ABSTRACT

THOMAS, JEFFREY T. A Modeling Framework to Evaluate State-level Energy Policy: A North Carolina Case Study. (Under the direction of Joseph DeCarolis, Anderson de Queiroz, and Sanmugavadivel Ranjithan).

As states across the U.S. lead the fight against climate change, they are increasingly enacting energy and climate policies aimed at the electricity sector, which is responsible for a third of national carbon dioxide emissions. Policies often aim to promote renewable energy sources or reduce carbon dioxide emissions, and can have dramatic impact on state energy portfolios. However, state governments often lack the ability to evaluate the long-term effect of proposed policies, which may lead to suboptimal policy design or unexpected consequences. This research aims to provide a framework by which stakeholders can evaluate the long-term effect of state-level policies on capacity investments, electricity cost, and emissions by performing a case study of North Carolina's electricity sector. Temoa, an open source energy economy optimization model developed at North Carolina State University, is chosen as a framework for this prescriptive policy analysis. Temoa minimizes the cost of North Carolina's electricity sector expansion and operation over a 35-year time horizon by making optimal investment and dispatch decisions to satisfy electricity demand. Publicly available data was drawn upon to build a dataset reflecting North Carolina's energy portfolio, in an effort to serve as a guide for energy stakeholders interested in performing their own policy analysis.

Results suggest that there are multiple pathways for North Carolina to decarbonize its electric sector, with minimal impact on electricity costs. The CO_2 limits for North Carolina proposed in the federal Clean Power Plan can be met with cleverly designed financial incentives promoting renewable energy, such as investment tax credits or production incentive, or regulatory policies, such as a carbon price or an expanded renewable portfolio standard. The total increase in solution costs above the baseline associated with each policy was less than 1.6% of North Carolina's GDP, and increases to the

levelized cost of electricity were less than 8% in any given year, if the carbon price is considered revenue neutral. Electricity costs were found to be most sensitive to electricity demand and natural gas prices.

Renewable energy plays a significant role in controlling electricity costs while reducing emissions. Baseline results indicate that North Carolina will likely need new energy policies to increase its future renewables share. Analysis of policy scenarios suggests that at least 35% of North Carolina's electricity must come from zero-carbon sources by 2050 to avoid increases in annual CO_2 emissions above 2015 levels. Scheduled retirements of nuclear reactors in North Carolina may increase the need for intermittent renewables to meet this goal, yet at high levels of solar PV, the "duck curve" effect was observed, which may create challenges for baseload and load following generators in the future. Expanded renewable portfolio standards, investment tax credits, carbon limits, and a carbon price were found to significantly increase renewable share, reduce electric sector carbon intensity by 30-40%, and meet Clean Power Plan carbon limits at average abatement costs ranging from $44 to $62 per ton of CO_2 avoided.

A Modeling Framework to Evaluate State-level Energy Policy:
A North Carolina Case Study

by
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BIOGRAPHY

Jeff Thomas was born and raised in Brookfield, a suburb of Chicago, Illinois, by Richard and Candace Thomas. He has two sisters, one and two years younger than him, and helping them on their math homework as a kid probably led him to excel in the sciences. He became an Eagle Scout at 17 after organizing material donations and the construction of a patient garden at Shriner's Children's Hospital. Knowing he wanted to be an engineer, but not quite sure what kind, he obtained his Bachelor's degree in General Engineering from the University of Illinois in Urbana, IL, in 2009. He graduated in the midst of the housing market collapse, but was lucky enough to get a job with General Electric as part of their Operations Management Leadership Program in Lincolnton, NC. He progressed through several manufacturing roles, moving from North Carolina to Maine and then back to North Carolina, all the while solving problems and wondering what else life had to offer. In 2012 he met his wife, Faith Warner, while living in Wilmington, NC. At the time, he was a well-paid engineer working at Danaher, building medium voltage switchgear for mining and electricity distribution applications and spending too much money on the weekend. They married June 20th, 2015, and about a month later he quit his job and started classes at NC State, pursuing a career in the green energy sector, hoping he might make the world just a little bit better than he found it.

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First and foremost, I would like to acknowledge the hard work that many people before me have put into the Temoa model. Next, I would like to thank Binghui Li, who spent countless hours building the NC dataset, and who always made time to answer my questions, no matter how near his own deadlines were. I would also like to thank Anderson Rodrigo de Queiroz, without who the stochastic optimization and energy storage portions of this thesis wouldn't exist. His patience while I worked through energy storage rules or frantically sent him corrected scenario trees was inexhaustible. I also want to thank Peter Ledford and Daniel Brookshire at the NC Sustainable Energy Association, and Stephen Kalland at the NC Clean Energy Technology Center, for their help in getting connected to the energy policy negotiations leading up to HB 589. I consider those meetings to be the unofficial "applied" portion of my M.S., and I am grateful for the invitation to peek in on North Carolina's world of energy policy.

I also wish to thank my advisor, Joe DeCarolis, who was an abiding sounding board for me throughout my degree program. He helped me develop the concept for this research long before I had written a single word, and he seemed to always have an ear to the ground for opportunities I might be interested in. He helped guide me from energy model skeptic to a true believer in the value of model insights, and I'm grateful for the travel and learning opportunities he made sure were available to me.

I want to thank my family – my mother and father and sisters Claire and Adrienne – for their emotional, mental, and financial support through my back-to-school adventure. Their interest in my life, and desire to know more about what I've been researching, has inspired me to new heights. I am so thankful I am blessed with a family as supportive and kind as mine. I don't believe I would be here, at this stage in my life, without their influence. Thank you, so much, for everything you've done for me.

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INTRODUCTION

Over the next few decades, electricity use in the United States is projected to rise 0.6% annually, and power plant retirements are expected to rapidly accelerate after 2020 [1]. At the same time, renewable energy sources are becoming cost competitive with traditional fossil fuel sources even while natural gas prices remain low. Utility companies are therefore presented with a complex question: what types of generating capacity should be added over the next several decades to provide affordable, clean, and reliable power to consumers? This capacity expansion question is also relevant to state governments, which can shape the future power system through new policy. Federal action to combat climate change is highly unlikely over the next four years, so it will fall primarily to state governments to address environmental concerns associated with electricity generation [2, 3]. U.S. states have enacted a myriad of policies that influence the adoption of renewable energy, including renewable portfolio standards (RPS), tax incentives, and net metering, and their prevalence has been increasing in recent years [4]. More ambitious examples include California [5], New York [6], and Massachusetts [7], which all have plans to significantly cut greenhouse gas emissions and increase the percentage of renewable electricity in the coming decades. State governments are often in a better position than the federal government to influence the electric power industry through policy, due to their primary regulatory authority over energy markets, building codes, land use, and taxes [8]; as such, energy policies have been used by states since the 1980s to spur investments in low-carbon energy sources [4, 9, 10].

Effective state-level energy policies must anticipate how specific policy designs will influence electricity costs over a long-term horizon. There is a need, therefore, for rigorous energy systems analysis that can quantify the potential effects of different state-level policies on generation portfolios and electricity prices over time. This need is particularly acute in North Carolina: electricity industry stakeholders have been pursuing renewable energy legislation since 2016 in the hopes of bringing a viable compromise bill to the General Assembly by 2017 [11]. My own experience in this policy negotiation process suggested that state governments and advocates for renewable energy often lack the analytical modeling capabilities to objectively examine the long-term effects of proposed policy designs, which can lead to sub-optimal choices [12].

A significant body of research has examined how energy policy has affected renewable generation and the resultant emissions and electricity costs in US states. The literature can be broadly categorized into two groups: those that utilize econometric analysis to quantify the effects or costs of *existing* policies after controlling for observable variables [13-28]; and those that use energy models to understand how *proposed* policies may impact the electricity generation sector [29-39]. Regardless of method, research in this area aims to evaluate policies for their efficacy and efficiency in meeting energy goals, thereby providing insight to policy makers.

Econometric studies vary in their methodology, categories of policies reviewed, and independent variables measured. Typically, these studies choose a dependent variable, such as the percentage of electricity generated from renewable sources or electricity prices, and quantify how that dependent variable is affected by changes in a set of independent variables. These may include the presence of certain energy policies [13, 24], measures of policy stringency [14, 23, 25], renewable energy resource availability [19, 23], the political ideology of state legislatures [14, 15, 23], or measures of the state's economic health [16, 19]. While the methods and data used for these studies can produce conflicting results, there is general agreement on the effect of certain policies. Early cross-sectional studies found that the presence of an RPS and its duration to be significant drivers of wind power deployment, while public benefit funds did not have a discernable effect [13, 17, 23]. Using time-series panel data and including policy design factors in their analysis (such as measures of RPS stringency), RPSs were found to increase the total renewable generation [14], particularly when they were mandatory, had electricity sales targets instead of capacity targets, set high targets, and discouraged or limited the import of renewable energy certificates from out of state [15, 16, 25]. Research also suggests that direct cash incentives are more effective than tax credits or property tax abatements in driving solar deployment [17], although there are not yet enough studies to draw strong conclusions. Statutory limits on greenhouse gas emissions, such as CO_2, have also been effective at increasing renewable investment and reducing power plant emissions [24]. In addition to policy, these studies also suggest other factors that increase renewable generation, such as electric sector deregulation, a robust state economy [14, 23], and renewable resources endowments [13, 14, 40]. This body of literature is useful in understanding which current energy policies have demonstrated efficacy through analysis of empirical data, and what design factors are vital to their success. Econometric analyses may look at either policy *efficacy* (how effective a policy is at achieving its stated goals), *efficiency* (whether the stated goals are achieved at the lowest possible cost) [41].

