltaic facilities (Solar_PV), pumped hydroelectric storage facilities (PHS), and onshore wind turbine facilities. The onshore wind resource type is broken down into three sub-types in each model region, representing the differences in grid interconnection costs and wind availability profiles associated with different types of developable sites in that region (Wind_1, Wind_2, and Wind_3) as per Brown and Botterud (2021)[3].

3.3.3 Existing Energy Resources

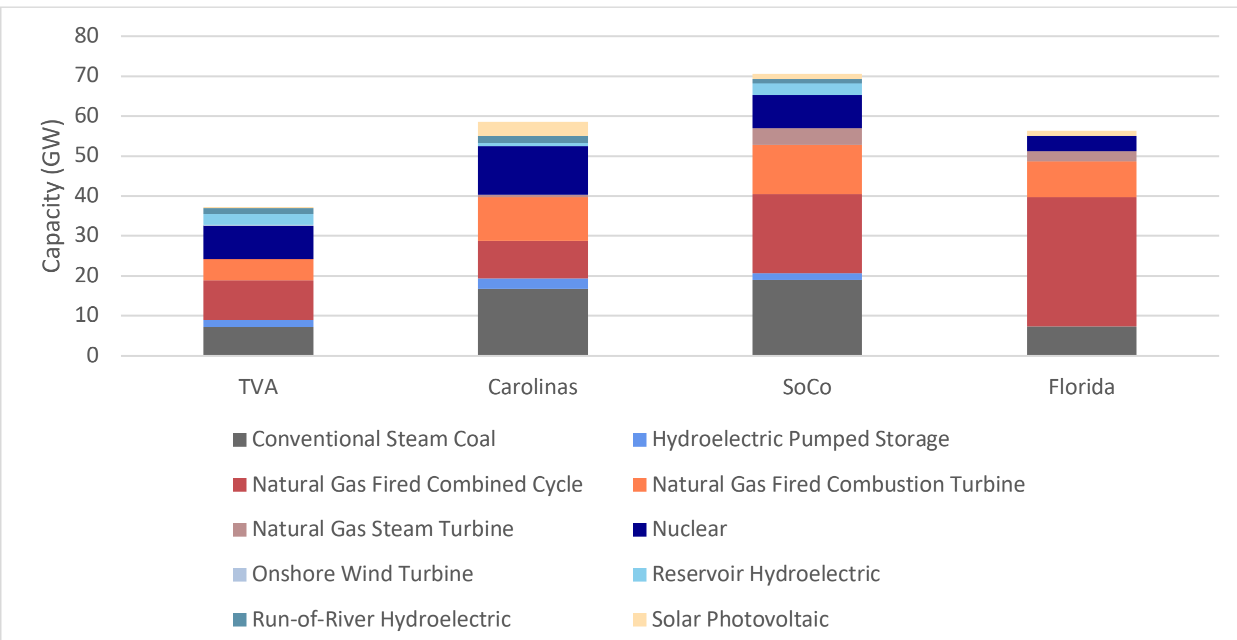

Figure 17: Brownfield capacity (GW) in each Southeast model region for each of the EIA technology types, with the "Conventional Hydroelectric" resource type broken down into "Run-of-River Hydroelectric" and "Reservoir Hydroelectric" subtypes. Source: EIA-860.

[3] We do not consider offshore wind resources due to data limitations; however, we acknowledge that the American Southeast has substantial offshore wind development potential and that offshore wind projects are being actively considered by utilities in the region.

	TVA	*Carolinas*	*SoCo*	*Florida*
Conventional Steam Coal	7,150	16,746	19,000	7,307
Hydroelectric Pumped Storage	1,809	2,657	1,635	0
Natural Gas Fired Combined Cycle	9,924	9,363	19,846	32,343
Natural Gas Fired Combustion Turbine	5,268	10,904	12,398	9,000
Natural Gas Steam Turbine	63	589	4,064	2,543
Nuclear	8,475	12,270	8,318	3,797
Onshore Wind Turbine	29	0	0	0
Reservoir Hydroelectric	2,735	834	2,939	0
Run-of-River Hydroelectric	1,537	1,623	1,144	12
Solar Photovoltaic	293	3,584	1,239	1,282

Table 8: Brownfield capacity (GW) in each Southeast model region for each of the EIA technology types, with the "Conventional Hydroelectric" resource type broken down into "Run-of-River Hydroelectric" and "Reservoir Hydroelectric" subtypes. Source: EIA-860.

The 2018 United States Energy Information Agency (EIA) EIA-860 form data (U.S. EIA, 2021c) was used to compute total existing capacity of the brownfield resource types listed above in each of the four model regions (see Figure 17 and Table 8). The Southeast model includes the following subset of technologies included in the EIA-860 form: "Solar Photovoltaic," "Onshore Wind Turbine," "Nuclear," "Natural Gas Steam Turbine," "Natural Gas Fired Combined Cycle," "Natural Gas Fired Combustion Turbine," "Conventional Steam Coal," "Conventional Hydroelectric," and "Hydroelectric Pumped Storage." "Conventional Hydroelectric" was subdivided into two subsets, "Run-of-River Hydroelectric" and "Reservoir Hydroelectric" based on individual plant classifications from the 2019 Oak Ridge National Laboratory Existing Hydropower Assets Plant Dataset (Johnson et al., 2019). Additionally, values for existing nuclear capacity in the SoCo region as computed from the EIA-860 data were augmented by 2.50 GW, the combined capacities of the Vogtle 3 and 4 units under construction in Georgia, and which are expected to be completed in 2022. Although the EIA-860 data includes a number of additional resource types that contribute to existing capacity, this selection account for 95% of the existing capacity across the four model regions.

3.3.3.1 Existing Thermal Power Plant Economic and Operational Characteristics

The PowerGenome data aggregation software (Schivley, 2021) was used to obtain the FOM costs ($/MW-yr), VOM costs ($/MWh), average heat rate (MMBtu/MWh), and minimum power output (%), for fossil fuel-fired power plants in each of the four model regions.[4] These parameters are summarized in Table 9, below.

[4] To address a data anomaly in the PowerGenome data in the average heat rate of existing natural gas-fired steam turbines in the Florida model region, the original value was replaced by the average of heat rates from the other three model regions. This value is noted with an asterisk (*) in Table 9.

Existing Natural Gas Fired Combined Cycle (NGCC_bf)				
Region	**FOM Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Heat Rate (MMBtu/MWh)**	**Minimum Power Output**
TVA	10,019	3.50	6.92	37%
Carolinas	10,641	3.56	7.27	42%
SoCo	11,606	3.58	7.27	53%
Florida	12,078	3.58	7.35	70%

Existing Natural Gas Fired Combustion Turbine (NGCT_bf)				
Region	**FOM Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Heat Rate (MMBtu/MWh)**	**Minimum Power Output**
TVA	7,326	11.30	14.75	46%
Carolinas	7,477	11.30	12.17	54%
SoCo	7,546	11.30	11.84	58%
Florida	7,697	11.30	12.92*	45%

Existing Natural Gas Fired Steam Turbine (NGST_bf)				
Region	**FOM Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Heat Rate (MMBtu/MWh)**	**Minimum Power Output**
TVA	17,798	7.35	10.35	40%
Carolinas	49,776	1.00	11.55	28%
SoCo	30,518	1.00	11.58	34%
Florida	29,173	1.00	11.17	15%

Existing Conventional Stem Coal (Coal_bf)				
Region	**FOM Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Heat Rate (MMBtu/MWh)**	**Minimum Power Output**
TVA	60,901	1.80	10.93	45%
Carolinas	59,806	1.80	10.18	34%
SoCo	59,412	1.80	10.32	49%
Florida	58,567	1.80	10.65	38%

Table 9: Economic and operational parameters for NGCC_bf, NGCT_bf, NGST_bf, and Coal_bf resource types. The value marked with an asterisk (*) represents a manually adjusted data field; see footnote 4 in the text for details. Source: PowerGenome data aggregation software (available at https://github.com/PowerGenome/PowerGenome).

Economic and operational characteristics of existing nuclear power plants are taken from Sepulveda, et al. (2018). Unlike those of existing fossil fuel-fired power plants, the operational characteristics of existing nuclear power are assumed to be identical across all model regions. These parameters are summarized in Table 10, below.

Existing Nuclear (Nuclear_bf)			
FOM Cost ($/MW-yr)	**VOM Cost ($/MWh)**	**Heat Rate (MMBtu/MWh)**	**Minimum Power Output**
118,988	2.32	10.46	50%

Table 10: Economic and operational parameters for the Nuclear_bf resource type. Source: Sepulveda, et al. (2018).

To model unit commitment of thermal resources, GenX requires parameters characterizing start-up costs, start-up fuel requirements, ramp-up and ramp-down rates, and minimum up-times and minimum down-times. These unit commitment parameters for existing thermal resources, which are identical across model regions and all model periods, are summarized in Table 11, below.

Resource	**Start Cost ($/MW/start)**	**Start Fuel (MMBtu/ MW/start)**	**Ramp Up**	**Ramp Down**	**Up Time (Hrs.)**	**Down Time (Hrs.)**
NGCC_bf	79	9.00	100%	100%	1	1
NGCT_bf	52	0.22	100%	100%	4	4
NGST_bf	75	9.00	16%	16%	12	12
Coal_bf	120	13.70	57%	57%	24	24
Nuclear_bf	1,000	0.00	25%	25%	36	36

Table 11: Economic and operational parameters associated with unit commitment for existing fossil resource types.

3.3.3.2 Existing Hydroelectric Plant Economic and Operational Characteristics

Like existing nuclear capacity, existing reservoir, run-of-river, and pumped storage hydroelectric facilities are assumed to have the same cost and operating characteristics across model regions. FOM and VOM costs for Hydro_RoR and Hydro_Res were taken from the 2018

NREL ATB (Vimmerstedt et al., 2018), and those for PHS from Immendoerfer et al. (2017) which are summarized in Table 12 and Table 13, below.

Resource	FOM Cost ($/MW-yr)	VOM Cost ($/MWh)	Minimum Power Output
Reservoir Hydroelectric (Hydro_RoR)	14,000	0.02	10%
Run-of-River Hydroelectric (Hydro_Res)	14,000	0.02	0%

Table 12: Economic and operational parameters associated with Hydro_RoR and Hydro_Res resources. Source: 2018 NREL ATB NPD4 Mid Cost Case.

Existing Hydroelectric Pumped Storage (PHS)			
FOM Cost ($/MW-yr)	**VOM Cost ($/MWh)**	**Charging Efficiency**	**Discharging Efficiency**
41,000.00	1.00	89%	89%

Table 13: Economic and operational parameters associated with PHS resources. Source: Immendoerfer et al. (2017)

3.3.4 New Energy Resources

The 2020 NREL ATB was used to obtain economic and operational characteristics of new natural gas-fired power plants (the ATB technology types “Natural Gas Fired Combined Cycle,” “Natural Gas Combustion Turbine,” and “Natural Gas Combined Cycle with Carbon Capture, Utilization, and Storage,” which correspond to the NGCT, NGCC, and NGCC-CCS technology types used in our Southeast model, respectively), nuclear (“Nuclear”) and VRE (“Utility Scale Solar Photovoltaic” and “Land-Based Wind,” corresponding to Solar_PV and Wind) resource types, respectively. These parameters were supplemented with those from various additional data sources which are noted below. We assume a 30-year capital recovery period (CRP) and “Market Factor” financials for all these technologies. The 2020 ATB is also used for Li-ion battery storage (Li-ion) economic and operational assumptions, where a 20-year CRP is assumed. For all technologies, we assume an after-tax weighted average cost of capital (WACC) of 4.5% (see Table 29 for a summary of key model parameters and assumptions).

3.3.4.1 Thermal Resources

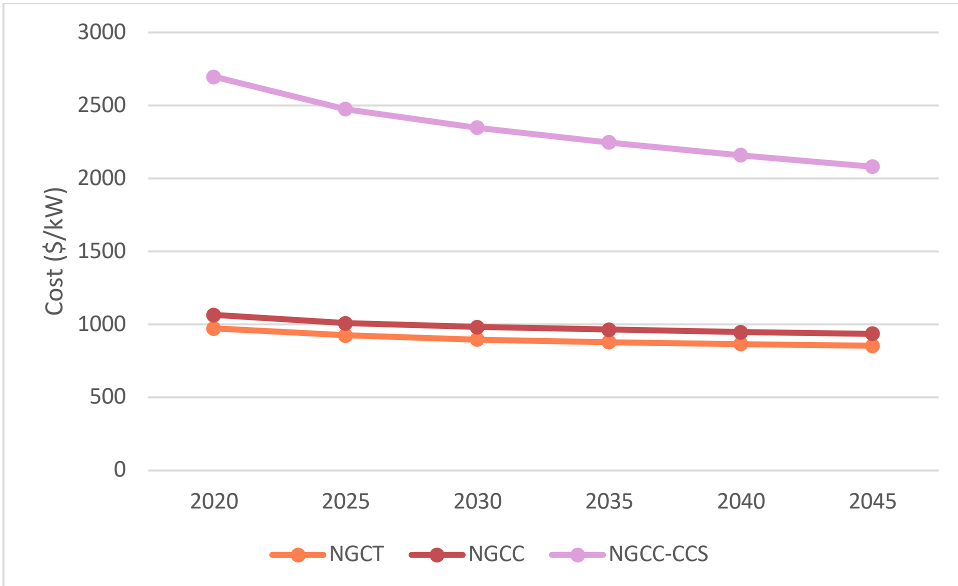

Figure 18: Overnight investment cost projections ($/kW) for new natural gas resources. Source: 2020 NREL ATB.

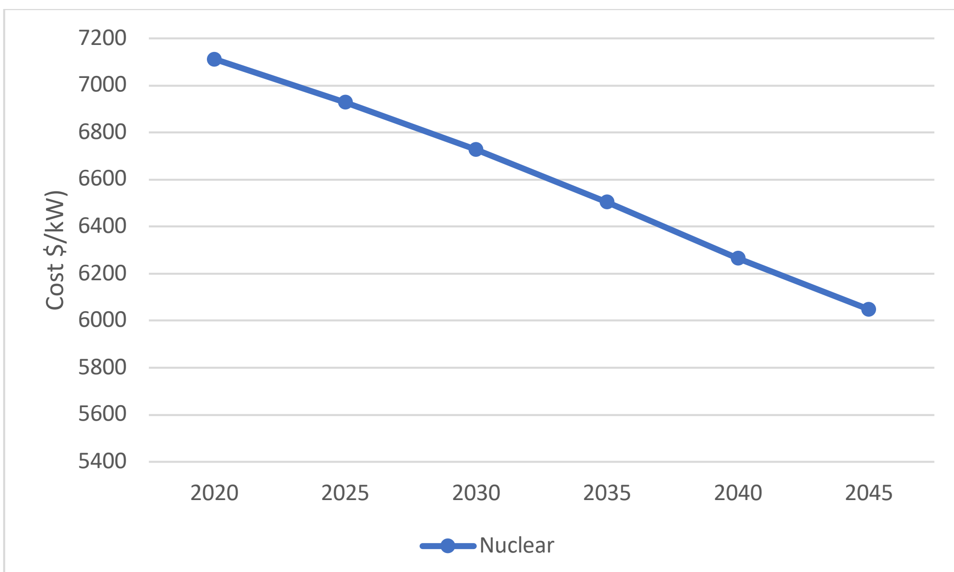

Figure 19: Overnight investment cost projections ($/kW) for new nuclear power plants. Source: 2020 NREL ATB.

The "AverageCF" capacity factor (CF) assumption was used for each of the three new NG resources. Table 14 summarizes the cost and operational parameters for new thermal power plants during 2020, and Figure 18 and Figure 19 show overnight investment cost projections, in $/kilowatt-hour ($/kW), for new thermal power plants through 2045.

Resource	Overnight Investment Cost ($/MW)	FOM ($/MW-year)	VOM ($/MWh)	Heat Rate (MMBtu/ MWh)
NGCT	973,606	11,395	4.50	9.51
NGCC	1,065,941	12,863	2.16	6.40
NGCC–CCUS	2,697,020	26,994	5.72	7.12
Nuclear	7,112,287	118,988	2.32	10.46

Table 14: Cost and operational parameter assumptions for new thermal power plants for the 2020 model period. Source: 2020 NREL ATB.