While retrospective policy analysis can be informative, insights gained from existing state policies often lack external validity when designing new policies, as each state has unique factors that can lead to unexpected effects. These factors may include the ability of the legislature to raise taxes to fund energy programs or the political attitudes of citizens towards energy policies. Prospective analysis of state-specific policies can also provide useful insight to stakeholders and decision makers. The development of bottom up, technology rich energy economic models, which simulate the deployment of technologies to meet demand for energy services at least cost, has enabled proposed policies to be explored in detail. However, much of the modeling effort has been focused on national policy. Prominent examples include an exploration of the potential effects of a national non-hydro RPS of 20% by 2020 using the Energy Information Administration’s National Energy Modeling System (NEMS), which forecasted a 16.5% decrease in CO_2 emissions and a modest 3% increase in electricity prices relative to the reference case in 2020 [30]. Palmer and Burtraw [39] proposed a cost-optimal national RPS of 15%, which they calculated using Resources for the Future's Haiku engine to model targets between 5% and 20%. The Department of Energy used the Regional Energy Deployment System (ReEDS) to model the effects of wind power penetration reaching up to 35% on national greenhouse gas emissions and electricity prices by 2050 [42]. More recently, bilevel optimization models have utilized multi-objective linear programming techniques to minimize CO_2 emissions under cost constraints [31], and to minimize the cost of policy intervention [37]. Considering the uncertainty inherent in large capacity expansion models, researchers have developed stochastic optimization techniques to model energy policy choices under policy, renewable resource availability, and load uncertainty [32-34, 43, 44].

Despite the valuable insights provided, the abundance of national-level modeling in the literature belies the relative lack of national-level energy policy. Congress has largely failed to implement any comprehensive energy policy, resorting instead to a patchwork of temporary tax incentives, fuel mandates, and energy efficiency measures, often with dubious success [45]. There have been relatively few studies focused on the implementation of state-level policies, despite the hundreds of policies enacted across all 50 states [46]. State-level RPSs, tax incentives, and a price on carbon have been considered for their effectiveness in reducing CO_2 emissions, utilizing long-term economic dispatch models in Michigan and surrounding states [29], the combined Utah/Arizona region [38], and California [35]. These modeling efforts considered leakage of CO_2 emissions and electricity trading between states, utilizing the commercial software packages Plexos, AURORAxmp, and CA-TIMES, respectively.

The aim of this thesis is to create such a framework for the evaluation of different electricity policies in North Carolina. This thesis addresses the following question: How do different energy policies affect the levelized cost of electricity (LCOE), installed capacity, renewable generation, and emissions in North Carolina? This analysis is carried out using a linear optimization model that minimizes the total cost of electricity sector investment and operation over a 35-year time horizon. The scenario results suggest which policies will have the least impact on electricity rates while achieving renewable energy or emission reduction goals. The broader intent of this research is to create an analytical process that draws on publicly available data and Tools for Energy Model Optimization and Analysis (Temoa), an open-source energy economic optimization model, to examine proposed energy policies within any state in the nation.

The remainder of this document is organized as follows. The METHODOLOGY section discusses the energy system optimization model and additional constraints created specifically for this research. The DATA section provides details on how the North Carolina dataset was constructed and calibrated. The ENERGY AND CLIMATE POLICIES section covers the proposed energy policies and discusses how they were modeled. The RESULTS AND DISCUSSION section presents model results for comparative scenario analyses and discusses the drivers behind the policy impacts, culminating in the CONCLUSION section, which distills insights gained through this effort.

METHODOLOGY

Understanding how energy policies impact the long-term energy portfolio of a state often requires an energy system model capable of performing capacity expansion planning and least-cost optimization. There are many energy model options, which generally fall into four major categories: data and resource assessment, capacity expansion, system operation, and network reliability [47]. Investigating the long-term impact of energy policies on the power sector is best performed by capacity expansion models [47], which simulate generation capacity investments over a long-term time horizon using estimated future costs. Capacity expansion models also represent basic power system dispatch, whereby generators are dispatched to meet demand at the lowest cost subject to policy constraints. Prominent capacity expansion models include the National Energy Modeling System, used by the Energy Information Administration (EIA) to generate the Annual Energy Outlook [1]; the Regional Energy Development System [48] used in the Department of Energy's Wind Vision report [42]; and the Open Source Energy Modeling System (OSeMOSYS), free, publicly available software which has been used to examine the climate, land, energy and water nexus [49] and to model smart grid components [50]. These models are typically national-scale and often lack the high spatial and temporal resolution required for state-level policy analysis and integrated resource planning (IRP). Sophisticated capacity expansion models are often inaccessible to many state governments and energy stakeholders given the time, cost, and expertise required to operate them. To help address this lack of access, an open source model was used to perform this analysis.

Tools for Energy Model Optimization and Analysis

Temoa, the open source energy economy optimization (EEO) model [51] chosen for this analysis, was first developed at North Carolina State University under a National Science Foundation grant [52]. Temoa was created to address two critical deficiencies associated with existing energy models: an inability to independently verify third party model results, and the difficulty of performing uncertainty analysis on complex models [53]. The former is addressed through Temoa's use of GitHub to maintain revision control of source code, so that any entity interested in recreating results can access the model. Temoa has the capability to perform stochastic optimization [54] and modeling to generate alternatives

[55], which are powerful uncertainty analysis tools that address both parametric and structural uncertainties. The source code is independent of the input dataset, so a dataset can be constructed for any energy system of interest. Datasets can represent user-specified sectors, such as transportation, electricity, and residential. This analysis focuses exclusively on the electricity sector.

Temoa functions by minimizing the total present cost of energy over a user-specified time horizon, subject to structural constraints that represent physical aspects of the system. The objective function is shown in Equation 1, which consists of four cost components: investment, variable, fixed, and salvage. The investment cost represents the total capital outlays required plus the cost of capital (loan interest); variable costs include operational expenses as well as importing fuel costs; and fixed costs are those incurred proportional to the capacity installed, and do not change with the amount of energy production. Salvage costs were introduced into the model to mitigate well-documented end effects of linear models with finite lifetimes [56], and are calculated using linear depreciation of assets over their lifetimes. The set indices $p, s,$ and d represent period, season, and time-of-day indices, respectively, while t and v represent technologies and vintages (the period in which capacity is installed), respectively.

$$\min \sum_{p} \sum_{t} \sum_{v} \Bigg(Capacity[t, v] \cdot (CostInvest[t, v] \cdot LoanAnnualize[t, v] + CostFixed[p, t, v]) + \sum_{s} \sum_{d} Activity[p, s, d, t, v] \cdot CostVariable[p, t, v] - SalvageCost[p, t, v] \Bigg)$$

Equation 1

Energy models used to study how energy policies effect renewable electricity deployment must be able to represent the temporal variability associated with non-dispatchable renewables. A dispatchable technology can ramp electrical output on demand, such as natural gas combustion turbines. Wind and solar vary with the prevailing meteorological conditions, and therefore cannot be dispatched on demand. Annual or even monthly model resolutions will fail to capture the diurnal variations in load and renewable output, which is a critical factor in system operation. To more accurately model the intermittency of renewables, a representative hourly resolution is used. The intra-annual electricity variations are represented by dividing each year within a period into multiple time slices (described below), each representing multiple hours. Electricity demand and generation are permitted to vary between time slices, but not within them. These time slices are expressed by two parameters in Temoa: segment fractions ($SEG_{s,d}$) and demand specific distribution ($DSD_{s,d,c}$). $SEG_{s,d}$ is the fraction of a year represented by each time slice, and $DSD_{s,d,c}$ is the fraction of annual demand allocated to that time slice.

An actual year consists of 8760 hours, each with unique load and generation outputs. Solving a model with that level of temporal resolution would be computationally prohibitive. For example, each time slice includes a decision variable indicating how much energy flows into and out of each combination of technology, input and output commodity, and vintage. Doubling the number of time slices would increase the number of inflow and outflow decision variables 256-fold. To reduce computation time, each period is split into 96 representative segments: four seasons, each partitioned into 24 times-of-day. Each time-of-day slice represents between 90 and 92 actual hours, depending on the season it is in. Dividing the number of hours per time slice by 8760 creates the segment fraction. The total demand in a period is distributed proportionally among the 96 segments to match seasonal and hourly electricity load profiles in North Carolina, creating the $DSD_{s,d,c}$ parameter. The representation of demand is expressed in more detail in the Electricity Demand section.

Additional Constraints

The results generated by Temoa represent the least cost optimal solution, subject to a variety of physical constraints. Many of these constraints, such as commodity balance and supply-demand balance, have been documented [53]. Due to the long-term planning horizon of capacity expansion models, short-term operating characteristics are typically neglected. However, due to the focus on state-level renewable energy policy, system reliability is an issue. Three additional constraints were added to better model the intermittency effects of wind and solar: a system-wide reserve margin, maximum generator ramp rates, and hourly storage of electricity.

Reserve Margin Constraint

The first set of constraints requires Temoa to build enough capacity in each period to satisfy minimum capacity reserve margins. The reserve margin is defined by the North American Electric Reliability Cooperation (NERC) as the amount of unused electric capacity at the time of peak load [57]. The purpose of capacity reserve margin is to guarantee that utilities can reliably meet peak demand. Each balancing authority under NERC sets a reference level, and assesses the ability of utilities to meet this reliability metric. North Carolina falls under the South-Eastern Reliability Cooperation (SERC) balancing authority, which sets a minimum 15% reference reserve margin [58]. The reserve margin requirements are evident in the integrated resource plans (IRP) of both Duke Energy and Duke Progress, where an internal goal of 15% (summer) is used in assessing the need for future capacity additions [59, 60]. The reserve margin constraint first finds the peak demand time slice for each period, and then requires enough capacity to meet this demand plus the specified reserve margin. A full formulation of this constraint can be found in Appendix A – Additional Constraint Formulation.

Ramp Rate Constraint

The ramp rate constraint limits the rate of change in generation from a technology between adjacent time slices. This reflects the real-world constraint on the ability of certain power plants to ramp their output. Within Temoa, nuclear and 40% of coal-fired capacity are classified as ‘baseload’, and are unable to change their output across the time-of-day time slices within the same season (see the Technical Parameters of this report for a more detailed discussion of baseload definitions). This partial baseload classification is used to ensure that at the aggregate level, coal plants do not operate below minimum set points [61, 62].

However, natural gas and the remaining 60% of coal-fired capacity are allowed to vary their output between hourly slices, but the rate of change is restricted to account for the hourly resolution of the model. Table 1 below provides the ramp rate constraints for coal and natural gas, drawn from a FERC report which compiled operational data from power plants within the PJM Interconnection [61]. Ramp rates for the relatively new integrated gasification combined cycle (IGCC) are drawn from empirical data and Department of Energy reports [63, 64]. Because the temporal resolution of Temoa is hourly, and natural gas can modify its output by over 100% of its capacity within an hour, ramp rate constraints are only applied to the load-following portion of coal. Other energy sources, such as wind, solar, biomass, diesel, landfill gas, and hydro, have unrestricted ramp rates. A full formulation of this constraint can be found in Appendix A – Additional Constraint Formulation.

Table 1: Ramp rate limits from PJM generation fleet, as a % of total capacity [61]. IGCC rates from DOE [63, 64].

Tech Name	Ramp Rate (%/min)	Ramp Rate (%/hr)
Coal, steam	0.7%	42%
Coal, IGCC	3.5%	210%
NG, combined cycle	1.8%	108%
NG, combustion turbine	3%	180%

Hourly Energy Storage Constraints

Energy storage is increasingly being deployed across the U.S. in numerous applications in order to avoid renewable electricity curtailment, increase power grid reliability and resiliency to contingencies, and serve as operating reserves that can respond quickly to peak demand. [65]. To model these varied applications accurately within Temoa, rules were devised to allow storage technologies to retain the remaining stored energy between time slices. This required exempting all energy storage technologies from the process balance constraint, a fundamental constraint that states the total energy out of a technology must be less than or equal to the total energy in multiplied by the efficiency, during any given time slice [53].

A new decision variable was created, $\mathbf{HS}_{p,s,d,t}$, which represents the amount of energy within a storage technology t for given a time slice, defined by period p, season s, and time of day d. The amount of stored energy is limited by the capacity of the storage device (in GW) multiplied by 8 hours. The operational characteristic of 8 hours reflects its assumed function as large-scale energy storage at the transmission level; in addition, cost estimates were drawn from 8-hour transmission-level storage [66, 67]. However, this is a technology-specific user specified parameter that can be adjusted for any energy storage technology within the hourly storage set. The energy stored is permitted to carry over between representative time-of-day slices and seasons, mimicking utility-scale storage behavior, but must zero out at the end of each period. This is to prevent Temoa from potentially taking advantage of differences in costs between early and late periods to store energy for years or even decades, something that storage is not designed for in reality. The mathematical formulation of the hourly storage constraint in Temoa is presented in Appendix A – Additional Constraint Formulations.

DATA

Energy system optimization modeling requires detailed, accurate data to produce results that are meaningful to policy negotiations. In addition, to enable interested parties to run Temoa-compatible models on their own, the data must be publicly available. The following section describes how the North Carolina dataset used in this research was constructed.

Temoa input datasets consist of user-defined technologies, which are linked through a set of user-defined commodities in a network diagram. Each technology is defined by a set of technical and economic parameters, such as capital cost, operations and maintenance costs, emission rates, conversion efficiency, and lifetimes. Individual technologies in the NC dataset do not refer to individual generators, but rather total installed capacity associated with a technology and its vintage. For example, state-wide electricity generation at advanced combined cycle natural gas plants is represented by 'ENGAACC', which converts the input commodity (natural gas) to the output commodity (pre-transmission and distribution electricity).

A simplified network diagram for the North Carolina dataset is shown in Figure 1. In this conceptual image, all power plants that use the same type of fuel are grouped into a single category, as they will be throughout this report. The final commodity, 'ELCDMD', represents the user-specified total end-use demand in North Carolina. Energy technologies consume energy commodities such as natural gas or solar, and produce either ELC (if from traditional fuels) or ELCRNWB (if from those technologies classified as renewable by the North Carolina legislature). The renewable electricity commodity is used to track total renewable generation to meet a RPS. Just as in the actual electricity market, these commodities must then flow through transmission and/or distribution technologies before they are converted to demand. The following section details the construction of the North Carolina dataset.

While many sources contribute to the NC dataset, the Environmental Protection Agency's (EPA) MARKAL/TIMES databases was the most heavily relied upon. The MARKAL/TIMES model was created and maintained by the International Energy Agency (IEA), and has been used by hundreds of institutes in over 80 countries, and is generally considered the "benchmark integrated energy system optimization platform available for use around the world" [68]. The EPA maintains its own dataset based on nine US Census defined regions [69]. For the purposes of this model, costs from region five (South Atlantic) were used for North Carolina.