Additional technical characteristics of thermal power plants, including those required for modeling unit commitment and minimum stable power output parameters, are summarized in Table 15, below. These parameters are identical across model regions and all model periods.

Resource	Capacity Size (MW)	Start Cost ($/MW/start)	Start Fuel (MMBtu/ MW/start)	Ramp Up	Ramp Down	Up Time (Hrs.)	Down Time (Hrs.)	Minimum Stable Output
NGCT	237	140	0.19	100	100	0	0	25%
NGCC	573	61	0.20	100	100	4	4	30%
NGCC-CCUS	377	97	0.20	100	100	4	4	50%
Nuclear	1,000	1,000	0.00	100	100	36	36	20%

Table 15: Additional cost and operational parameter assumptions for new thermal power plants.

3.3.4.2 Variable Renewable Energy Resources

The 2020 NREL ATB was used for investment costs and FOM costs for solar PV and wind resources. "Class 5" assumptions were used for wind resources. Although the 2020 ATB specifies an $0/MWh VOM cost for onshore wind, this value was set to $.01/MWh to ensure that solar PV is dispatched first by the model. Table 16, below, summarizes the cost and operational parameters in 2020 and Figure 14 shows overnight investment cost projections ($/kW) for new solar PV and wind resources through 2045.

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Resource	Technology Advancement Assumption	Overnight Investment Cost ($/MW)	FOM ($/MW-year)	VOM ($/MWh)
Solar_PV	Advanced	1,340,034	15,694	0.00
	Moderate	1,353,543	15,852	0.00
Wind	Advanced	1,556,755	41,734	0.01
	Moderate	1,578,350	42,496	0.01

Table 16: Cost and operational parameter assumptions for solar PV and wind resources for the 2020 model period. Source: 2020 NREL ATB.

Model region-specific interconnection costs, generated via the software tools developed in Brown and Botterud (2021), are added to the above overnight investment costs as specified in Table 17, below.

	Interconnection Cost Adder ($/MW)			
Region	**Solar_PV**	**Wind (Bin 1)**	**Wind (Bin 2)**	**Wind (Bin 3)**
TVA	74,563	114,464	157,338	102,886
Carolinas	43,015	68,955	70,192	66,547
SoCo	53,837	78,887	114,347	130,954
Florida	30,200	37,898	68,386	93,796

Table 17: Interconnections cost adders ($/MW) for solar and wind resources. Computed via software tools introduced in Brown and Botterud (2020).

Additionally, solar PV and wind resources are subject to maximum installed capacity constraints, computed using the same software tools, and specified in Table 18, below.

	Maximum Capacity Limits (MW)			
Region	**Solar_PV**	**Wind (Bin 1)**	**Wind (Bin 2)**	**Wind (Bin 3)**
TVA	2,420,648	179,342	96,299	23,181
Carolinas	2,035,425	157,135	73,001	11,349
SoCo	2,758,571	155,550	190,210	54,325
Florida	933,392	18,245	73,346	31,618

Table 18: Maximum capacity limits (MW) for solar and wind resources. Computed via software tools introduced in Brown and Botterud (2020).

Finally, solar PV and wind resources were subject to maximum installation limits for the 2025, 2030, and 2035 model periods. A single instillation limit was applied to the three wind resource bins in aggregate. These limits were derived from the 2030 "Step 1" capacity limit used in the EPA's Power Sector Modeling Platform v6 for "Solar PV" and "Onshore Wind" as specified in Table 4-14 in "2020 Update" documentation (EPA, 2020a). These nationwide annual capacity limits were scaled down proportional to the share of 2019 U.S.-wide annual generation attributed to the Southeast model regions and multiplied by 5 to reflect the 5-year timespan of each model period, resulting in a 48,053 MW/period limit for solar PV, and 78,941 MW/period limit for wind. These installation limits are summarized in Table 19, below.

	Maximum Installation Limits (MW/period)					
	Peroid 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**
Solar_PV	N/A	48,053	48,053	48,053	None	None
Wind	N/A	78,941	78,941	78,941	None	None

Table 19: Maximum installation limits each model period (MW/period) for solar PV and wind resources. "N/A" is specified in Period 1 since no capacity additions of any kind are allowed.

For reference, average CFs of solar PV and wind resources is summarized in Table 20, below.

	Average Capacity Factors (%)			
Region	**Solar_PV**	**Wind (Bin 1)**	**Wind (Bin 2)**	**Wind (Bin 3)**
TVA	24%	37%	31%	21%
Carolinas	25%	37%	29%	20%
SoCo	26%	35%	32%	28%
Florida	27%	33%	31%	29%

Table 20: Average capacity factors (%) of solar PV and wind resources. Source: NREL EFS load profile with "High" electrification and "Moderate" technological advancement.

3.3.4.3 Lithium-ion Battery Storage Resources

The 2020 NREL ATB was used for investment costs of Li-ion battery storage (see Figure 15), and operational assumptions were provided by MIT researchers on the electrochemical team of the upcoming Future of Storage Study. Note that costs for discharging power (MW) and energy capacity (MWh) are considered separately in the model, which allows it to optimize the duration of storage discharged at rated power within the specified range. These parameters are summarized in Table 21 and Table 22, below, for 2020, and Figure 15 shows overnight investment cost projections ($/kW and $/kWh) for new Li-ion battery storage discharge and energy capacity through 2045.

Lithum-ion Battery Storage (Li-ion)		
Technology Advancement Assumption	**Overnight Discharge Investment Cost ($/MW)**	**Overnight Energy Investment Cost ($/MWh)**
Advanced	214,966	246,899
Moderate	260,021	298,647

Table 21: Investment cost assumptions for Li-ion battery storage in the 2020 model period. Source: 2020 NREL ATB.

Lithium-ion Battery Storage (Li-ion)								
Technology Advancement Assumption	**FOM Discharging Cost ($/MW-yr)**	**FOM Energy Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Charging Efficiency**	**Discharging Efficiency**	**Minimum Duration (Hrs.)**	**Maximum Duration (Hrs.)**	**Self-Discharge (Fraction/Hr.)**
Advanced	250	1,420	1.00	92%	92%	0.25	200	0.002
Moderate	750	2,230	1.00	92%	92%	0.25	200	0.002

Table 22: Cost and operational parameter assumptions for Li-ion battery storage in the 2020 model period.

3.3.4.4 Pumped Hydroelectric Storage Resources

Pumped hydroelectric storage supply curves from the 2018 Hydropower Vision study (O'connor et al., 2016) at the Regional Energy System Deployment model (ReEDs) balancing area (BA) level were used to estimate capital costs and maximum capacity limits for new facilities. For each ReEDs BA, four bins were provided which represent PHS sites at different costs per MWh. ReEDs BAs were aggregated to approximate the PHS storage potential within each of the four Southeast model regions. Where the ReEDs BA intersected only a portion of an IPM region, the resource potential was scaled down proportional to the intersected area.

The supply curve data suggests that there is potential for new PHS investment only in the SoCo and TVA model regions, although EIA-860 data indicates that there is already existing PHS capacity in the Carolinas model region. We limit PHS maximum allowable capacity to that of the lowest-cost bin in each respective region, plus total existing capacity, and only allow new PHS capacity to be built in the TVA and SoCo regions. The capital costs and maximum new PHS capacities allowed in each model region are summarized in Table 23, below.

Hydroelectric Pumped Storage (PHS)		
Region	**Maximum Capacity (MW)**	**Overnight Investment Cost ($/MW)**
TVA	4,450	1,509,439
SoCo	2,535	1,894,728

Table 23: Investment costs ($/MW) and maximum capacity limits (MW) for PHS. Source: Analysis of 2018 Hydropower Vision study PHS supply curves.

Additional technical assumptions for new PHS are identical to those of existing PHS facilities, which are summarized above in Table 13.

3.3.5 Technology Lifetimes and Brownfield Retirements

All technologies were assigned an operational lifetime, and each technology's economic lifetime (used to compute annual investment costs) was assumed to be equal to its operational lifetime. Plant retirement data from the EPA's eGRID2019 dataset (EPA, 2020b) was used to compute capacity-weighted average lifetimes of fossil fuel-fired power plants. Lifetimes for new and existing NGCC and NGCT power plants, as well as existing natural gas steam turbine (NGST) power plants, were computed based on a nation-wide capacity weighted average of plant retirement ages, while lifetimes for existing coal plants approximate the capacity weighted average retirement age of coal plants within each Southeast model region using data from the closest approximate eGrid region ("SRTV" eGrid region corresponding to "TVA", SRVC corresponding to the Carolinas, "SRSO" corresponding to SoCo, and "FRCC" corresponding to Florida). Nuclear power plants are assumed to have either a 60 or 80-year operational life, based on whether we assume that all existing nuclear plants receive a SLTE. Table 24, below, summarizes lifetimes of all resources across model regions.

Resource	Lifetime (yrs.)			
	TVA	*Carolinas*	*SoCo*	*Florida*
Conventional Steam Coal	59	54	51	40
Hydroelectric Pumped Storage	50	50	50	50
Natural Gas Fired Combined Cycle	27	27	27	27
Natural Gas Fired Combustion Turbine	44	44	44	44
Natural Gas Steam Turbine	55	55	55	55
Nuclear	60/80	60/80	60/80	60/80
Onshore Wind Turbine	30	30	30	30
Reservoir Hydroelectric	100	100	100	100
Run-of-River Hydroelectric	100	100	100	100
Solar Photovoltaic	30	30	30	30
Li-ion Battery Storage	15	15	15	15
Natural Gas Fired Combined Cycle w/CCS	30	30	30	30

Table 24: Operation and economic lifetime assumptions for resources in the Southeast model.

Based on the model region- and resource-specific lifetimes, total expected lifetime retirements were computed for existing capacity of each resource type for each model period. For each existing generating facility, we added its assumed operational lifetime to the year the facility began operation (specified by the "Operating Year" field in the EIA-860 dataset) to obtain the year we expect that facility to retire. We require the model to retire that facility at the start of the first model period whose year exceeds or equals the expected retirement year. For example, suppose a coal plant located within the SoCo model region was built in the year 1990. Since we assume that coal plants located in this region have a lifetime of 51 years, we would expect the plant to retire in 2041. Using 5-year model periods beginning in the year 2020, the first period which exceeds this expected retirement year is the 2045 model period. Thus, we would "retire" that plant at the start of the 2045 model period.

3.3.6 Fuel Types and Costs

The 2020 EIA Annual Energy Outlook (AEO) (U.S. EIA, 2020a) Reference Case was used for the fuel costs associated with NG, coal, and nuclear power plants. "Electric Power" fuel costs in \$/MMBtu for "natural gas," "steam coal," and "uranium," were used for each of these resource types, respectively. Additional EIA data (U.S. EIA, 2021b) was used to establish CO_2 content for each fuel type, in tonnes per MMBtu (see Table 26). Since the coal-fired power plants in the Southeast use coal from both the western and eastern United States (U.S. EIA, 2013), we use the average of CO_2 emissions per MMBtu of bituminous and subbituminous coal to approximate the emissions rate from these facilities. NGCC plants with CCS were assumed to have a 90% CO_2 capture rate, and a capture and sequestration cost of \$20/tonne CO_2. Fuel costs and CO_2 content are summarized in Table 25 and Figure 20, below.

		Fuel Cost (\$/MMbtu)						
	Year	2020	2025	2030	2035	2040	2045	2050
Fuel Type	*Uranium*	0.67	0.68	0.69	0.70	0.71	0.72	0.73
	Coal	2.05	1.94	1.94	1.94	1.94	1.94	1.94
	Natural Gas	2.64	3.29	3.61	3.72	3.78	3.83	4.04
	Natural Gas w/ CCS	3.60	4.25	4.57	4.68	4.75	4.79	5.00

Table 25: Fuel cost projections from 2020 to 2050. NGCC plants with CCS were assumed to have a 90% CO_2 capture rate, and a capture and sequestration cost of \$20/tone CO_2. Source: 2020 EIA AEO Reference Case.

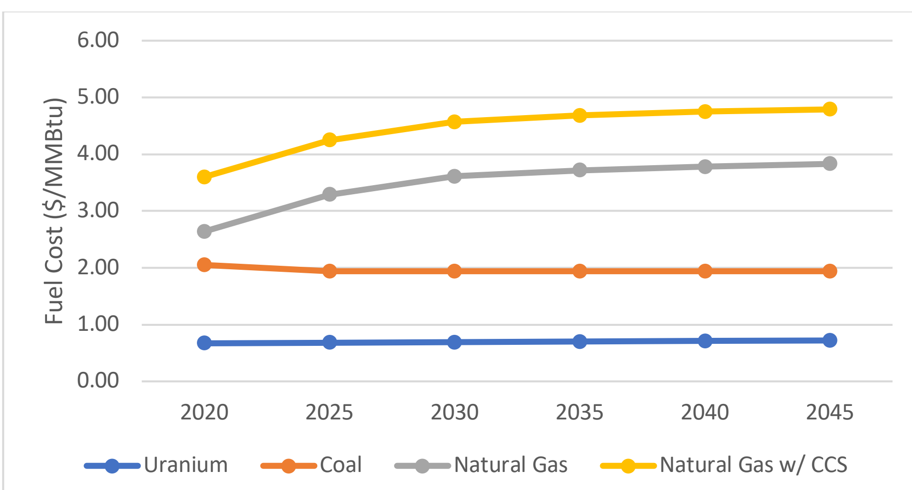

Figure 20: Fuel cost projections from 2020 to 2045. Source: 2020 EIA AEO Reference Case.

Fuel Type	CO2 Content (tonnes/MMbtu)
Uranium	0.0000
Coal	0.0953
Natural Gas	0.0531
Natural Gas w/ CCS	0.0053

Table 26: CO_2 content of fuel sources. Source: EIA.

3.3.7 Network Topology and Costs

The Southeast model includes representations of four high-voltage transmission lines which connect, from source to sink, SoCo to TVA, Carolinas to TVA, SoCo to Florida, and Carolinas to SoCo. Transmission lines are assumed to be 500 kilovolts (kV) and line distances were computed by approximating the straight-line distance between the geographic center of each model region using a geospatial mapping tool. Maximum transmission line capacity values were taken from Table 3-20 of the EPA Platform v6 model documentation (EPA, 2018). Transmission loss percentages were approximated as 0.01% of line distance. These parameters are summarized in Table 27, below.

Transmission Line	Line Capacity (MW)	Line Distance (km)	Transmission Loss
SoCo to TVA	5,554	370	0.037
Carolinas to TVA	276	590	0.059
SoCo to Florida	3,600	600	0.060
Carolinas to SoCo	3,000	500	0.050

Table 27: Transmission line representations in the Southeast model.

Transmission network expansion was enabled in GenX, and all transmission lines were eligible for reinforcement up to 30,000 MW of capacity. New transmission lines were assumed to have a CRP of 40 years and after-tax WAAC of 4.5%. Line reinforcement costs, adopted from

Section 6.2 of the ReEDs Version 2019 documentation (M. Brown et al., 2020), were assumed to be $960 /MW-km for new 500 kV transmission lines.

3.3.8 Load Timeseries Data

State-level load data are derived from the 2018 NREL Electrification Futures Study (EFS) (Mai et al., 2018) load profiles. Load data for even years (2020, 2030, 2040, and 2050) were taken directly from the study's dataset; load data for odd years (2025, 2035, 2045) were approximated by interpolating data from the even-numbered years. For example, 2025 load was approximated as the pointwise average of projected hourly load in 2020 and 2030. Load profiles represent the "High" electrification and "Moderate" technological advancement scenarios, and leap days were removed.

State-level load data from the EFS dataset was aggregated to approximate total load for each of the four model regions. Utility customer sales data from the 2018 EIA-861 dataset (U.S. EIA, 2021e), labeled by balancing area (BA), were used to approximate the percentage of each state's total load to be assigned to each model region. Then, state-level load profiles from the EFS dataset were aggregated using weightings proportional to these values to generate region-specific load profiles. The BAs corresponding to each model region, and the percentage of each state's load assigned to each model region, are summarized in Table 28, below.

		Percent of Total Customer Sales			
	Region	**TVA**	**Carolinas**	**SoCo**	**Florida**
State	*Tennessee*	98.0%	0.0%	0.0%	0.0%
	Alabama	26.2%	0.0%	73.8%	0.0%
	North Carolina	0.6%	95.3%	0.0%	0.0%
	South Carolina	0.0%	100.0%	0.0%	0.0%
	Georgia	2.4%	0.0%	97.6%	0.0%
	Florida	0.0%	0.0%	5.6%	94.4%
	Mississipi	32.3%	0.0%	23.3%	0.0%

Table 28: Percent of statewide 2018 utility customer sales attributed to each of the four Southeast model regions, aggregated by balancing area. Source: 2018 EIA-861.

The region-specific load profiles were then adjusted to account for power interchange between BAs within the four Southeast model regions and those outside of them. There are six interconnections to consider which allow for such power interchange: SOCO-MISO, TVA-AECI, TVA-EEI, TVA-LGEE, TVA-MISO, and TVA-PJM. EIA-930 form data downloaded via the EIA's hourly electric grid monitor (U.S. EIA, n.d.) includes hourly interchange, in MWh, between each of these BA interconnections, starting from July 2015. Negative interchange values represent power flows into a BA, while positive interchange values represent power flows out of a BA. It also includes net-generation within each BA.

The EIA-930 form data contained many missing values, and so we looked to equivalent hours in future or past years as proxies for the missing data. For example, if interchange data were missing for May 1st, 2017 at 12:00pm, we looked to see if data were available on May 1st, 2018 at 12:00pm. If so, we would set the missing interchange value to that observed at that date and time. If data were also missing for the 2018 data, we continue to 2019, 2020, etc. If we still have not identified a viable substitute datapoint after this "forward pass," we consider past years in the same manner. If still no viable data points were identified through this "backwards pass," we assume an interchange value of 0 MWh for that hour.

Hourly net interchange from the TVA BA was computed by taking the sum of hourly interchange between TVA-AECI, TVA-EEI, TVA-LGEE, TVA-MISO, and TVA-PJM. Since the MISO BA is the only non-model BA connected to the SoCo model region, hourly transfers from the SOCO BA to the MISO BA represent the entire external net hourly interchange. Next, for both the TVA and SOCO BAs, an hourly scaling factor was computed by taking the pointwise difference between net-generation and interchange and dividing by net-generation. We defined outlier hours as those with a scaling factor greater than 1.5 or less than 0.5, representing power flows into the BA greater than 50% of the net-generation within that BA in that hour, or power flows out of the BA greater than 50% of the net-generation within that BA in that hour, respectively. These outlier hours were replaced by the average of all hourly scaling factors excluding outlier hours in their respective BAs. Next, the hourly scaling factors for each BA were averaged across years to compute an average scaling factor for each hour. For example, an average scaling factor for June 15 at 3:00pm in the SOCO BA was computed by taking the average of scaling factors computed for that same date, time, and BA in 2016, 2017, 2018, and so on through the final year available in the dataset. Finally, each hour in the annual load profile projections computed for the S_SOU and S_C_TVA model regions was scaled by its corresponding hourly scaling factors computed for the SoCo and TVA model regions, respectively, to obtain an interchange-adjusted representation of regional load.

3.3.9 Variable Renewable Energy Resource Timeseries Data

Seven years of historical annual CF data (2007-2013) was generated for solar PV and wind resources using the methodology outlined in Brown and Botterud (2020). For solar resources, we assumed a horizontal 1-axis-tracking PV, and for wind resources, we assumed a Gamesa G126/2500 turbine at 100-meter height.

EIA-923 data (U.S. EIA, 2021d) was used to compute historic monthly net-generation, in gigawatt-hours (GWh), of all run-of-river and reservoir hydroelectric plants in each of the four model regions from 2007-2013. Monthly net-generation was then downscaled to hourly resolution by dividing monthly generation by the number of hours in each month (for leap years, non-leap year number of hours per month were used). Finally, the average hourly CF for each hydroelectric plant type in each model region was computed by dividing the hourly net-generation by the nameplate capacity of the respective hydroelectric plant type in each model region.

3.3.10 Time Domain Reduction

Representative and extreme weeks were selected from among the seven years of historic VRE and hydropower CF data and the annual simulated load data in order to reduce the required computational and memory requirements of GenX model simulations.

Extreme weeks were chosen from each of the four Southeast model regions. Average weekly CFs were computed for solar PV and wind resources. For solar PV resources, the week with the lowest average solar PV CF in each model region was included in the set of extreme weeks. Since there are three wind resource "bins," the week with the lowest area-weighted average CF across the three bins in each model region was included in the set of extreme weeks. Finally, the week with the greatest hourly load in each model region was included in the set of extreme weeks, as well as the week with the greatest hourly total system load across the four regions (shown in Figure 21). In total, 9 unique extreme weeks were selected by this methodology.

Representative period selection followed the methodology outlined in Mallapragada et al. (2018). First, each timeseries was normalized to values between 0 and 1 (inclusive). Next, load and VRE hourly timeseries were split into week-length groupings, and "stitched together" as in Mallapragada et al. (2018) to form 365 vectors, one for each week of the seven years represented by the historic VRE timeseries data (the six, year-long timeseries representing hourly load from 2020, 2025, … , 2045 were repeated seven times so that they could be combined with the VRE timeseries data). Vectors corresponding to extreme weeks were dropped, and *k*-means clustering was applied to the set of remaining vectors to group them into clusters of similar weeks, such that such that the total number of extreme weeks and clusters summed to 14, resulting in five clusters. The five representative weeks represented used in the model were selected from each cluster by choosing the vector with the lowest Euclidian distance from the cluster centroid.

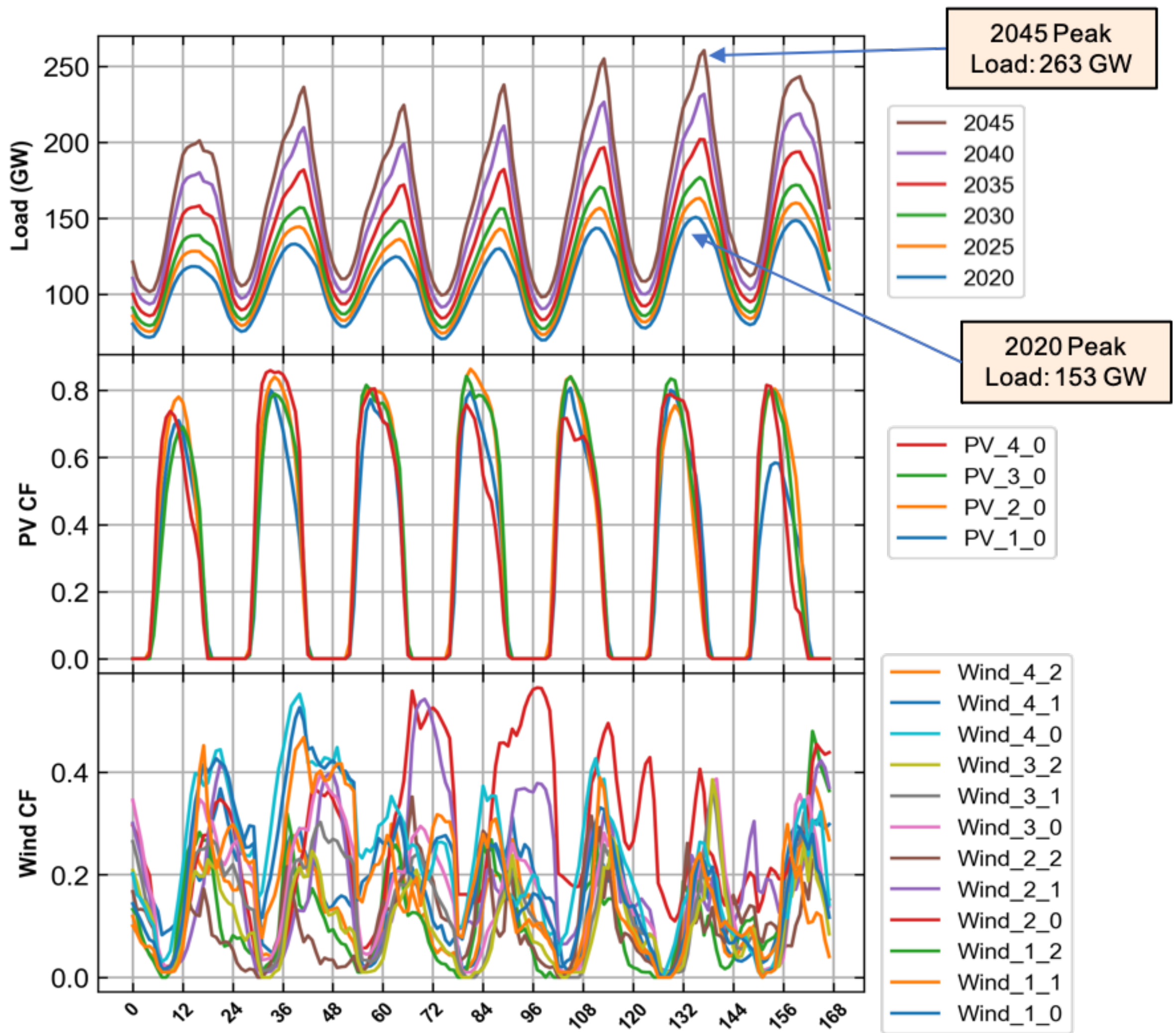

Figure 21: Load profiles (GW) and solar PV and wind capacity factor (CF) profiles for the model-wide peak load week, included as one of the extreme weeks in the model. Peak capacity grows from 153 GW in 2020 to 263 GW in 2045. Solar PV and wind CF profiles are named according to the convention PV_[Region]_0 and Wind_[Region]_[Bin], where 1, 2, 3, and 4 correspond to the TVA, Carolinas, SoCo, and FRCC regions, respectively.

3.3.11 Summary of Key Data Sources and Model Assumptions

Table 29, below, summarizes key model parameters and assumptions described throughout Section 3.3.

Assumption	Value
Dollar Year	2018
WACC	4.50%
CRP (Li-Ion)	20 years
CRP (Transmission)	40 years
CRP (All Other Resources)	30 years
NREL ATB Financials	Market Factor
NREL ATB Wind Class	Class 5
NREL EFS Technology Advancement	Moderate
NREL EFS Electrification	High
Number of Extreme Periods	9
Number of Representative Weeks	5
Value of Lost Load	$50,000/MWh

Table 29: Summary of key model parameters and assumptions.

4 Part IV: Results and Discussion

4.1 The Role for Natural Gas Under Unconstrained Emissions Scenarios

4.1.1 Reference Case

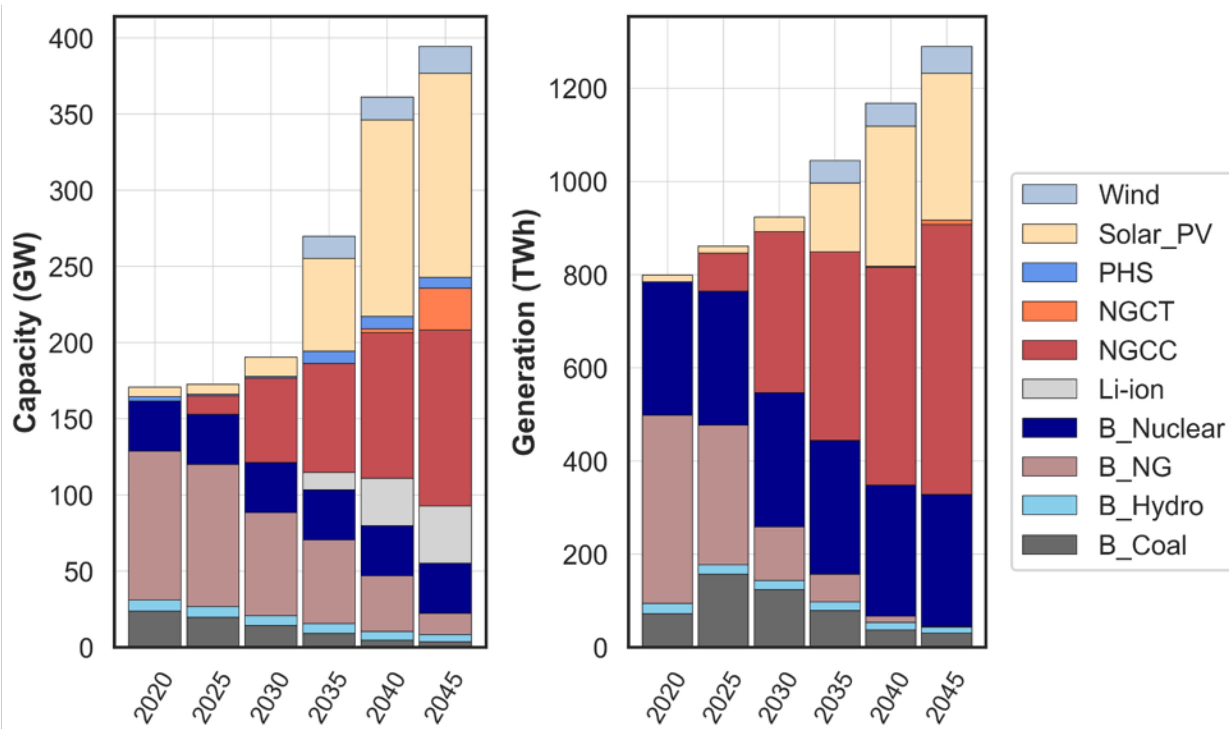

Figure 22: System-wide capacity (GW) (left) and annual generation (TWh) (right) for the Reference Case. Discharge and charge from storage resources (Li-ion and PHS) are excluded from the annual generation plot.

The model outcomes in the Reference Case (Figure 22) suggest that, in the absence of CO_2 emissions limits, under "moderate" (baseline) VRE and storage technology costs, and with all existing nuclear plants receiving second lifetime extensions (SLTEs), natural gas-fired generation will continue to be a substantial part of a least-cost resource mix in the American Southeast under cost optimal resource planning. New NG capacity is installed every period in which new capacity investments are allowed (see Figure 22, left). Nonetheless, the 2045 grid looks notably different than the 2020 grid, as VREs and Li-ion battery storage grow to become a substantial percentage of total installed capacity. Total NG capacity as a share of total system capacity rises from 57% in

2020 to a maximum of 65% in 2030, before falling to 40% in 2045. This decline is driven by a substantial buildout of VREs, predominately, solar PV and some Li-ion battery storage capacity. Although combined solar PV and wind capacity were a negligible percentage of the capacity mix in 2020 (<4% of total capacity), their share grows to 38% in 2045. Additionally, new PHS resources, allowed only in the TVA and SoCo model regions (see section 3.3.4.4), are built out to their capacity instillation limits in 2035.

Annual generation trends show that despite their sharp rise as a percentage of total capacity, the contribution of solar PV and wind resources to annual generation still lags substantially behind the contribution of NG resources by mid-century (see Figure 22, right). In 2045, NG power plants contribute 46% of annual generation, compared to only 29% of annual generation from solar PV and wind resources. Nonetheless, by 2045, the grid is substantially cleaner, with carbon intensity declining from 284 gCO_2/kWh in 2020 to 182 gCO_2/kWh in 2045. Existing nuclear power plants provide most of the remaining share of generation in 2045; they provide 36% of total annual generation in 2020, and by 2045, still provide over a fifth of total generation, since the assumed SLTEs allow all existing nuclear capacity to stay online through 2050 (see Table 5).