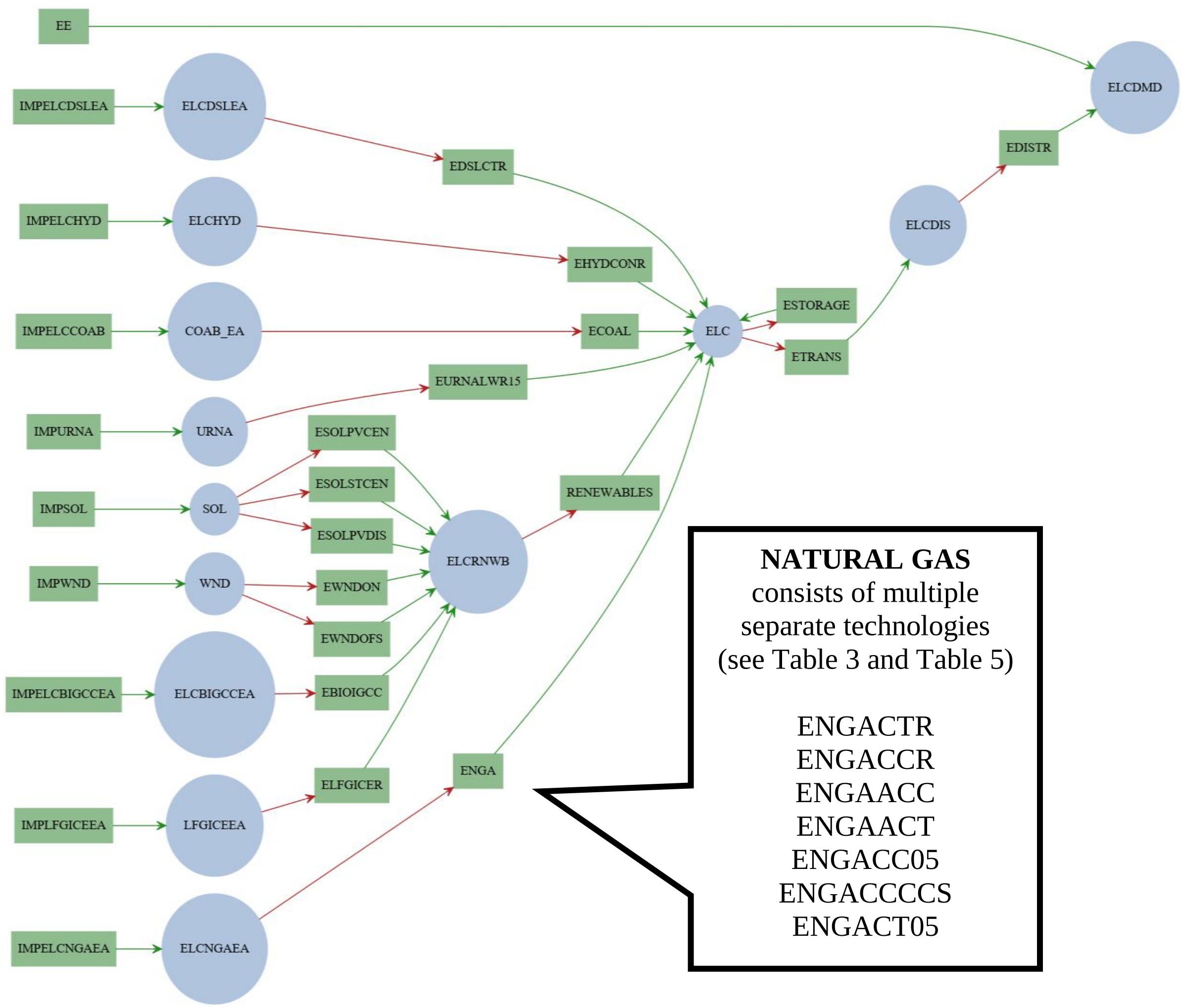


Figure 1: Simplified network diagram of North Carolina dataset. Green boxes are technologies; blue circles are commodities. Pollution control retrofits and fuel blending technologies have been omitted for clarity.

Electricity Demand

North Carolina electricity demand is exogenous to the model, so aggregate electricity demand must be specified for each optimization period as an input parameter. In 2015, the total electricity generation in North Carolina was 128,388 GWh [70]. The North Carolina Energy Policy Council predicts that the demand for NC electricity will grow at an annual rate of 1.2% between 2015 and 2030 [71] which equates to a 20% increase by 2030. Note that this growth rate is based on the IRPs of Duke Energy Progress and Duke Energy Carolinas, the two largest utilities serving North Carolina, providing over 70% of total electricity sales [72]. Although Dominion Energy, another electricity company which primarily serves the northeastern corner of North Carolina, predicts a slightly higher growth rate for its territory within NC, its sales accounted for less than 4% of North Carolina's total electricity generation [72]. Municipalities and electric cooperatives provide the remainder of NC electricity. Therefore, I assume that total NC electricity demand will increase at a yearly growth rate of 1.2% from 2015 to 2050, using historical NC electricity consumption in 2015 as the base year. Table 2 shows the annual electricity demand predictions for North Carolina.

Table 2: Projected electricity demand in North Carolina.

Period	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Demand (TWh)	128	136	145	154	163	173	184	195

As discussed in the METHODOLOGY section, each period is represented by 96 time slices, described by two parameters: the fraction of the total year represented by each time slice ($SEG_{s,d}$), and the demand specific distribution ($DSD_{s,d}$), which represents the total amount of annual demand that falls within each time slice. Activities within each time slice are assumed to be indivisible within the model, with both load and electricity generation held constant. The $DSD_{s,d}$ parameter, which depicts the seasonal and diurnal variations in demand, is the ratio of the demand during a time slice and the total annual demand. The demand during a given time slice is calculated by summing all hourly loads during time of day d and season s. Combined hourly electricity load data for Progress Energy (FERC ID 233) and Duke Energy (FERC ID 157) in 2014, obtained from the Federal Energy Regulatory Commission (FERC) Form 714 [73], was used for this analysis. Sorting loads from greatest to least by time slice by load produces a load duration curve. Figure 2 displays the representative load duration curve used in Temoa against the actual load duration curve in North Carolina. Note that the load in Temoa fails to capture parts of the peak demand due to its the lower resolution (96 time slices versus 8760 hourly values). The lower peak load in Temoa would result in a non-binding reserve margin constraint. To compensate for the discrepancy in peak load values, the 15% reserve margin requirement imposed by FERC is increased to 60% within Temoa, which approximates the 41 GW reserve capacity requirement in 2015.

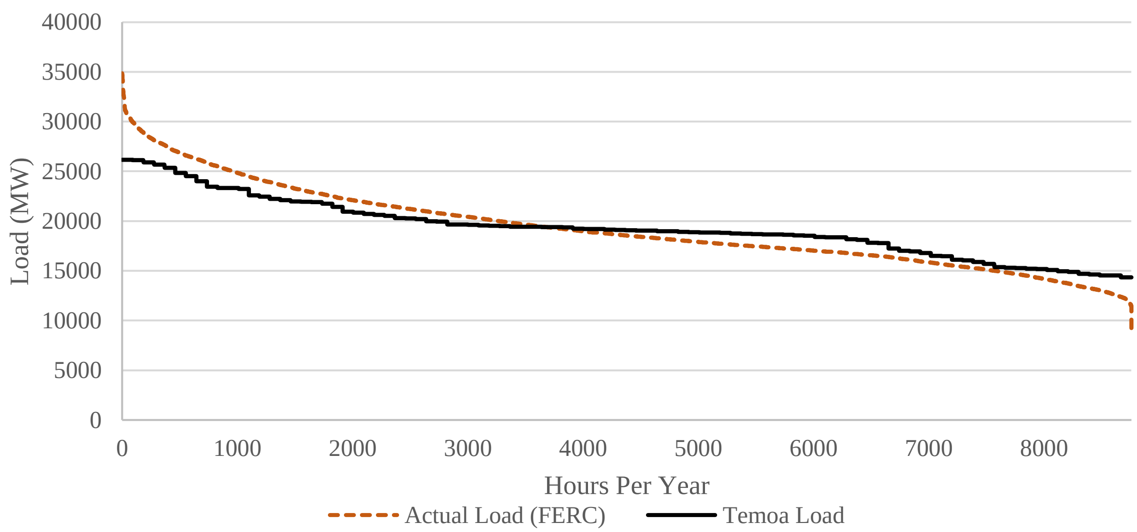


Figure 2: Load duration curve for North Carolina: actual 2014 data from FERC filings [73] and Temoa representations with 4 seasons and 24 time slices per season. Each time slice represents approximately 91 hours.

Temoa allows each technology to be assigned a maximum capacity factor for each season and time of day. Setting capacity factors to match the available resources is used to constrain maximum output for solar and wind. For example, setting the solar capacity factor to zero for hourly slices 1 through 6 and

20 through 24 prohibits solar electricity generation at night. The construction of hourly capacity factors will be discussed in more detail in the Technical Parameters section.

Technologies and Commodities

There are two categories of energy generation technologies used in the construction of the input dataset for North Carolina: residual (or existing) technologies, and future technologies. Residual technologies represent those energy generation technologies which already exist in North Carolina, and a summary of those technologies and their corresponding Temoa name is presented in Table 3. This data was drawn from EIA Form 860, which annually reports all electricity generators in each state by prime mover and energy source [74]. Each existing electric sector generator is mapped to a specific Temoa technology, which is described in detail in Appendix B – EIA to Temoa Mapping.

Table 3: Capacity of residual technologies in North Carolina [74].

Technology	Description	2015 Capacity (MW)
EBIOSTMR	Biomass – steam turbine	402
ECOASTMR	Coal – steam turbine	10,803
EDSLCTR	Diesel	403
EHYDCONR	Conventional Hydro	2,004
EHYDREVR	Hydro – Pumped Storage	86
ELFGGTR	Landfill Gas – Gas Turbine	15
ELFGICER	Landfill Gas – Integrated Gasification	60
ENGACCR	Natural Gas – Combined Cycle	4,766
ENGACTR	Natural Gas – Combustion Turbine	6,050
ESOLPVR	Centralized Solar PV	1,437
EURNALWR	Nuclear	5,114
	TOTAL	31,140

It should be noted that within a single technology representation, not all generators are the same – older power plants tend to be less efficient and costlier to operate. In addition, as power plants age and reach the end of their useful life, their capacity must be retired. The capacity expansion problem therefore requires a retirement profile, which reduces the residual capacity of each technology based on an exogenously specified schedule.

To this end, Temoa is capable of differentiating age within a single technology category using vintages. The vintage represents the year in which capacity for a specific technology was put into service. This differentiation is done by splitting the residual capacity displayed in Table 3 into the appropriate vintage. Using EIA Form 860 data [74], vintages were set up into 5-year bins. For example, capacity built between 1993 and 1997 (inclusive) is categorized as a 1995 vintage. For simplicity, all capacity added prior to 1958 is grouped into the 1960 vintage.

The next step in creating a retirement profile is to specify technology lifetimes. Temoa retires the capacity associated with a given vintage if its lifetime is exceeded at the beginning of an optimization period. Data from the EPA [69], National Renewable Energy Laboratory (NREL) [75], and Pacific Northwest National Laboratory's MiniCam [76] were compared to the actual lifetimes of decommissioned plants in the US, provided by the EIA [74]. From this data, lifetimes were chosen for the Temoa model (Table 4).