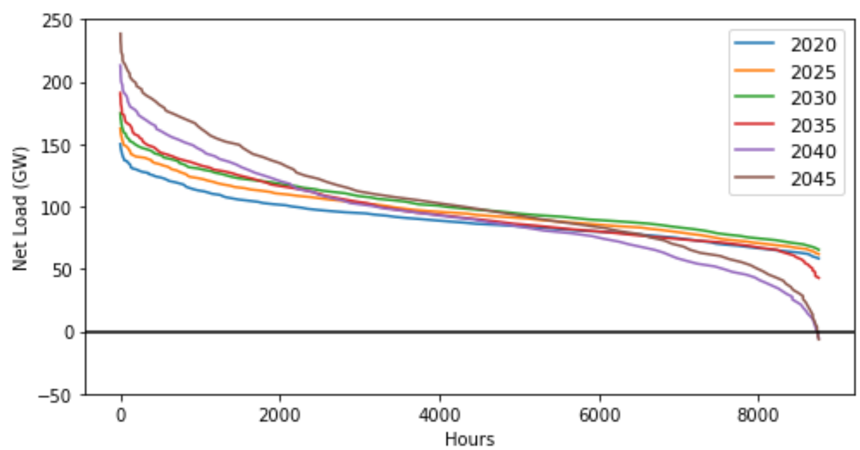

Figure 23: Net load duration curves (net system-wide load minus dispatched solar PV and wind generation) for the Reference Case for all model periods.

Although new NG capacity plays a major role in meeting a growing demand for energy under the Reference Case, the operation of those plants and the types of plants that are built change over the course of the planning horizon, as the grid adapts to support a greater share of VRE capacity. Indeed, by 2040 and 2045, VREs are able to meet all or nearly all system-wide load during some hours as seen by hours with negative net load in Figure 23. While generation attributed to NG resources remains relatively steady through 2045, its share of total annual generation is only 5% lower in 2045 than in 2020, and the average annual CFs of NG plants steadily decline (see Figure 31 and Figure 32). While new NGCC plants operate at a 77% average annual CF in 2025, this number drops to 57% in 2045. Furthermore, while only NGCC plants are built through 2035, NGCT plants are deployed in the final two model periods, aligning with the sharp increases of VRE resources and Li-ion battery storage. While NGCT plants represent only 3 out of the 27 GW of new NG capacity built in 2040, in 2045, they represent over half – 25 out of 45 GW – of new NG capacity. Although their VOM costs are twice those of NGCC plants and their heat rate is greater, NGCT plants have lower FOM costs and overnight capital costs, and have no minimum on- or off-times, making them well suited for use as low CF "peaker" plants (see Table 14 and Table 15). The model's dispatch decisions support this – NGCT plants operate at far lower average CFs compared to the NGCC plants, at 4% and 56% average CFs in 2045, respectively. These results suggest an evolving role of NG resources in future grids even in the absence of emissions constraints.

4.1.2 Impact of Low-cost VREs and Storage

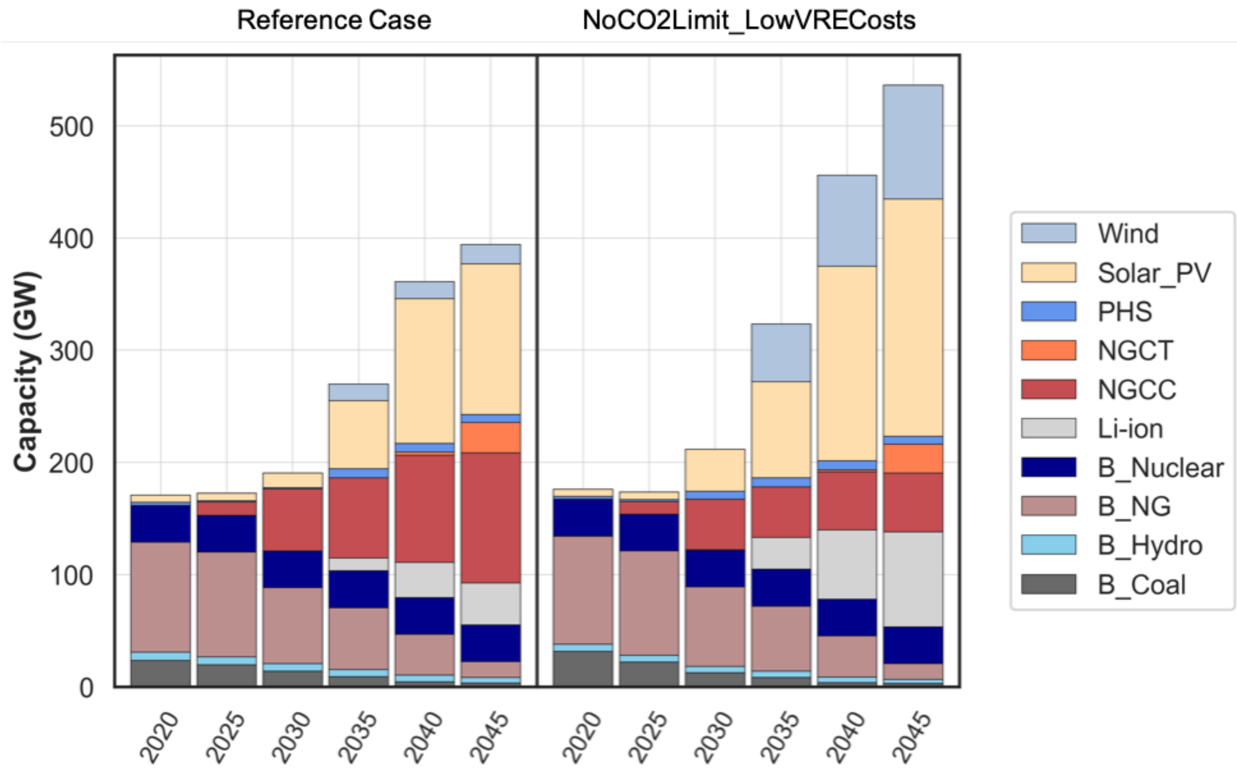

Figure 24: System-wide capacity (GW) for the Reference Case (left) and NoCO2Limit_LowVRECosts case (right).

Considerable uncertainty surrounds future projections of VRE and battery storage costs. For example, a 2021 expert elicitation study published in *Nature Energy* estimates declines of wind energy costs ranging from 37%-49% in 2050, but concludes that there is "considerable uncertainty" surrounding future costs (Wiser et al., 2021). This uncertainty is reflected in the cost projections of VREs and battery storage across sources. For instance, in the EIA's 2020 Annual Energy Outlook, 2050 overnight capital costs for utility-scale solar PV are 3.5x greater in the high-cost VRE case than the low-cost case; in NREL's 2020 ATB, overnight capital costs associated with 4-hour battery storage are 2.5x greater under "Conservative" technology advancement assumptions than "Advanced" ones.

We evaluate the possibility of steep declines in VRE and Li-ion battery storage costs in the absence of CO_2 emissions limits in the NoCO2Limit_LowVRECosts scenario. Compared to cost assumptions under the Reference Case, capital costs of solar PV and wind decline an additional 12% and 22% from 2020 to 2045, respectively; additionally, cost reductions for these resources proceed at a faster rate between 2020 and 2030 for solar PV and wind resources (see Figure 14). Capital costs for Li-ion battery storage discharge and energy capacity both decline an additional 13% between 2020 and 2045 compared to the Reference Case (see Figure 15). These lower costs lead to greatly reduced investment in new NG capacity, and far greater investment in solar PV, wind, and Li-ion battery storage (see Figure 24, right) at cumulative costs – the sum of investment costs, operational costs, and non-served energy costs over the planning horizon – 1.5% lower than that of the Reference Case. Unlike the Reference Case, where the combined capacity of solar PV and wind is roughly equal to total installed NG capacity in 2045, in the low-cost VREs and storage scenario, there is over three times as much combined solar PV and wind capacity in 2045 than NG capacity. These additional resources lead to a 36% greater total system capacity in 2045 compared to the Reference Case. Furthermore, while NG resources provide the greatest contribution to annual generation of all resource types in 2045 in the Reference Case, VREs provide the majority of energy by mid-century in the low-cost VRE and storage scenario – solar PV and wind resources provide 60% of annual generation in 2045, while NG accounts for only 16%. Despite the dominance of VREs in later model periods, however, new solar PV and wind capacity are not built until 2030 in both scenarios, presumably an outcome of the model's ability to anticipate cost reductions in later periods.

4.1.3 Impact of No Second Lifetime Extensions for Existing Nuclear

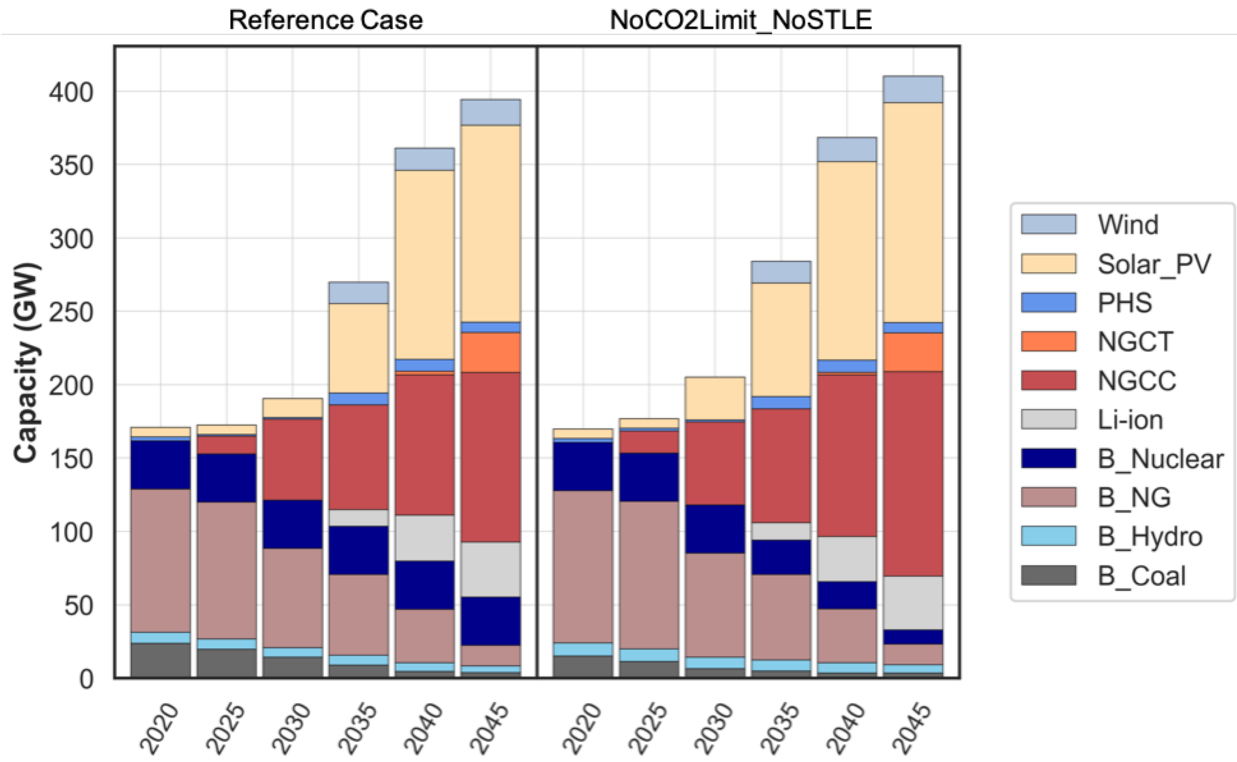

Figure 25: System-wide capacity (GW) for the Reference Case (left) and NoCO2Limit_NoSLTE case (right).

Nuclear plants in the United States are licensed to operate for 40 years, after which plant operators may apply for license renewals. Each license renewal extends the plant's operational lifetime an additional 20 years, and as of 2018, some plant operators have begun applying for their second license renewals, which would extend the plant lifetime to a total of 80 years (NRC, 2018). As a source of zero-carbon electricity, and accounting for 28% of total utility-scale generation in 2019 in the Southeast (see Figure 3), these second lifetime extensions (SLTEs) can help ensure that existing nuclear capacity in the Southeast remains operational through 2050 (see Table 5). However, there is no guarantee that all nuclear operators will choose to apply for SLTEs, nor that the Nuclear Regulatory Commission, the federal agency responsible for approving license renewals, will grant them to all applicants.

The NoCO2Limit_NoSLTE case evaluates the "worst case" scenario in which no existing nuclear plants receive SLTEs. This causes cumulative costs to increase by 1.8% compared to the Reference Case. This results in only 29% of existing nuclear capacity in the Southeast model remaining by 2045, and with existing nuclear capacity first beginning to retire in the 2035 model period (see Figure 25, right). Although this leads to greater mid-century capacity of solar PV, wind, and NG resources, increased deployment of new NG is more pronounced. New NG capacity is 16% greater in 2045 compared to the Reference Case, while solar PV and wind capacity are 11% greater. Changes in annual generation are even more tilted toward NG – annual generation from new NG increase 28% compared to the Reference Case, while combined dispatched solar PV and wind generation is only 10% greater.

4.1.4 CO_2 Emissions Under Unconstrained Emissions Scenarios

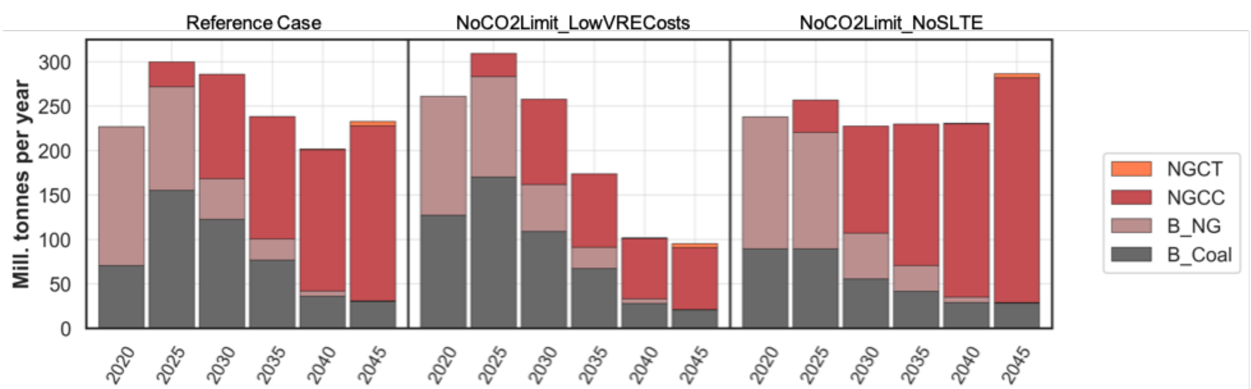

Figure 26: Annual CO2 emissions by resource type in million tonnes per year for the Reference Case (left), NoCO2Limit_LowVRECosts case (center), and NoCO2Limit_NoSLTE case (right).

Cumulative emissions, the sum of annual emissions over the 30 years of the planning horizon, across the three unconstrained emissions scenarios range from 6.0 Gt of CO_2 in the scenario with low VRE and storage costs to 7.4 Gt in the Reference Case. The scenario without SLTEs of existing nuclear plants only had slightly lower cumulative emissions than the Reference Case, at 7.4 Gt.

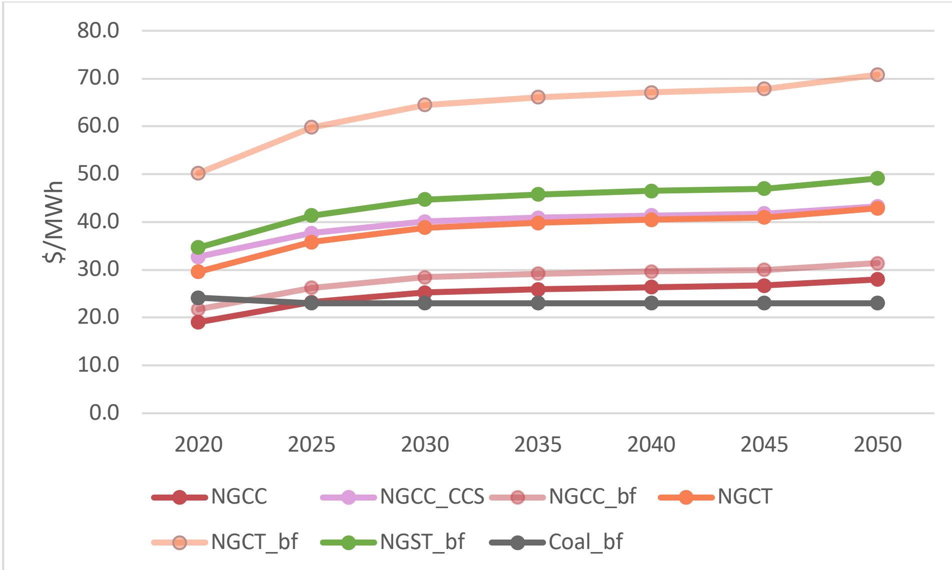

Figure 27: Marginal cost of generation of fossil resource types in the TVA model region over all model periods. Note that the marginal cost of generation for existing coal (Coal_bf) is flat beginning in 2025, while it rises through 2050 for NG resource types. Marginal cost of generation in the other three model regions follows similar trends.

At around 230 Mt per year, annual emissions in the Reference Case are practically identical in 2020 and 2045 (see Figure 26, left). The 32% increase in emissions between 2020 and 2025 can be attributed to a substantially greater utilization of existing coal capacity, which has the lowest marginal cost of operation of all fossil resources (both new and existing NG) beginning in 2025 (see Figure 27). This can be attributed to a projected decline in the cost of coal and increase in the cost of NG between 2020 and 2025 (see Table 25; fuel costs are adopted from the EIA Annual Energy Outlook 2019 Reference Case). Despite high average annual CFs (>90%) for all coal plants beginning in 2025, lifetime retirements lead to a declining contribution of coal to annual emissions. This drives emissions reductions up until 2040 even as new NG capacity comes online to help meet growing energy demand. With most existing coal capacity already having retired by 2040, however, CO_2 emissions attributed to new NG capacity built in 2045 are not offset by reductions from retiring coal capacity, leading to an increase in emissions between these model periods.

The high levels of VRE resource deployment and utilization when VRE and storage costs are low leads to 19% lower cumulative emissions, as well as substantially lower annual emissions by mid-century (see Figure 26, center). Compared to the Reference Case, annual emissions in 2040 are 50% lower, and in 2045, are 59% lower. Notably, however, emissions are *greater* in the first two model periods than in the Reference Case, by 15% in 2020 and 3% in 2025. This can be attributed to the 34% and 12% greater coal capacity and 81% and 12% greater contribution of coal to total annual generation during these two model periods, respectively. With lower cost VREs and storage on the horizon, less existing NG capacity is retired and less new NG capacity is built during the first two model periods; instead, there is a greater reliance on high-emitting but low marginal cost existing coal capacity in the transition period.

While low-cost VREs and storage leads to reduced annual CO_2 emissions in later model periods, disallowing SLTEs of existing nuclear plants has the opposite effect (Figure 26, right). Increased reliance on NG under this scenario contributes to annual CO_2 emissions being 14% and 23% above those in the Reference Case in 2040 and 2045, respectively. However, cumulative emissions *decrease* by 1.0%. This counterintuitive result can be attributed to comparatively lower emissions in the 2025, 2030, and 2035 model periods, by 14%, 20%, and 3.5%, respectively. When SLTEs are not granted, early deployment of new NG and VREs is more attractive, and existing NG plants are incentivized to stay online for longer, since these resources will be needed in greater amounts once existing nuclear plants begin to retire. In 2025, there is 2.9 GW of additional new NG and an additional 7.5 GW of existing NG compared to the Reference Case, and in 2030, there is 1.4 GW of additional new NG, an additional 3.1 GW of existing NG, and 16.4 GW of additional VRE capacity. This additional capacity, totaling 10.4 GW in 2025 and 25.4 GW in 2030, suffices to push existing coal capacity offline, driving the emissions reductions; coal capacity is 8.2 GW lower in 2025 and 7.6 GW lower in 2030 compared to the Reference Case, representing 42% and 52% capacity reductions, respectively.

4.1.5 Discussion

Even in the absence of a CO_2 emissions policy, the role of NG in future low-carbon energy systems in the American Southeast is uncertain – accelerated cost declines for VREs and battery storage alone may determine whether NG constitutes the majority or minority of capacity under a least-cost mid-century resource mix. However, even when these technology costs are low, nearly 80 GW of new NG capacity is built, including 25 GW in 2045, suggesting that NG still may have a role to play in grids with high levels of VREs absent CO_2 emissions considerations.

Annual and cumulative CO_2 emissions trends compared to the Reference Case observed in the two experimental scenarios underscore that a holistic, pathway-aware approach should be taken when thinking about emissions reductions. For example, the mid-century increases in annual emissions which result when nuclear SLTEs are not granted are offset by lower annual emissions in early model periods. Furthermore, while intuition may suggest that low-cost VREs and storage would lead to annual emissions reductions across model periods, emission increases are observed relative to the Reference Case through 2030, owing to increased utilization existing coal resources instead of new NG being deployed due to expectations (with prefect foresight in case of the model) of increasing demand and declining capital costs of VREs and storage in future periods.

Finally, it is notable that in the Reference Case, emissions are nearly identical in 2020 and 2045 despite a 1.7x increase in load, highlighting the outsized contributions of coal generation to annual emissions despite constituting a small percentage of total capacity compared to NG. However, the upward trend in emissions between the 2040 and 2045 model periods, combined with the fact that most existing coal capacity has retired by mid-century, suggests that emissions will continue trending upwards past the model's 2050 planning horizon without an emissions reduction policy. The effects of potential emissions limits on planning outcomes, costs, and cumulative emissions impacts will be examined in the following section.

4.2 The Role for Natural Gas Under Constrained Emissions Scenarios

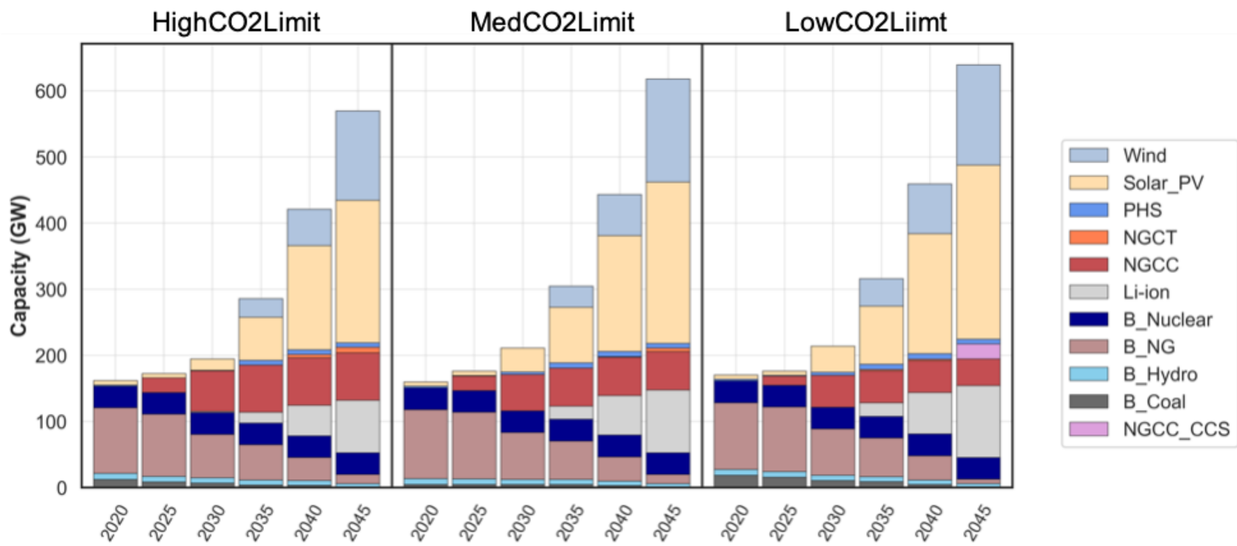

Figure 28: System-wide capacity (GW) for the HighCO2Limit (left), MedCO2Limit (center), and LowCO2Limit (right) scenarios.

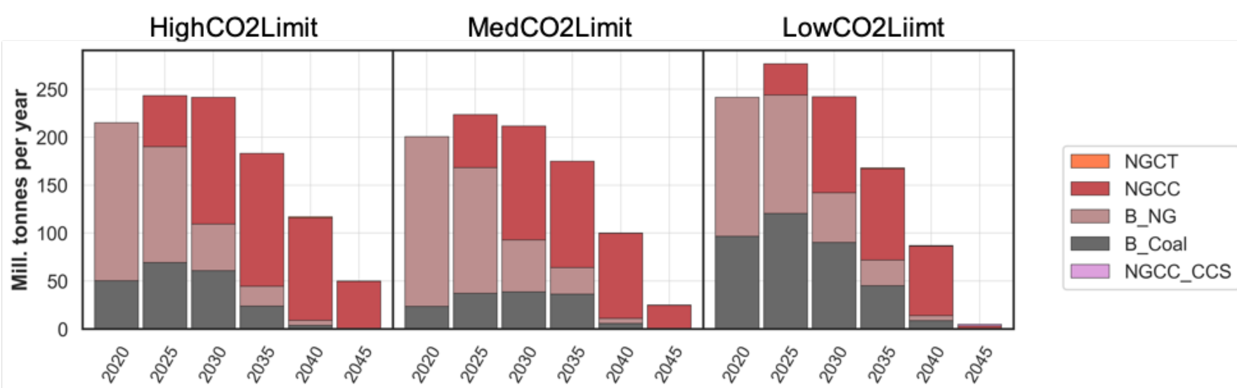

Figure 29: Annual CO_2 emissions by resource type in million tonnes per year for the HighCO2Limit (left), MedCO2Limit (center), and LowCO2Limit (right) scenarios. Across the three scenarios, annual emissions in 2035 and onward are equal to the annual emissions limit imposed by each respective emissions policy.

Imposing constraints on annual CO_2 emissions in the HighCO2Limit, MedCO2Limit, and LowCO2Limit scenarios leads to reduced cumulative deployment of new NG capacity and substantial increases in solar PV, wind and Li-ion battery storage capacity compared to the Reference Case (see Table 31, Table 32, and Figure 28). The least restrictive "high" emissions policy, evaluated in the HighCO2Limit scenario, leads to a 40% reduction in total NG capacity without CCS and a 127% increase in combined solar PV, wind, and battery storage capacity in 2045, compared to the Reference Case; the most restrictive "low" emissions policy, evaluated in the LowCO2Limit scenario, lead to a 70% reduction and 176% increase, respectively. The effects of this massive increase in VREs and storage on grid operations by mid-century can be seen in the net load curves for the three scenarios, which all show substantially more hours than the Reference Case where system-wide VRE generation exceeds demand, and in which storage resources can be charged (see Figure 30).

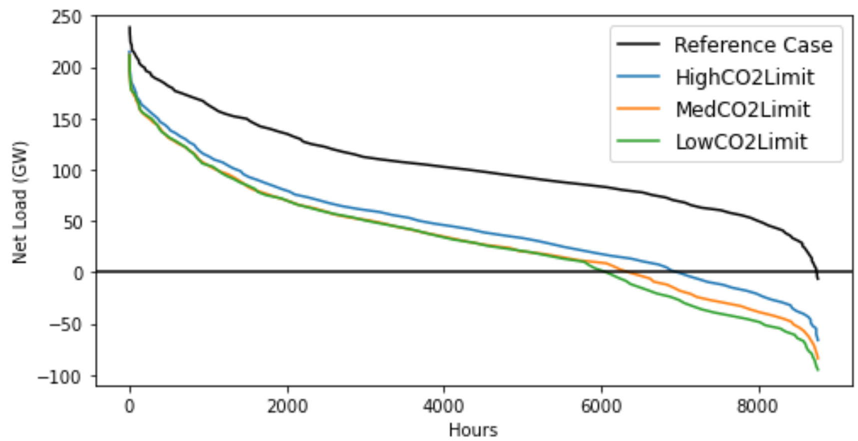

Figure 30: 2045 net load duration curves (net system-wide load minus dispatched solar PV and wind generation) for the Reference Case and HighCO2Limit, MedCO2Limit, and LowCO2Limit scenarios.

Despite their emissions constraints, all three scenarios include new NG capacity. NGCT capacity is built in 2040 and 2045 under "high" and "medium" emissions polices; under the "low" emissions policy, NGCT capacity is built in 2035. The "low" emissions policy case is unique in that it is the only in which new NGCC and NGCT capacity are retired early, with total new NG capacity without CCS declining in 2045; 8 GW of NGCC capacity, or 17% of 2040 NGCC capacity, retires between the final two model periods, as does 1.8 GW of NGCT capacity, representing all 2040 NGCT capacity. Furthermore, this scenario is the only in which NGCC-CCS plants are built, the 23 GW built in 2045 representing a third of all NG capacity in the final model period. In all three cases, new NG capacity tends to be built earlier and existing NG capacity tends to retire later compared to the Reference Case, mirroring the capacity deployment trends in the unconstrained emissions scenario when costs of VREs and storage are low or when SLTEs are not granted (see section 4.1.2 and explanation of early-period emissions reductions when SLTEs are not granted in section 4.1.4). For example, 31% of cumulative NGCC deployments through the planning horizon occur in 2025 under the "high" emissions policy, as do 31% under the "medium" emissions policy; under the Reference Case, only 11% do. Additionally, average CFs for new NGCC plants are slightly greater relative to the Reference Case in 2025 under the three emissions reductions policies and are substantially lower relative to the Reference Case in later model periods as emissions constraints become stricter (see Figure 31). For existing NG resources, average CFs closely track those of the Reference Case in all three emissions reductions scenarios (Figure 32).

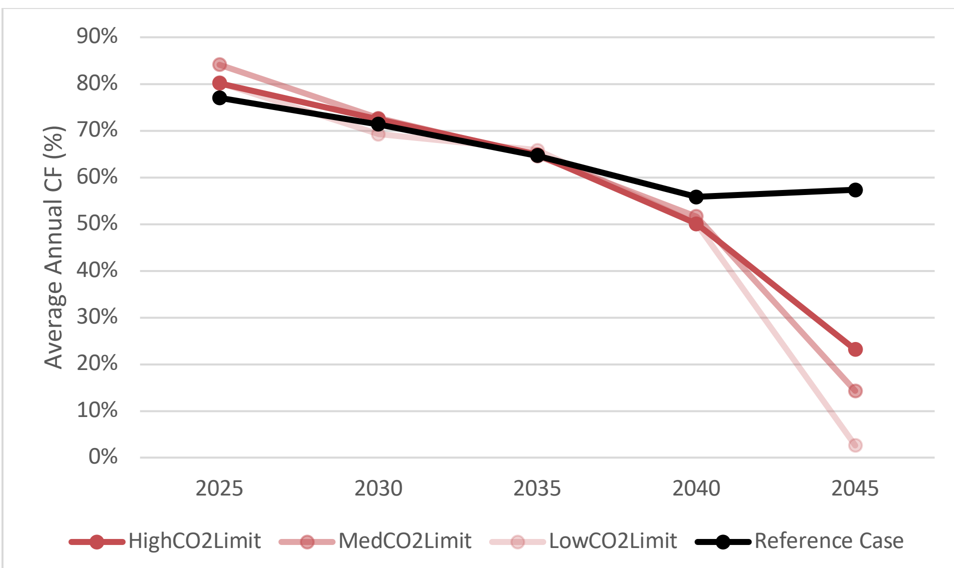

Figure 31: Average annual capacity factors (%) for NGCC resources under "high", "medium", and "low" emissions policies, compared to the Reference Case.