Table 4: Comparison of technology lifetimes in years for the US and across energy models [69, 74, 75].

Technology	**Category**	**Avg Lifetime (entire US)**	**NREL**	**MiniCAM**	**EPA MARKAL**	**Temoa (this paper)**
EBIOSTMR	BIOMASS	49	**45**	**45**	40	**45**
ECOASTMR	COAL	53	**60**	45	40	**60**
EDSLCTR	DIESEL	41	*n/a*	*n/a*	50	**45**
EHYDCONR	HYDRO	68	*n/a*	*n/a*	120	**70**
EHYDREVR	HYDRO	*n/a*	*n/a*	*n/a*	40	**70**
ELFGGTR	LFG	16	**30**	45	**30**	**30**
ELFGICER	LFG	14	**30**	45	30	**30**
ENGACCR	NG-CC	30	30	45	30	**40**
ENGACTR	NG-CT	37	30	45	30	**40**
ESOLPVR	SOLAR	10	**30**	**30**	**30**	**30**
EURNALWR	NUC	32	**60**	**60**	40	**60**

With pre-existing capacity split into 5-year vintage bins, and technology lifetimes specified, Temoa has the information needed to model retirements over the 35-year optimization time horizon. Figure 3 presents the retirement profile for the six largest categories of pre-existing capacity. Of the 31.1 GW of pre-existing capacity available to meet demand in 2015, only 1.9 GW remains in 2050. This increasing gap between pre-existing capacity and demand must be met through the addition of new capacity.

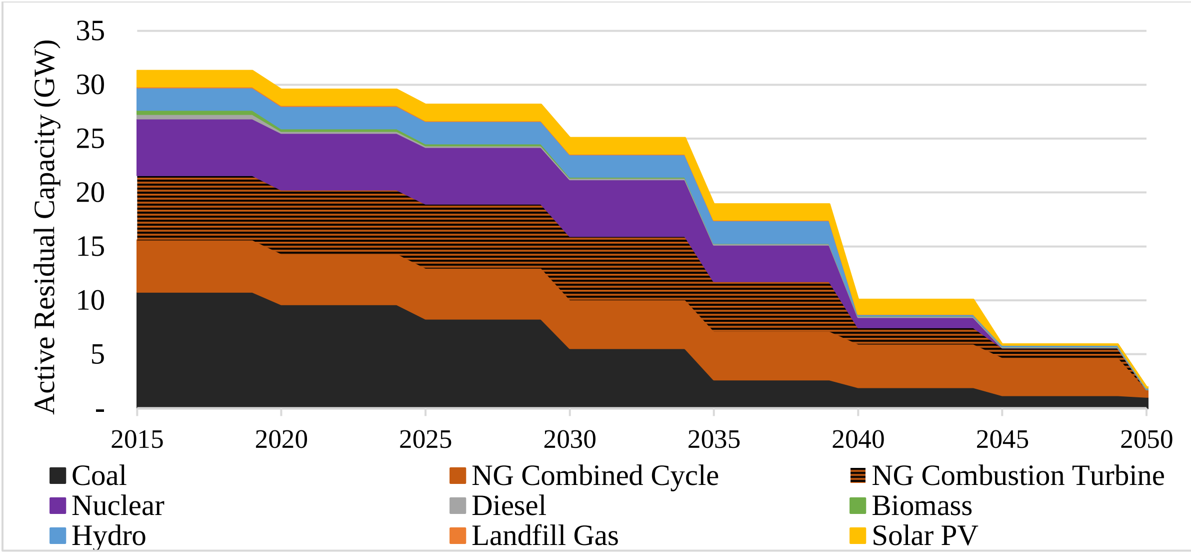


Figure 3: Retirement profile for existing capacity in North Carolina.

New capacity is added as needed by Temoa in each period to satisfy electricity demand. For this analysis, new generation technologies were drawn from the EPA MARKAL database [69] and are displayed in Table 5. Technologies from this database have detailed technical and cost projections by US Census region and provide sufficient representation of electric generation technologies. Each of the 37 generation technologies used in Temoa represents a specific fuel source (e.g., coal or solar) and prime mover (e.g., combustion turbine or combined cycle). It is important to note that not all future technologies are currently deployed in North Carolina, but they are made available for future investments. In addition, due to geographical and environmental limitations, new hydro plants are not represented within the NC dataset. The costs and technical parameters that define each technology will determine which technologies are deployed in future periods. The set of four utility-scale energy storage technologies in the NC dataset use electricity for both input and output commodities, and are allowed to store energy between time slices.

Table 5: Future energy generation technologies used in NC dataset.

Technology Name	Description
ENGACC05	Natural Gas - Combined-Cycle (Turbine)
ENGACT05	Natural Gas - Combustion Turbine
ENGAACC	Natural Gas - Advanced Combined-Cycle (Turbine)
ENGAACT	Natural Gas - Advanced Combustion Turbine
ENGACCCCS	Natural Gas Combined Cycle -- CO_2 Capture
ECOALSTM	Pulverized Coal Steam - 2010
ECOALIGCC	Integrated Coal Gasification Combined Cycle
ECOALIGCCS	Integrated Coal Gasification Combined Cycle -- CO_2 Capt.
ECOALIGCCS_b	Integrated Coal Gasification Combined Cycle -- CO_2 Capt., BASELOAD
ECOALIGCC_b	Integrated Coal Gasification Combined Cycle, BASELOAD
ECOALSTM_b	Pulverized Coal Steam - 2010, BASELOAD
ECOASTMR_b	Residual Coal Steam, BASELOAD
EURNALWR15	Nuclear Light Water Reactors
EBIOIGCC	Biomass Integrated Gasification Combined-Cycle
EGEOBCFS	Geothermal - Binary Cycle and Flashed Steam
ESOLPVCEN	Solar PV Centralized Generation
ESOLPVDIS	Solar PV Distributed Generation (rooftop solar)
ESOLSTCEN	Solar Thermal Centralized Generation
EWNDON	Onshore Wind (Generation Class 4)
EWNDOFS	Shallow Offshore Wind (Generation Class 5)
ESLION	Energy storage: lithium ion batteries
ESFLOW	Energy storage: flow batteries
ESCAIR	Energy storage: compressed air (natural storage spaces)
ESZINC	Energy storage: zinc batteries
EE	Energy Efficiency measures (limited to 5% of annual demand)

The function of commodities within Temoa is to link technologies together to form a network diagram. Examples include physical commodities (such as imported natural gas) as well as theoretical (such as renewable electricity). Importing technologies are used to assign prices to primary energy commodities, such as natural gas or subbituminous coal. In addition, commodities are used to account for emissions

– the NC dataset tracks electric sector CO_2, SO_2, and NO_X. A full list of commodities used is given for reference in Appendix C – Commodities.

In order to reflect real-world limitations on natural gas production and usage, an upper bound is placed on the natural gas supply. This upper bound is based on a historical analysis of natural gas consumption by all NC sectors (electricity, residential, commercial, industrial, and transportation) [77], as well as future projections of population growth [78] and national natural gas production [1]. The upper bound placed on natural gas consumption accounts for new pipelines scheduled for completion in North Carolina, and assumes that the electricity sector will continue to increase its share of natural gas. Figure 4 displays the historical natural gas consumption in the electricity sector, as well as the projected upper bound of natural gas used in the Temoa model.

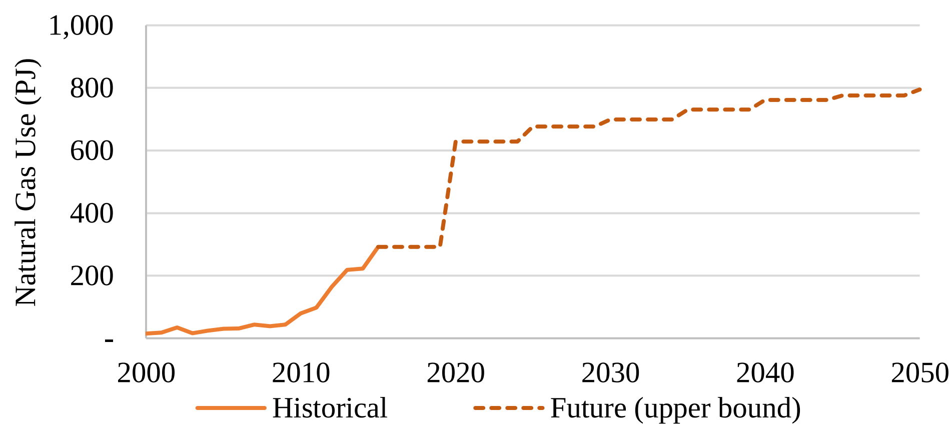


Figure 4: Natural gas historical use and future capacity limits.

Technical Parameters

Each technology in Temoa must be supplied with a set of technical parameters that characterize its operation within each period. The properties in Table 6 broadly define the operational characteristics of each technology in a way that allows the model to meet required physical constraints. Efficiency and emission activity of a technology are linked to vintages within a technology, whereas the remaining parameters are the same for all vintages and through all optimization periods.

Table 6: Technical parameters used to define operation of electricity technologies in Temoa.

Parameter	Description	Source
Efficiency	The ratio of energy out of a technology to energy in (inverse to heat rate)	EPA MARKAL [69] and EIA [74]
Availability Factor	The maximum amount of electricity that can be produced in a given hourly time slice, relative to nominal capacity	NREL: Wind & Solar [79, 80] Other: EPA MARKAL [69]
Capacity Credit	The contribution to peak demand made by non-dispatchable technologies	International Energy Agency [81, 82]
Emission Factor	Kilotons of CO_2, SO_2, and NO_x emitted per PJ of energy generated	EPA eGRID [62]
Baseload Classification	Classification of a technology as a “baseload” prevents electricity generation from changing throughout the day to follow varying demand	EIA [83]
Maximum Ramp Rate	The maximum rate of change in electricity production allowed in a power plant, expressed in percent of total capacity per hour. See Ramp Rate Constraint section for definition and data.	FERC [61]

Efficiencies

In gathering data for the efficiency parameter, the primary data source was the EPA MARKAL database. EPA provides regional estimates of the heat rate of each technology (residual and new) used in the Temoa analysis under the INP(ENT)c parameter. Because the data from the EPA represents regional averages, EIA Form 860 (generator capacity) and Form 923 (net generation by state) was used to check the applicability of South Atlantic estimates in North Carolina. For example, MARKAL estimates that residual natural gas combined-cycle generators in the South Atlantic have an efficiency of 42.2% [69]. However, an analysis of state-level data shows an efficiency of 47.4% [70, 84]. For consistency, state-level data was used to correct the efficiencies of residual technologies only. Energy storage round-trip efficiencies were gathered from cost analyses [67, 85] and supporting literature [66, 86, 87], and differ for each of the four energy storage technologies within the NC dataset.

Availability Factor

In Temoa, the availability factor serves as the upper bound on the capacity factor. The capacity factor is defined as the ratio of actual electricity output to the nameplate capacity of a resource [83], and is specified for each time slice. For dispatchable fossil fuel technologies, the maximum capacity factor is set to 90% for all time slices to reflect the fact that power plants are not able to run at full power year-round due to periodic shutdowns for required preventative maintenance. For non-dispatchable technologies, such as wind and solar, the availability factor reflects the resource availability. Data for solar PV was drawn from NREL [79], which consist of 1 year of 5-minute solar power and hourly day-ahead forecasts for approximately 6,000 simulated PV plants. The practical difference between the utility and distributed solar is the configuration, where utility-scale has single axis tracking, while distributed solar is fixed tilt equal to latitude. In addition, data for both onshore and offshore wind is drawn from NREL [80]. To convert these hourly capacity factors to the time slice capacity factors used in Temoa, first the hourly data was categorized by the season and time of day slices used in Temoa. The average capacity factor across all sites in North Carolina during a specific season and time of day slice was used in the Temoa dataset. This process resulted in the hourly capacity factor profiles for wind and solar shown in Figure 5, with average values shown in Table 7.

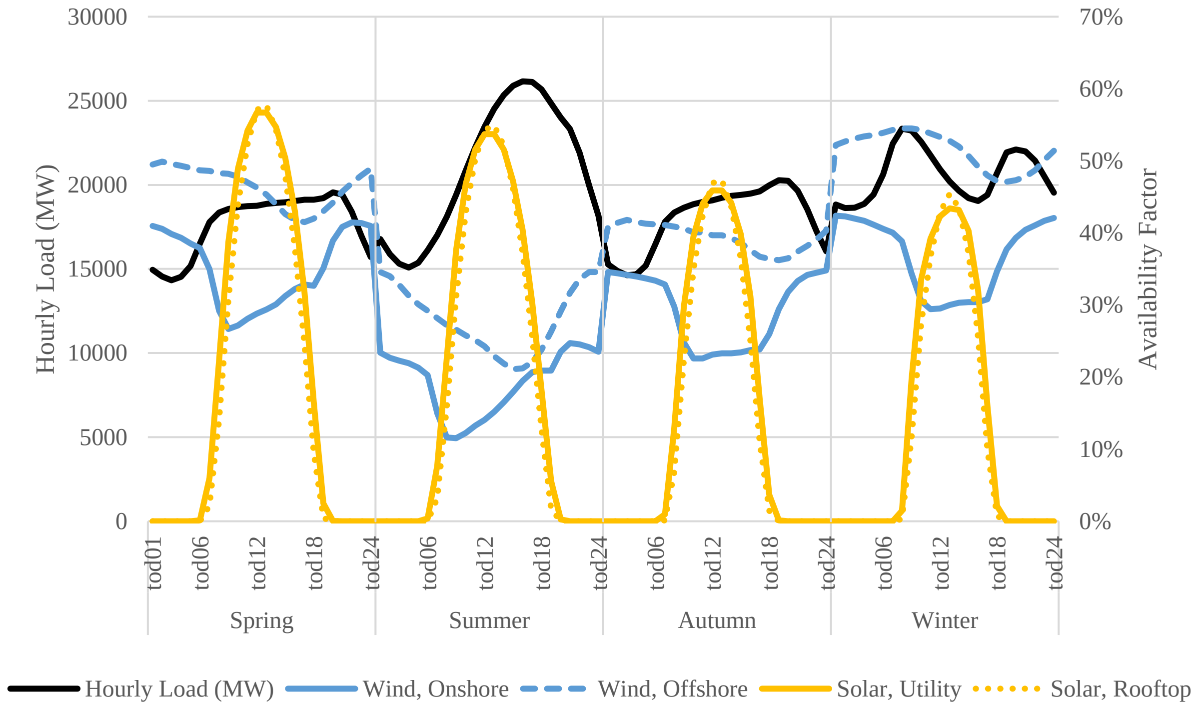


Figure 5: Temporal variation in demand and availability factors for wind and solar.

Capacity Credits

The hourly capacity factors plotted in Figure 5 indicate that, with some exceptions, wind tends to be most productive during hours of low demand, while solar is most productive during higher demand times. This concept of varying contributions to peak demand relates to: capacity credit, which is a measure of how much a resource is able contribute to reducing peak demand [81, 82, 88]. Dispatchable generation, such as coal or natural gas, usually have capacity credits close to their nameplate because they can be relied upon to generate during peak periods. Non-dispatchable resources, such as wind and solar, receive less capacity credit. Methods for estimating the capacity credit of renewable sources differs depending on the metric used [82]. Temoa uses the capacity credits to discount the contribution of non-dispatchable capacity toward the reserve margin constraint.

One method of estimating capacity credits is the Effective Load Carrying Capability (ELCC). The ELCC of a power generator represents its ability to effectively increase the generating capacity available to a utility or power grid without increasing the utility's loss of load risk. Capacity credits of solar and wind derived from the ELCC method are used in the NC dataset [89]. Although previous studies show that capacity credits are affected by factors such as location and existing renewable energy penetration, modeling capacity credits as dependent variables will introduce non-linearities into the Temoa formulation. The reserve margin calculation multiplies the capacity available per period (a decision variable) by the capacity credit; if the capacity credit were dependent on the capacity available, there would be a non-linearity with respect to the capacity decision variable. Therefore, it is assumed that capacity credits will remain constant at 20% for both onshore and offshore wind, and 35% for all forms of solar PV, summarized in Table 7 [81, 82, 88, 89]. For simplicity, all forms of dispatchable technologies are assumed to have a capacity credit of 100%.

Table 7: Average annual capacity factors for non-dispatchable renewable energy.

Resource Type	**Technology**	**Average Availability Factor**	**Capacity Credit**
Wind	EWINDON	30.0%	20%
	EWINDOF	41.3%	20%
Solar	ESOLPVR	16.0%	35%
	ESOLPVCEN	16.9%	35%
	ESOLPVDIS	15.2%	35%

Emission Factors

Emission factors are primarily obtained from the EPA's MARKAL database and eGRID data [62, 69]. This database provides historical emission rates for generators across the country. This study considers three types of emissions: NO_X, SO_2, and CO_2. Generators in North Carolina were analyzed and cross-referenced to generator details found in EIA Form 860 [74] to calculate technology specific emission rates. In addition, a network of emission control devices allows Temoa to install carbon capture retrofits and sequestration on coal steam plants if necessary to meet emission limits. The emission rates used in the NC dataset are summarized in Table 8 for fossil fuel generation technologies. Technologies that utilize biomass are considered carbon neutral, as most biomass generation in North Carolina is from wood waste products [70].