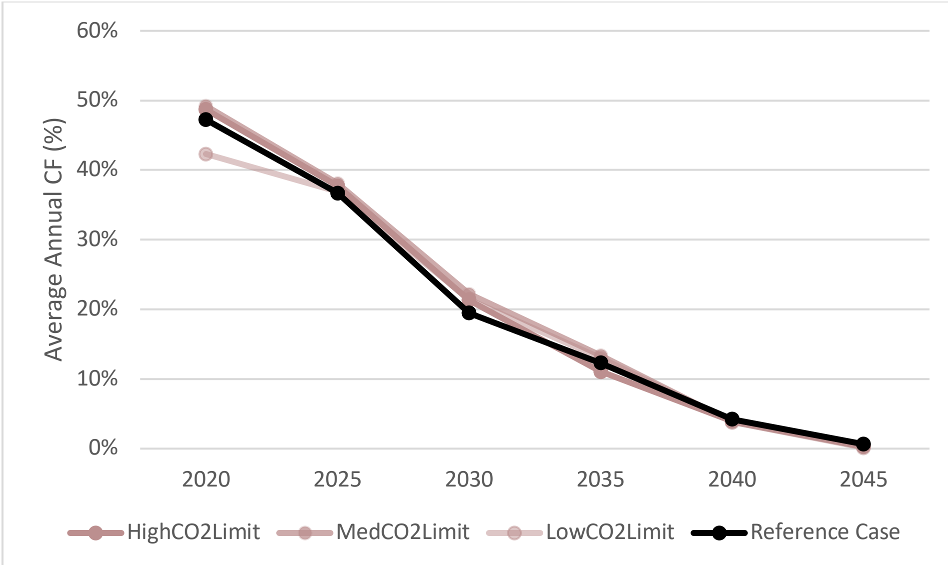

Figure 32: Average annual capacity factors (%) for existing natural gas (B_NG) resources under "high", "medium", and "low" emissions policies, compared to the Reference Case.

Introducing CO_2 emissions constraints leads to increased total costs, which increase 2.6%, 3.7%, and 5.8% compared to the Reference Case, and all three policies lead to substantial cumulative CO_2 emissions reductions compared to the Reference Case, at 29%, 37%, and 31% under "high," "medium," and "low" emissions policies, respectively (see Table 30). Emissions constraints become binding beginning in 2035 in all three scenarios, after which annual emissions are equal to the upper bound of each scenario's respective annual emissions constraints (see Figure 29). Although the "low" emissions policy has the most stringent emissions limits, the "medium" emissions policy leads to the greatest cumulative emissions reductions across the three policies. This can be attributed to the extremely limited role for fossil resources in later periods under the "low" emissions policy, which incentivizes existing fossil capacity to remain in the capacity mix instead of new NG capacity being built. This results in increased utilization of existing coal plants, which drives the greater emissions in the earlier periods.

4.2.1 CO_2 Emissions Policies under Low VRE and Storage Costs

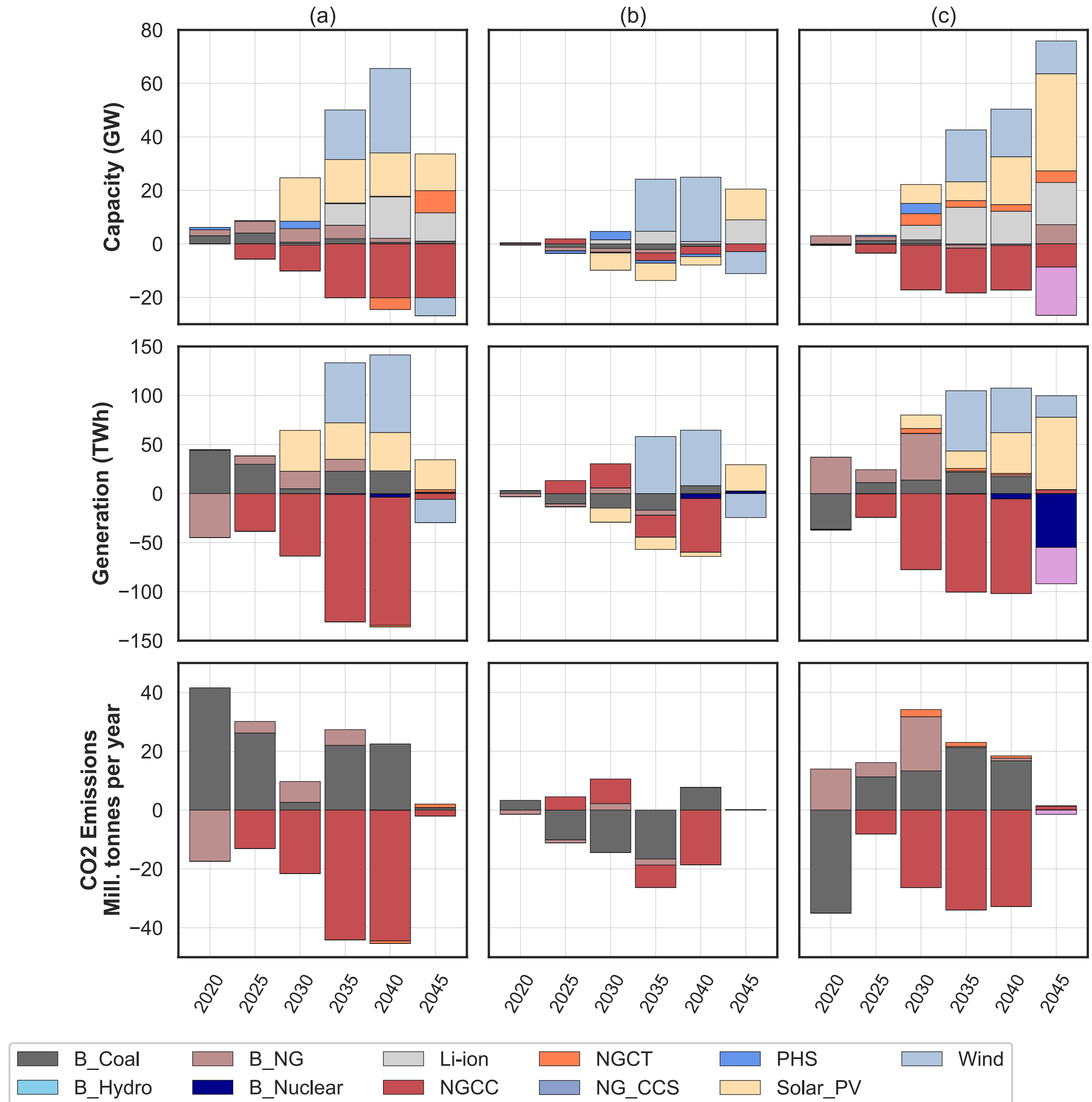

Figure 33: Effects of low solar PV, wind, and Li-ion battery storage costs across different CO_2 emissions policy scenarios. Difference in capacity (GW), annual generation (TWh) and annual CO_2 emissions (million tonnes per year) between the HighCO2Limit_LowVRECosts and HighCO2Limit (column (a)), MedCO2Limit_LowVRECosts and MedCO2Limit (column (b)), and LowCO2Limit_LowVRECosts and LowCO2Limit (column (c)) scenarios by resource type.

Figure 33 shows the impacts of low VRE and storage costs on the capacity mix to be compliant with the "high," "medium," and "low" CO_2 emissions policies. Even in the absence of CO_2 emissions constraints, low-cost VREs and storage lead to a substantially increased deployment of solar PV, wind, and storage capacity and decreased NG capacity by mid-century (see section 4.1.2). The effects of these low technology costs carry over when emissions policies are introduced, leading to greater NG displacement by VREs and storage than under the emissions policies alone. The introduction of low VRE and storage costs leads to a 15%, 13%, and 28% decline in cumulative NGCC and NGCT capacity over the planning horizon compared to cumulative capacity under the "high," "medium," and "low" emissions policies alone, respectively. Although cumulative solar PV and wind deployment only increase by 2%, 1%, and 12% across these three respective cases, Li-ion storage discharge capacity increases by 13%, 11%, and 20%, and energy capacity increases by 31%, 25%, and 37% (see Table 31 and Table 32). This result suggests that low-cost storage rather than low-cost VRE deployment is the greater driver of NG capacity reductions under these scenarios.

The introduction of low VRE and storage costs leads to greater reductions in cumulative emissions than the emissions reductions policies alone, driving an additional 0.7%, 3.1% and 2.1% of cumulative emissions reductions compared to scenarios with "high," "medium," and "low" emissions policies and baseline technology costs, respectively. Finally, while the introduction of emissions policies under baseline technology costs led to 2.6% to 5.8% increases in cumulative costs compared to the Reference Case, with low VRE and storage costs, cumulative costs under the three polices are within 1% of the cumulative cost of the NoCO2Limit_LowVRECosts scenario. This result reinforces the expectation that low VRE and storage costs increase the cost-effectiveness of CO_2 emissions reductions.

4.2.2 CO_2 Emissions Policies without SLTEs for Existing Nuclear Plants

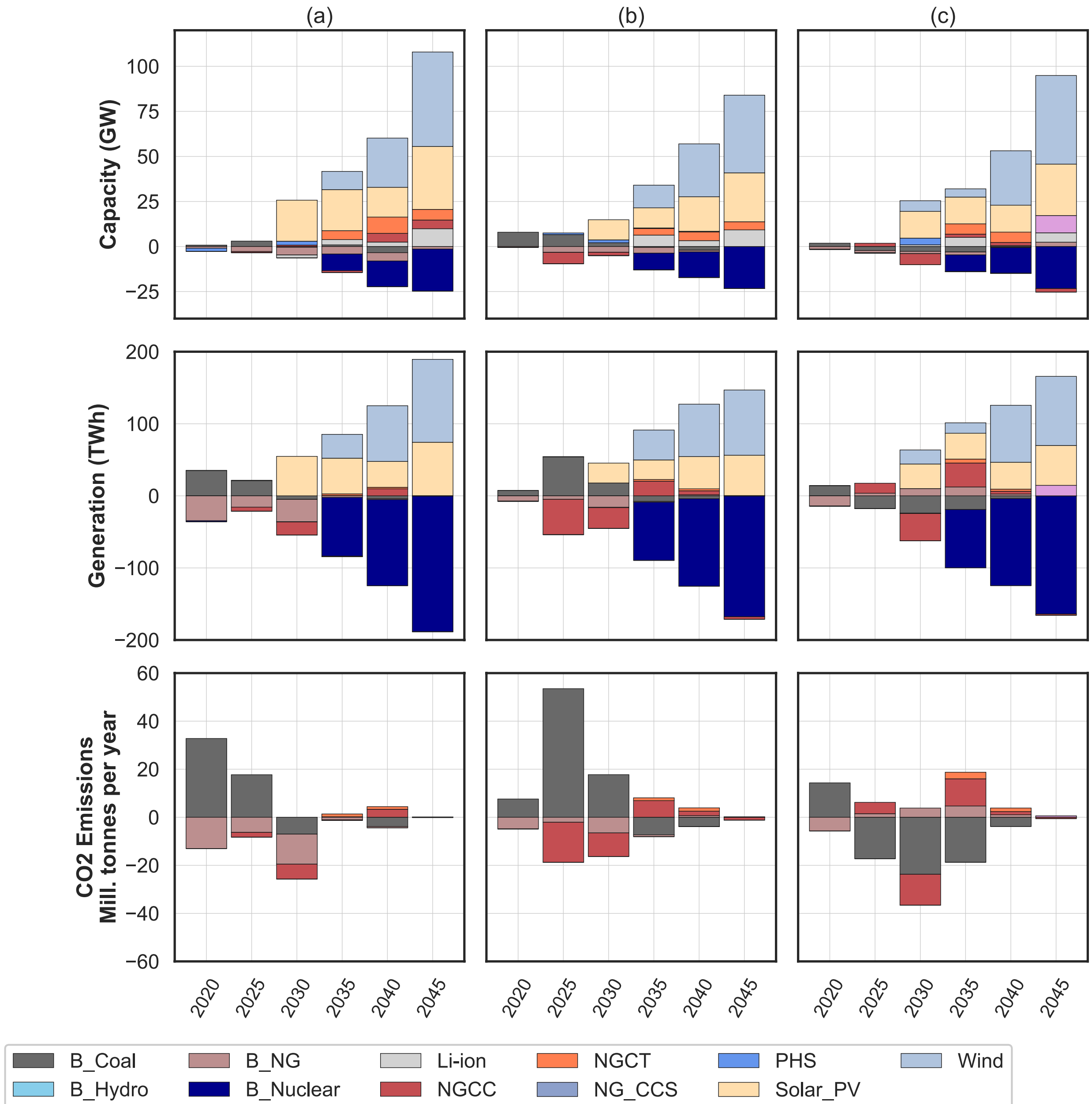

Figure 34: Effects of disallowing second lifetime extensions (SLTEs) across different CO_2 emissions policy scenarios. Difference in capacity (GW), annual generation (TWh) and annual CO_2 emissions (million tonnes per year) between the HighCO2Limit_NoSLTE and HighCO2Limit (column (a)), MedCO2Limit_NoSLTE and MedCO2Limit (column (b)), and LowCO2Limit_NoSLTE and LowCO2Limit (column (c)) scenarios by resource type.

Figure 34 shows the how the capacity mix responds when no SLTEs are granted to existing nuclear capacity under the three emissions policies. Disallowing SLTEs under emissions policies makes it more expensive to adhere to the imposed CO_2 emissions budgets, increasing cumulative costs by an additional 3.5-4.0% relative to the Reference Case (see Table 30). Substantial additional capacity is required to meet load as existing nuclear capacity begins to retire; although some additional NG capacity is built, solar PV, wind, and Li-ion battery storage constitute most of the capacity additions across the three emissions policies. For example, disallowing SLTEs under the "high" emission policy leads to 22.6% more combined solar PV, wind, and Li-ion battery storage discharge capacity in 2045, but only 9.9% more total NG capacity. Nuclear plant retirements have the additional effect of increasing deployment of NGCC with CCS. When no SLTEs are granted, NGCC-CCS capacity in 2045 increases by 42% under the "low" emissions policy, relative to the case when SLTEs are granted. Furthermore, while there is no NGCC-CCS deployed in 2045 under the "medium" emissions policy when SLTEs are granted, 6.0 GW is built in 2045 when they are disallowed.

When no SLTEs are granted for existing nuclear plants, impacts on cumulative emissions vary across the three emissions policies (see Table 30). Under the "high" emissions policy, cumulative emissions are nearly identical whether or not SLTEs are granted. Under the "medium" emissions policy, cumulative emissions increase 4.2% from 4.7 Gt CO_2 to 4.9 Mt CO_2 when SLTEs are not granted. Under the "low" emissions policy, however, cumulative emissions decrease from 5.1 Gt CO_2 when all nuclear plants receive SLTEs to 4.9 Mt CO_2 when they are not granted, a 3.5% drop. Since foresight allows the model to plan for forthcoming nuclear retirements by building low-carbon capacity that will be needed in later model periods early on, greater deployment of NG capacity in 2025 and VRE capacity in 2030 (see Figure 34, top right) allow for reduced generation from existing coal-fired power plants (see Figure 34, center right), leading to the lower emissions observed in this scenario.