Note that we assume new pulverized coal plants will be equipped with state-of-the-art SO_2 and NO_X removal devices and thus no future retrofitting will be required. However, existing coal plants assume uncontrolled emissions of SO_2 and NO_X, and emission control retrofits are required to meet air quality standards. In this study, SO_2 removal through Flue Gas Desulfurization (FGD) is categorized based on coal type and sulfur level, and NO_X removal technologies include Low NO_X burners (LNB), Selective non-Catalytic Reduction (SNCR) and Selective Catalytic Reduction (SCR). The capacities of existing retrofit installations are drawn from the EPA eGrid database. In addition, Temoa can install carbon capture and sequestration (CCS) on both existing and new coal units to meet CO_2 emission limits.

Table 8: Emission rates for North Carolina dataset.

Fossil Fuel Technology	Emission Activity (kilotons / PJ_{out})		
	CO_2	NO_X	SO_2
ENGACTR	204	0.019	0.001
ENGACT05	158	0.015	0.0008
ENGAACT	126	0.012	0.0006
ENGACCR	136	0.0128	0
ENGACC05	100.3	0.0094	0
ENGAACC	93.4	0.0088	0
ENGACCCCS	11.0	0.010	0
EDSLCTR	314.3	0.487	1.605
EBIOSTMR [a]	0	0.273	0.790
EBIOIGCC [a]	0	0.196	0.104
ECOALSTM	227.9	0.892	3.057
ECOALSTM w/ CCS	55.9	0.892	3.057
ECOALIGCC	42.3	0.883	3.026
ECOALIGCCS	10.8	0.842	2.886
ECOASTMR	251.2	0.983	3.369

[a] *Biomass resources are assumed to be carbon neutral.*

Baseload Classification

According to the EIA, baseload technologies are designed to satisfy minimum system demand, and "produces electricity at an essentially constant rate and runs continuously" [83]. If a technology is classified as baseload, Temoa does not allow the amount of electricity generated to vary hourly within a season. The North Carolina dataset treats nuclear as baseload, per public statements by Duke Energy and Duke Energy IRPs [59, 60, 90]. In addition, coal is split into two technologies: 40% of coal capacity is considered baseload per eGRID data [62], while the other 60% is subject to ramp rate constraints. These ramp rate constraints are imposed to control how fast non-baseload coal can change its hourly generation profile, and is discussed in the Reserve Margin Constraint section of this thesis.

Costs

As discussed in the METHODOLOGY section, Temoa minimizes the total net present cost, which is broken into the four main categories: investment costs, fixed costs, variable costs, and salvage value (which is dependent on the investment costs and remaining lifetime at the end of the time horizon). Investment costs represent the initial capital outlay plus loan costs needed to build new capacity; fixed costs represent operations and maintenance costs that are independent of operations; and variable costs include operational expenses for different technologies (both electricity generation and fuel expenses).

Investment costs in the MARKAL dataset are in units of million dollars per gigawatt of capacity added [M$/GW], in 2005 dollars. The costs used in this North Carolina dataset are 2015 constant dollars, so the cost estimates from the EPA were adjusted using the Consumer Price Index [91]. These costs are the “overnight” capital costs, which assume that the capacity added is available at the beginning of the period in which the costs are incurred [92]. For nuclear and fossil fuel technologies, costs within the MARKAL database are relatively mature and were directly transferred into Temoa.

Wind and utility-scale solar generation is specified for five cost categories and five generator classes in the MARKAL database. For wind, with which North Carolina developers do not have significant experience owing to the lack of wind deployment, the regional average was used. For utility-scale solar PV, which North Carolina developers have significant project experience due to a recent solar boom [93], costs used are the cost category B only. These costs are slightly lower than actual project costs in the region [94], which reflect operational efficiencies within the solar development community in North Carolina. Finally, as the MARKAL database does not predict costs for distributed solar, North Carolina specific project costs and trends were used to estimate the costs of rooftop solar

[95, 96]. A full listing of new technologies and their investment costs can be found in Appendix D – Cost Figures.

Energy storage costs for the four technologies (lithium ion, zinc, and flow batteries, and compressed air) are still nascent, with utility energy storage just recently becoming mainstream. Investment costs for each of these storage technologies were primarily drawn from detailed industry cost analyses by Lazard [67, 85], and supplemented by literature specific to lithium ion batteries in the context of capacity expansion modeling [66].

Energy efficiency and demand-side management reduce demand by a maximum of 5% in each period. The technology represents measures taken by utilities to reduce demand, such as information and voluntary programs, building codes, government energy use, efficient appliance subsidies, and others. The technology is assumed to have a variable cost of $0.043 per kWh (no investment or fixed costs), which is an average drawn from a variety of econometric evaluations of these programs' cost in states across the US [97-106].

Variable costs are costs incurred that are proportional to electricity generated, such as fuel, consumable reagents, and operation expenses. Fixed costs are proportional to the capacity installed and are not a function of electricity generated. Both variable and fixed cost estimates for each technology were obtained from the MARKAL database following the same methodology as discussed above. Fuel costs are accounted for through fuel importing technologies and represented as variable costs. Fuel costs were obtained from the EIA's Annual Energy Outlook 2017 reference case [1] and are displayed in Figure 6. A complete listing of investment, variable, and fixed costs can be found in Appendix D – Cost Figures.

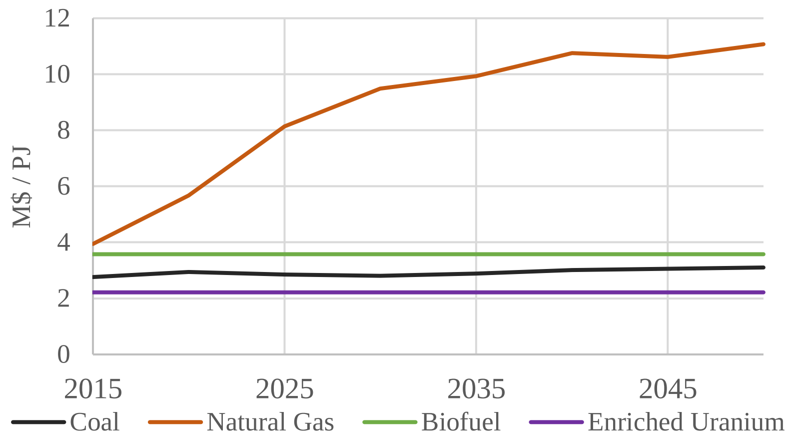


Figure 6: Fuel prices used in the NC dataset. Data drawn from EIA's AEO 2017, reference case without Clean Power Plan [1], nuclear costs from [107, 108].

The costs and technical parameters described above were used to create the baseline dataset for North Carolina. To test the effects of different energy policies, policy instruments of interest were identified and then translated to changes in the baseline dataset.

Loan Interest and Loan Lifetimes

Temoa treats expenditures as if they are 100% financed through debt, and interest payments are added into the costs on an annualized basis. Therefore, each technology needs a loan interest rate and a lifetime over which the loan is paid and the interest is discounted. These rates can also be used to establish "hurdle rates", an imprecise method of either encouraging or discouraging investment in a technology that reflects non-quantifiable assumptions [109]. A standard 10% interest rate is assigned to all technologies per the EPA MARKAL database, with a few exceptions. Nuclear investments are often considered riskier than other thermal plants due to a history of cost and schedule overruns, and the EPA MARKAL interest rate of 15% is assigned to new nuclear construction [110]. In addition, solar and biomass interest rates are set at 6%, reflecting the favorable loan interest rates and terms obtained by developers [111, 112] through minimum 15-year purchase power agreements (PPA) mandated by the Public Utilities Regulatory Policies Act (PURPA) [93, 113]. The length of the loan for each technology is 30 years, following estimates within the EPA MARKAL database, except for solar and biomass (15 years) and energy storage (20 years). PURPA qualified facilities, such as solar and biomass, have the loan life set to equal the length of the PPA, reflecting financing opportunities available to developers. The shorter term for energy storage reflects the 20-year lifetime of these technologies.

Existing Energy Policy and Environmental Regulations

The final step in constructing the baseline dataset involves applying the energy policies that already exist in North Carolina. There are 74 state and local renewable energy and efficiency related policies in North Carolina, sixteen of which are state-wide policies [46]. Local policies are not applied to the baseline dataset because of their relatively small effect on the energy market across the state. Of the sixteen state-wide policies, six address energy efficiency through rebates for energy efficient devices, green building codes, energy efficiency loans, and energy standards for public buildings. Energy efficiency is included in the model as a technology that directly reduces demand, with the maximum electricity reduction allowed per period informed by these policies. The remaining ten state-wide policies address renewable energy, and are presented in Table 9. Each policy is assessed to determine if it can or should be included in the Temoa baseline dataset, and if it needs to be included, how it affects the technical parameters or costs of renewable energy.