4.2.3 CO_2 Emissions Policies with Additional Regulatory Measures

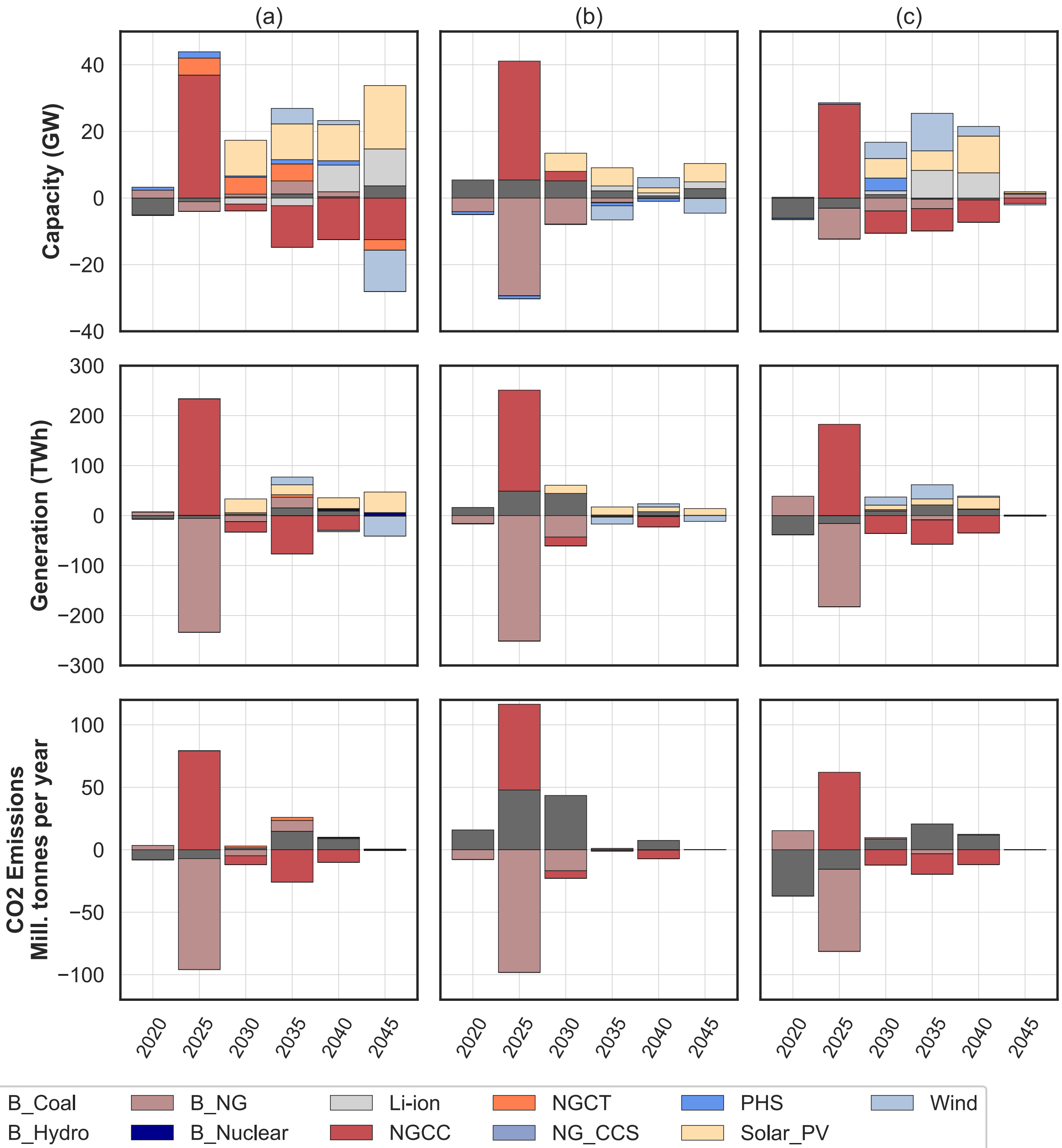

Figure 35: Effects of constraining all new NG deployment without CCS to 2025 across different CO_2 emissions policy scenarios. Difference in capacity (GW), annual generation (TWh) and annual CO_2 emissions (million tonnes per year) between the HighCO2Limit_NG2025 and HighCO2Limit (column (a)), MedCO2Limit_NG2025 and MedCO2Limit (column (b)), and LowCO2Limit_NG2025 and LowCO2Limit (column (c)) scenarios by resource type.

Concerns about climate change are leading to rapidly shifting altitudes regarding the role of fossil fuels in a low-carbon future. For example, the IEA's "Net Zero by 2050" report recommends no new investment in coal-fired power plants without CCS, and no investment in new oil and gas fields (IEA, 2021), and the Biden Administration had proposed a "carbon-pollution free" electric power sector by 2035 (The White House, 2021). Additionally, the "2035 Report", published by researchers at the University of California Berkeley and GridLab, suggests that a reliable, affordable, 90% decarbonized U.S. grid by 2035 is possible without new coal or NG plants, besides those already under construction (Phadke et al., 2021). These developments suggest the possibility of future regulatory actions which limit the construction of new fossil infrastructure. As a result, we consider a sensitivity where all new NGCT plants and NGCC plants without CCS may only be built in 2025, its impacts on the capacity mix shown in Figure 35. This constraint raises cumulative costs an additional 1.3-2.1% compared to the Reference Case over emissions policies alone.

Since new NG cannot be built after 2025, all NG capacity that is to be utilized in future model periods must be built that year. Although the inability to deploy new NG without CCS in future periods has the intended effect of reducing cumulative new NGCC and NGCT capacity 9% to 17%, it also leads to 2.9-3.1x higher NG deployment in 2025 across the three emissions policies (see Table 31 and Table 33). Under perfect foresight, the model still attributes value to the flexible operating capacity of NG resources to balance increasing VRE generation in future periods.

The constraint on new NG construction after 2025 causes cumulative emissions to decrease an additional 2% and 2.9% compared to the Reference Case over the "high" and "low" emissions policies alone, respectively; on the other hand, the addition of the constraint under the "medium" emissions policy leads to a 3.1% increase due to increased coal capacity utilization predominately in 2025 and 2030. This emissions policy was strict enough to decrease new NG deployment in 2025 relative to the "high" emissions case with the same restriction on new NG without CCS (Scenario 12), but not strict enough to incentivize early deployment of VREs and storage in early periods as observed to the "low" emissions case with the same restriction (Scenario 14), resulting in increased coal filling this gap in capacity (see Figure 35, top row).

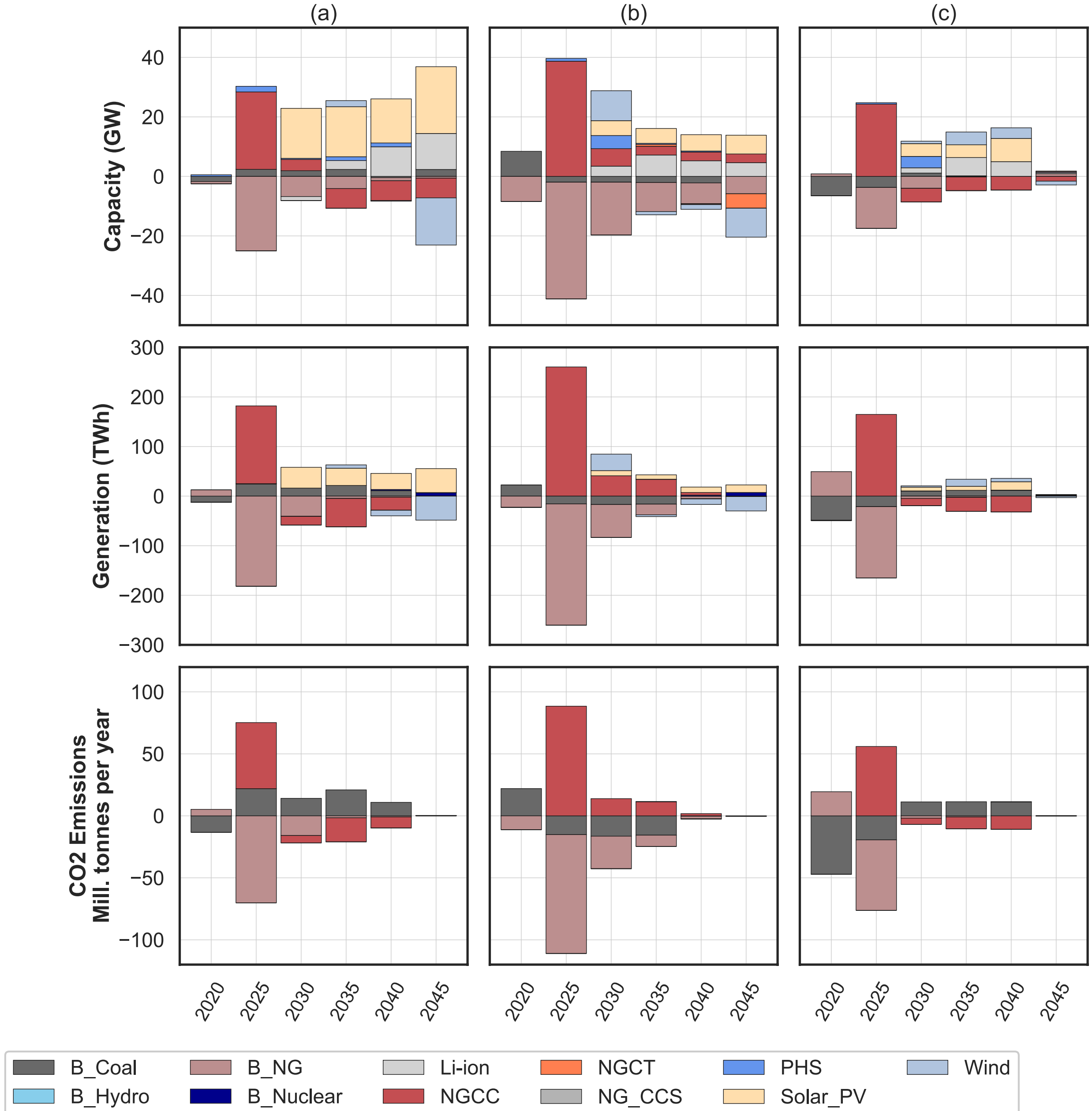

Figure 36: Effects of assuming no salvage value for new NGCC and NGCT capacity via full-cost financial assumptions across different CO_2 emissions policy scenarios. Difference in capacity (GW), annual generation (TWh) and annual CO_2 emissions (million tonnes per year) between the HighCO2Limit_NGFullCost and HighCO2Limit (column (a)), MedCO2Limit_NGFullCost and MedCO2Limit (column (b)), and LowCO2Limit_NGFullCost and LowCO2Limit (column (c)) scenarios by resource type.

Just as changing attitudes surrounding the role of fossil infrastructure are influencing the attitudes of key industry analysts and policy makers, so to too are they affecting the attitudes of investors and regulators, who are increasingly concerned about potential "stranded asset" risk and the future book value of NG infrastructure. Under a net-zero grid by 2050, for example, there may be little or no "salvage value" for NG plants without CCS. Figure 36 explores the impact of enforcing this no salvage value assumption for NG plants without CCS beyond the model horizon under the three CO_2 emissions policy scenarios. In other words, these scenarios require that all investment costs associated with new NGCT and NGCC capacity without CCS be paid in full by the end of the 2050 model planning horizon. Under this assumption, most new NG capacity is built in 2025 and is replacing existing NG capacity, mirroring the capacity buildout observed in scenarios where new NG without CCS may only be built in 2025. Since all costs associated with these plants must be paid for within the model horizon no matter when they are built, the model is incentivized to maximize the use of these facilities to get the most "bang for its buck" by investing in them early on. However, a small percentage of NG capacity is built after 2025 – 25.7%, 1.1% and 13.5% of all new NG capacity is built after 2025 under the "high," "medium," and "low" emissions polices and "full-cost" financial assumptions, respectively. All three cases lead to less cumulative emissions relative to the Reference Case than under "rental" financial assumptions by an additional 0.7% ("high" emissions policy) to 3.7% ("medium" emissions policy), but at increased cumulative system costs ranging from 1.1% ("low" emissions policy) to 3.5% ("medium" emissions policy) (see Table 30).

4.2.4 Discussion

The role of NG in future low-carbon energy systems declines with increasing stringency of CO_2 emissions policies. Not only is less NG capacity built, but average CFs of new NGCC plants decline as the stringency of CO_2 emissions limits increase (see Figure 31). However, we find that more stringent emissions reductions policies do not necessarily lead to lower cumulative emissions over the planning horizon. For example, the "low" emissions policies require an extremely limited role for fossil fuels by mid-century, and to minimize spending on new fossil infrastructure, higher-emitting coal plants remain in the capacity mix longer and provide greater contributions to annual generation, leading to greater cumulative emissions. Since CO_2 is a long-lived climate forcer, it is important to consider not only the impacts of CO_2 emissions reductions policies on mid-century emissions, but on how these policies may affect cumulative emissions from the capacity mixes which takes us there.

Notably, all "low" emissions policy scenarios evaluated under baseline VRE and storage technology costs included early retirements for newly built NG capacity. This suggests that it may be economic to build new NG plants even if their economic lifetimes are shorter than their operational lifetimes on pathways towards highly decarbonized future grids under a range of technology and policy scenarios. However, no early retirements of new NG capacity are seen under low cost assumptions for VREs and storage, attributable to the fact that less cumulative new NG capacity is built to begin with compared to the other "low" emissions policy cases (see Table 31). This suggests that early economic retirement of new NG capacity is not a given in future resource planning scenarios.

Under baseline VRE and storage costs, cumulative costs of CO_2 emissions policy scenarios increase by 2.6-9.9% compared to the Reference Case (see Table 30). Interestingly, when VRE and storage costs are low, cumulative costs are 2.1% and 0.5% lower than the Reference Case even under "high" and "low" emissions polices, respectively. Incidentally, SLTEs of existing nuclear plants reduce cumulative costs by 4 percentage points compared to when they are not granted under the "low" CO_2 emissions policy, and highlight the role of the existing nuclear fleet in cost-effective decarbonization of the power sector. However, it is notable that no new nuclear plants are deployed in any of the scenarios considered; due to its extremely high capital costs, new nuclear is unable to compete with lower-cost resources. This result is influenced, in part, by increasingly bullish cost projections for VREs and storage, while cost projections for new gigawatt-scale nuclear capacity trend upwards. For example, while 2050 capital cost projections under "moderate" technology advancement assumptions declined 65% for 4-hour battery storage and 3% for onshore wind between the 2018 and 2020 NREL ATBs, projected 2050 costs for nuclear increased 6% (projected costs for utility-scale solar PV increased 2%).

The two regulatory measures considered – those which constrain new NG buildout after 2025 or avoid "stranded" costs for NG by assuming that NG without CCS has no salvage value post-planning horizon – lead to similar least-cost capacity mixes under the three CO_2 emissions reductions policies at comparable cost increases relative to the Reference Case. The no salvage value assumption leads to greater flexibility of outcomes of the two regulatory measures, in that new NG may be built in any model periods besides 2020. Even so, both cases lead to new NG being built predominately in 2025, accelerated retirements of existing NG capacity, increased VRE and storage deployment, and in all but one case (Scenario 13, with no new NG without CCS after 2025 and a "medium" CO_2 emissions reductions policy), reductions in cumulative emissions compared to when emissions policies alone are implemented. These outcomes suggest that regulations which seek to limit NG development further in the future may promote additional new NG development this decade, although these policies can be beneficial as a whole by leading to greater reductions in cumulative CO_2 emissions through 2050.

Scenario Name	Scenario Number	Change in Cumulative Cost (%)	Change In Cumulative Emissions Reductions (%)
Reference Case	*0*	-	-
NoCO2Limit_LowVRECosts	1	-1.5%	19.2%
NoCO2Limit_NoSLTE	2	1.8%	1.0%
HighCO2Limit	3	2.6%	29.3%
MedCO2Limit	4	3.7%	37.0%
LowCO2Limit	5	5.8%	31.3%
HighCO2Limit_LowVRECosts	6	-2.1%	30.0%
MedCO2Limit_LowVRECosts	7	-1.8%	40.1%
LowCO2Limit_LowVRECosts	8	-0.5%	33.4%
HighCO2Limit_NoSLTE	9	6.1%	29.1%
MedCO2Limit_NoSLTE	10	7.5%	34.4%
LowCO2Limit_NoSLTE	11	9.9%	33.7%
HighCO2Limit_NG2025	12	4.7%	31.4%
MedCO2Limit_NG2025	13	5.8%	33.9%
LowCO2Limit_NG2025	14	7.2%	34.3%
HighCO2Limit_NGFullCost	15	5.1%	30.0%
MedCO2Limit_NGFullCost	16	7.2%	40.7%
LowCO2Limit_NGFullCost	17	7.0%	34.2%

Table 30: Change in cumulative cost and cumulative emission reductions over the model horizon (2020-2050) relative to the Reference Case. SLTE stands for "second lifetime extension."

Scenario Name	Scenario Number	Cumulative New NGCC Capacity (GW)	Cumulative New NGCT Capacity (GW)	Cumulative New NGCC-CCS Capacity (GW)
Reference Case	*0*	115.6	27.3	0.0
NoCO2Limit_LowVRECosts	1	52.4	25.8	0.0
NoCO2Limit_NoSLTE	2	139.5	26.4	0.0
HighCO2Limit	3	71.7	8.3	0.0
MedCO2Limit	4	57.8	5.5	0.0
LowCO2Limit	5	48.5	1.8	22.8
HighCO2Limit_LowVRECosts	6	51.6	16.6	0.0
MedCO2Limit_LowVRECosts	7	54.9	0.0	0.0
LowCO2Limit_LowVRECosts	8	31.8	4.3	4.8
HighCO2Limit_NoSLTE	9	76.5	14.2	0.0
MedCO2Limit_NoSLTE	10	57.8	10.0	6.0
LowCO2Limit_NoSLTE	11	50.3	7.6	32.4
HighCO2Limit_NG2025	12	59.2	5.1	0.0
MedCO2Limit_NG2025	13	57.7	0.0	0.0
LowCO2Limit_NG2025	14	41.8	0.0	22.9
HighCO2Limit_NGFullCost	15	65.1	0.0	0.0
MedCO2Limit_NGFullCost	16	60.7	0.6	2.4
LowCO2Limit_NGFullCost	17	43.9	0.0	23.1
Peak System Load (2045): 263 GW				

Table 31: Cumulative new capacity (GW) installed over the model horizon (2020-2050) for NGCC, NGCT, and NGCC-CCS resources. Peak system load in 2045 is included as a point of comparison. Note that in some scenarios some of the installed capacity is retired before the end of the model horizon. SLTE stands for "second lifetime extension."

Scenario Name	Scenario Number	Cumulative Solar PV Capacity (GW)	Cumulative Wind Capacity (GW)	Cumulative Li-ion Discharge Capacity (GW)	Cumulative Li-ion Energy Capacity (GWh)
Reference Case	*0*	127.7	17.4	37.5	96.4
NoCO2Limit_LowVRECosts	1	205.0	101.2	84.8	334.0
NoCO2Limit_NoSLTE	2	143.5	17.9	36.6	85.7
HighCO2Limit	3	209.1	134.9	81.1	276.6
MedCO2Limit	4	237.9	155.6	94.9	364.2
LowCO2Limit	5	257.0	151.5	108.7	465.0
HighCO2Limit_LowVRECosts	6	222.9	128.2	91.2	361.3
MedCO2Limit_LowVRECosts	7	249.4	147.4	105.5	453.9
LowCO2Limit_LowVRECosts	8	293.3	163.7	129.9	638.6
HighCO2Limit_NoSLTE	9	244.1	187.3	89.4	285.0
MedCO2Limit_NoSLTE	10	265.0	198.8	104.1	400.8
LowCO2Limit_NoSLTE	11	285.5	200.6	114.8	500.6
HighCO2Limit_NG2025	12	228.2	122.5	90.4	374.4
MedCO2Limit_NG2025	13	243.4	151.2	96.9	394.9
LowCO2Limit_NG2025	14	257.5	151.0	110.0	468.2
HighCO2Limit_NGFullCost	15	231.6	119.1	91.8	393.4
MedCO2Limit_NGFullCost	16	244.2	145.9	103.0	421.6
LowCO2Limit_NGFullCost	17	257.3	150.2	110.8	471.1
Peak System Load (2045): 263 GW					

Table 32: Cumulative new discharge capacity (GW) installed over the model horizon (2020-2050) for solar PV, wind, and Li-ion battery storage resources; cumulative new energy capacity (GWh) across all model periods for Li-ion battery storage. Peak system load in 2045 is included as a point of comparison. Note that in some scenarios some of the installed capacity is retired before the end of the model horizon. SLTE stands for "second lifetime extension."

Scenario Name	Scenario Number	2025 New NGCC and NGCT Capacity (GW)	2025 Existing NG Capacity (GW)	2025 Existing Coal Capacity (GW)
Reference Case	*0*	7.6	93.2	19.7
NoCO2Limit_LowVRECosts	1	11.3	93.0	22.0
NoCO2Limit_NoSLTE	2	15.0	100.7	11.4
HighCO2Limit	3	22.3	94.1	8.3
MedCO2Limit	4	22.0	100.7	4.5
LowCO2Limit	5	13.7	97.8	15.4
HighCO2Limit_LowVRECosts	6	16.6	98.4	12.4
MedCO2Limit_LowVRECosts	7	23.9	99.3	3.3
LowCO2Limit_LowVRECosts	8	10.4	99.4	16.7
HighCO2Limit_NoSLTE	9	21.7	91.2	11.3
MedCO2Limit_NoSLTE	10	15.7	97.4	11.1
LowCO2Limit_NoSLTE	11	15.5	96.5	13.2
HighCO2Limit_NG2025	12	64.3	91.1	7.2
MedCO2Limit_NG2025	13	57.7	71.3	9.9
LowCO2Limit_NG2025	14	41.8	88.6	12.4
HighCO2Limit_NGFullCost	15	48.4	69.0	10.7
MedCO2Limit_NGFullCost	16	60.7	61.5	2.6
LowCO2Limit_NGFullCost	17	38.0	84.0	11.7
Peak System Load (2025): 153 GW				

Table 33: Capacity (GW) at the end of the 2025 model period for new NG (combined NGCC and NGCT), existing NG, and existing coal resources. Peak system load in 2025 is included as a point of comparison. SLTE stands for "second lifetime extension."

5 Part V: Conclusion

5.1 Limitations and Future Research

5.1.1 Least-Cost Modeling Framework

While this analysis utilizes an advanced, multi-period capacity expansion model, there are limitations to this modeling framework that pave the way for further research.

First, we assume perfect foresight of future policies and costs. While this assumption is useful for scenario analysis, grid planners and regulators do not make decisions under perfect foresight; rather, they operate under uncertainty about the future. Future research may introduce uncertainty into this modeling framework through extension of the algorithms used in this study, such as the stochastic dual dynamic programming algorithm (Pereira & Pinto, 1991). This would enable modeling of concurrent cost and policy pathways with varying likelihoods, and for evaluation of the effect of uncertainty on resource planning decisions. Separately, imperfect-foresight can be modeled through a rolling model horizon approach, in which foresight extends to a limited number of future model periods, as opposed to the end of the planning horizon. This approach may more accurately emulate how resource planning decisions are made in practice.

Second, we do not account for operating or planning reserve requirements due to the substantially greater computational requirements they impose, even though many states' integrated resource planning processes require consideration of them. However, newer, more computationally efficient versions of the GenX capacity expansion model may allow future researchers to simulate detailed investment and planning scenarios with this additional operational detail.

Finally, our capacity planning framework does not represent up-stream costs associated with new capacity, such as additional NG pipelines, nor does it consider the health, environmental, and climate cost impacts associated with extracting and burning fossil fuels. In addition, the emissions reduction policies considered do not account for CO_2-equivalent methane emissions which may be associated with deployment of new NG resources, and which like CO_2, contribute to climate change. Future research should evaluate how incorporating these factors into an expanded least-cost planning framework affects optimal investment pathways.

5.1.2 Brownfield and Greenfield Resource Representations

There are some notable limitations in the representation of brownfield and greenfield capacity in the Southeast model. First, we limit new PHS capacity to that of the lowest-cost resource sites, which are maxed out even under the Reference Case, although there is the potential for additional capacity at higher-cost sites identified by the regional PHS supply curve analysis. Second, we do not consider the possibility of lifetime extensions of existing capacity, retrofits, or other one-time capital projects that may lead to increased efficiency, lower emissions, or reduced costs. Existing coal-fired power plants have already been retrofit with CCS technology in the United States and Canada and retrofitting existing NGCC plants is technically feasible (EPRI, 2015). Duke Energy has recently announced a partnership with molten-salt thermal storage startup Malta to study the possibility of converting an existing coal unit in North Carolina to a clean energy storage facility (Duke Energy, 2021). Furthermore, major turbine manufactures are developing the technology to allow for high-volume hydrogen firing of NGCC turbines and are aiming to demonstrate viable, 100% hydrogen firing in the coming years (Sonia Patel, 2019). The ability to model retrofits of new or existing NG resources for CCS, molten-salt thermal storage, or hydrogen co-firing would present a more accurate representation of how the grid may evolve in practice; for example, the current model configuration only allows for CCS to be deployed via investment in brand new NGCC plants outfitted with the technology.

Future grids may include several new technology types which are not represented in our model, including long-duration energy storage technologies such as hydrogen, advanced electrochemical storage such as flow batteries and thermal storage; small modular reactors or other advanced nuclear technologies; or hydrogen-fired power plants. Additionally, our analysis is limited to supply-side resources: we do not consider the effects of demand-side energy management or energy efficiency on resource planning outcomes. What's more, under a high-electrification future, as assumed here, a far greater percentage of load could be flexible, such as that attributed to electric vehicle charging or space heating. Future research may consider modeling a wider range of resource types, including but not limited to the aforementioned technologies, and evaluate their impact on optimal resource configurations.

5.2 Policy Implications

As utilities, regulators, and policy makers think about how they might transition the electric power sector to net-zero emissions by mid-century, they must confront difficult decisions about what to build and when to build it, what to retire and when to retire it. These decisions can be especially difficult when thinking about natural gas-fired generation, which offers valuable grid services at the cost of GHG emissions. While utilities nationwide have put forth plans for new NG capacity before utility regulators, some stakeholder groups are voicing their opposition to new NG, including over proposals by utilities operating in the American Southeast such as Duke Energy (St. John, 2021) and Southern Company (St. John, 2020). The analysis presented here contributes several key findings which may introduce nuance to these contentious conversations, and which suggest concrete policy implications. The resulting recommendations, and the findings which support them, are presented below.

5.2.1 Recommendation 1: Consider Natural Gas as a Potential Resource in CO_2 Reductions Pathways

Finding: New NG capacity is deployed in all scenarios considered, including cases with low-cost VRE and storage assumptions. Furthermore, all scenarios have greater new NG capacity deployed in 2025, the first model period where new NG capacity is allowed, than the Reference Case, suggesting that mid-century emissions reductions policies, and lower future costs of VREs and storage, may lead to increased deployment of NG in the near-term under perfect-foresight and high-electrification growth assumptions. This is consistent with findings of other researchers, such as Jayadev et al. (2020), who find that NG capacity growth is "strong and robust" even under a carbon tax assumption, and MacDonald et al. (2016) who describe NG as a "cost effective" complement to VREs.

Recommendation: Regulators should consider NG as a potential resource to be utilized on low-carbon transition pathways, as it provides flexible generation through mid-century to support massive new investments in VREs and battery storage. What's more, increased NG investment in the near-term is not necessarily incompatible with mid-century emissions reductions targets; on the contrary, increased new NG capacity can lead to greater cumulative emissions reductions through 2050 if it facilitates early coal plant retirements.

5.2.2 Recommendation 2: Grid Operators Should Prepare for a Changing Role for Natural Gas

Finding: The role of NG in the grid will likely change in the coming decades – average CFs for NG plants trend downwards even in the Reference Case, and NGCT "peaker" plants play a greater role in grids with greater VRE capacity in later model periods across scenarios.

Recommendation: Grid operators should plan for an evolving role of NG in the future capacity mix, where NG power plants are operated at lower average annual CFs, whether or not emissions reductions policies are expected. In states with existing emissions reductions goals, such as North Carolina, or if emissions policies are forthcoming, grid operators should plan for NG plants to operate at even lower capacity factors as emissions restrictions become more stringent.

5.2.3 Recommendation 3: Minimize Ratepayer Impacts of Early Plant Retirements

Finding: In all "low" emissions reductions scenarios with baseline VRE and storage cost assumptions, some newly built NG capacity is retired before the end of its economic life, including when no salvage value is assumed after the planning horizon. This suggests that in some cases, it may be cost-optimal to pay full-costs for new NG plants even if they are not utilized for their full operational lifetimes.

Recommendation: State lawmakers and regulators should develop policies which allow for accelerated cost recovery of some new NG assets. By anticipating and planning for early plant retirements, policymakers can reduce or prevent risk of asset stranding, while minimizing risk of continued emissions into mid-century. Regulators, utilities, and consumer advocates should recognize that accelerated depreciation timelines may be cost-optimal under certain circumstances, and embrace advanced planning tools which can aid them in making such determinations.

5.2.4 Recommendation 4: Design CO_2 Emissions Reductions Policies with Care

Finding: In most scenarios evaluated, the "low" emissions policies led to greater cumulative CO_2 emissions over the planning horizon than "medium" emissions policies, which can be attributed to greater utilization of existing coal capacity during early model periods, instead of new VRE or NG capacity being deployed.

Recommendation: Policy makers must be careful when designing emissions reductions policies which place limits on CO_2 emissions and take care to ensure that these policies don't incidentally lead to greater emissions before emissions limits come into effect. In particular, some additional flexibility in mid-century CO_2 emissions (e.g., "medium" as opposed to "low" emissions policies) might contribute to greater cumulative emissions reductions through mid-century by creating a policy environment more conducive to investing in more efficient and lower-carbon fossil capacity in the near term, which may allow higher emitting plants to retire early. Alternatively, policy makers may consider implementing targeted emissions reductions policies which prioritize rapid retirements of the existing coal fleet.

5.2.5 Recommendation 5: Ensure Technological Readiness of CCS

Finding: NGCC power plants with CCS are deployed under all "low" emissions policies, including when VRE and storage costs are assumed to be low, and under some "medium" emissions policies, suggesting a role for CCS technology in achieving low-carbon grids across scenarios.

Recommendation: Since CCS may play an important role in mid-century capacity mixes under various emissions reduction pathways, R&D and other policies which support the technology, such as the 45Q federal tax credit for sequestered CO_2, should be prioritized.

5.2.6 Recommendation 6: Keep Existing Nuclear Capacity Online to Support Cost-effective Decarbonization

Finding: Continued operation of existing nuclear capacity through mid-century helps to reduce costs associated with the transition to a low-carbon grid; however, new nuclear plants are not economical under any of the scenarios evaluated.

Recommendation: When it is possible to safely do so, existing nuclear capacity should be kept online through 2050 as a source of substantial zero-carbon electricity without the need for investments in additional capacity. This will require that nuclear plant operators apply for, and the Nuclear Regulatory Commission approve, second license renewals. However, if SLTEs are not to be granted, policy makers should ensure low-carbon capacity replacements instead of increased utilization of existing coal plants.

5.2.7 Recommendation 7: Complement Short-term Deployment of Natural Gas with Long-term Limits

Finding: Regulations which prohibit new NG or make investments in new NG less attractive, such as assuming that NG plants has no salvage value after 2050, lead to similar resource planning outcomes, namely the early buildout of new NG capacity in 2025, and in all but one scenario, result in lower cumulative emissions than under CO_2 emissions reductions policies alone.

Recommendation: Policy makers and regulators may consider promoting long-term limits on new NG deployment or require shorter capital-recovery periods for new NG investments as a means to promote additional emissions reductions on top of policies which directly limit CO_2 emissions. Conversely, they should oppose policies that disincentivize displacing coal with lower-carbon resource options such as new NG or VREs in the short-term.

5.3 Conclusion

In this thesis, I examine the role of NG generation in future low-carbon energy systems by modeling least-cost resource portfolios in the American Southeast. I utilize a multi-period optimization modeling framework to model capacity mixes through mid-century under various policy and technology scenarios that assume a greater role for electricity in the broader energy system. My findings suggest a role for NG in future low-carbon girds even along deep decarbonization pathways under the modeling assumptions considered here. These results support policy recommendations which provide increased nuance in decision making regarding short-term and long-term NG deployment and the design and implementation of emissions reductions policies. It is important to note, however, these results are not proscriptive, but rather provide insights on key drivers of costs, emissions, and other planning outcomes under a limited set of model assumptions. They suggest one possible set of least-cost operational and investment outcomes; how actual outcomes follow or deviate from these pathways will be the result of an ongoing dialogue between utilities, regulators, ratepayers, lawmakers, and other stakeholders. As such, it is my hope that this analysis and its findings serve as the starting point for a broader discussion among a diverse set of stakeholders about the role of natural gas in future low-carbon grids not only in the American Southeast, but nationwide.

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