Of these policies, regulatory policies that affect permits and development are assumed to already be reflected in the investment costs. Solar capital costs were adjusted based on reports documenting the cost of completed projects, which would include permit and developing costs and rebates [95]. Property tax abatements are likewise ignored due to the complexity of modeling them within Temoa. The NC GreenPower production incentive could be modeled within Temoa by reducing variable cost, but the annual size cap of 100 kW is too small to affect an energy market with over 31 GW of capacity. The only policy that can be translated into Temoa is the Renewable Energy and Energy Efficiency Portfolio Standard (hereafter referred to as an RPS). This legislation sets requirements for utilities to generate a certain percentage of their electricity sales from renewable sources. These requirements are enumerated in Table 10 below. The RPS is implemented in Temoa via the minimum activity constraint. This is handled by creating an intermediary technology which converts the commodity “renewable electricity” into “electricity” at 100% efficiency and zero cost. Each technology in Temoa that is covered by the RPS (solar, geothermal, wind, biomass, landfill gas, and small hydro) is modified to generate “renewable electricity”. The minimum activity constraint is then applied to the conversion technology in each Temoa optimization period.

Table 9: A list of state-wide policies in North Carolina targeting the renewable energy sector [46].

Name	Category	Created	Program Description
Active Solar Heating and Cooling Systems Exemption	Financial Incentive	1/1/2000	Solar heating/cooling systems cannot be appraised for more than their material value
Property Tax Abatement for Solar Electric Systems	Financial Incentive	8/11/2008	Exempts 100% of residential solar value when assessing property taxes, 80% of business taxes
NC GreenPower Production Incentive	Financial Incentive	4/18/2005	Limited production incentives for renewable energy (annual cap of <100 kW of solar PV)
Model Wind Ordinance	Regulatory Policy	8/28/2008	Provides a permitting template for communities interested in promoting wind energy
Template Solar Energy Development Ordinance	Regulatory Policy	1/9/2014	Provides a permitting template to communities interested in promoting solar energy
Wind Energy Permitting Standards	Regulatory Policy	6/18/2013	Sets standards for municipalities reviewing wind farm permit requests
Net Metering	Regulatory Policy	10/26/2005	Generation from distributed solar PV receives retail rates from utility
Solar Rights	Regulatory Policy	7/31/2007	Prohibits municipalities from adopting ordinances banning solar developments (except under certain conditions)
Interconnection Standards	Regulatory Policy	4/19/2005	Set standards for approval process for connecting new distributed generation
Renewable Energy and Energy Efficiency Portfolio Standard	Regulatory Policy	8/6/2007	Sets a minimum renewable energy generation target for state utilities

Table 10: North Carolina RPS [114].

		Carveouts			
Calendar Year	**RPS Requirement**	**Solar Energy**	**Swine Waste [a]**	**Poultry Waste (MWh) [a]**	**Maximum % of Total Demand Allowed from Energy Efficiency**
2012	3%	0.07%	0.07%	170,000	2%
2015	6%	0.14%	0.14%	900,000	3%
2018	10%	0.20%	0.20%	900,000	3%
2021 and thereafter	12.5%	0.20%	0.20%	900,000	5%

[a] Swine and poultry waste are not included in the model, as accurate cost data was unavailable. The state RPS lists these requirements in MWh, and not as a percentage of total demand.

There are two federal policies that are of interest in this research: a federal renewable investment tax credit and air pollution regulations. The federal investment tax credit applies to residential and business investments [46], which reduces the investment costs of eligible technologies by 30% for investments made before 2020; 26% for investments made before 2022; and 10% for investments made thereafter. Within Temoa, the residential tax credit applies only to distributed solar, while the business tax credit applies to utility scale solar, wind, and geothermal.

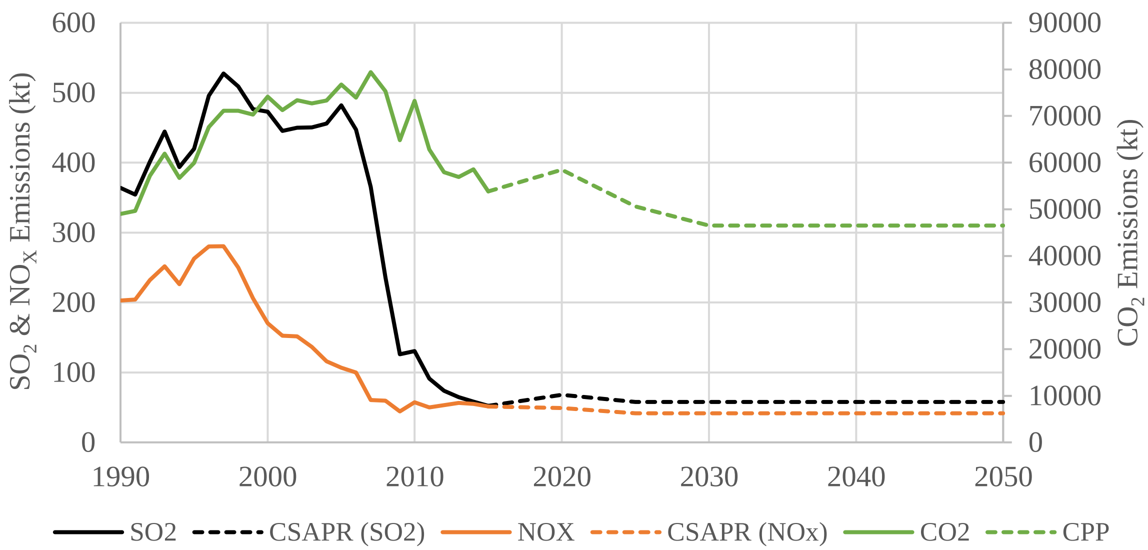


Figure 7: SO_2, NO_X, and CO_2 historical emissions (solid) and regulatory limits (dotted). Sources: Historical emissions- EIA [115]; CO_2 limits - CPP [116]; NO_X and SO_2 limits – Cross-State Air Pollution Rule [117].

In 2011 the US EPA finalized the Cross-State Air Pollution Rule (CSAPR) as a replacement to the CAIR program, requiring 28 states in the eastern United States to reduce SO_2, annual NO_X and ozone season NO_X emissions from fossil fuel-fired power plants [117]. North Carolina is among the 28 affected states that will reduce the annual SO_2 and NO_X emissions. CSAPR sets an “assurance limit” in

2015 and 2017 for each state which takes into account their historical production and available control technology [117]. This assurance limit consists of a "budget" (primary allocation) and "variability" (provided for flexibility). To model this policy in Temoa, we apply the 2015 assurance limit in the first period, and the 2017 budget limit in all later periods, as we assume no policy changes in our baseline dataset (and thus no additional regulation of SO_2 and NO_x limits beyond CASPR limits). The CASPR limits are displayed in Figure 7, along with the CPP limits on CO_2.

ENERGY AND CLIMATE POLICIES

Energy policy scenarios are created by modifying the baseline North Carolina dataset (described in the DATA section) to reflect the requirements of each policy. This section will discuss why each policy was selected, how it is represented in Temoa, and any simplifying assumptions made that may affect the interpretation of results. A summary of the policies evaluated is presented below in Table 11.

Investment Tax Credits

From 2007 to its expiration in 2016, North Carolina had a 35% renewable energy investment tax credit (ITC) for individuals and corporations [46]. The North Carolina House of Representatives voted overwhelmingly to extend the credit, but it ultimately was rejected by the Senate due to opposition to renewable energy and financial incentives [118]. Despite its short run in North Carolina, ITCs remain a popular energy policy tool across the nation [46], so a 35% ITC is selected as the first policy scenario. Within Temoa, the ITC reduces the investment cost of eligible technologies, and is applicable to all new capacity built between 2020 and 2050. Eligible technologies include all types of solar, wind, biomass, geothermal, landfill gas, and energy storage. Large hydropower facilities are excluded from the tax incentive, as it was not included in the state's previous ITC [46]. Temoa assumes the entire tax credit can be claimed, without regard to actual tax liability or maximum system size, common design factors for a ITC. However, developers have become adept at maximizing these tax credits even in the face of such limitations [119], so this assumption is not unreasonable and should not significantly affect results. As Temoa treats each technology as a state-level aggregate of individual projects, it is assumed that the individual projects each comply with required size limits.

Production Incentives

Production incentives are another policy tool used to promote renewables. The non-profit NC GreenPower provides financial incentives to renewable energy producers on a limited basis, with a cap of 100 kW for PV systems imposed in 2015 in response to the program's popularity [46]. A state-wide expansion of this program is the second policy scenario studied. Within Temoa, a production incentive of 0.03 $/kWh reduces the variable cost of eligible new technologies built between 2015 and 2045 for the first ten years of their operation. The set of technologies this applies to is the same as the ITC with the exception of energy storage. As renewable sources such as wind and solar have no variable costs directly associated with their use, the production incentive results in a "negative" variable cost. The amount of 0.03 $/kWh was chosen as it is in line with the federal incentive of 0.023 $/kWh [120], and is less than the 0.06 $/kWh offered by the NC GreenPower incentive [46]. The Temoa model assumes that there is no maximum benefit amount for the program, and that each individual project within the aggregate technology satisfies any project size restrictions.

Renewable Portfolio Standards

One of the more frequently discussed state energy policies is the RPS, with 29 states enacting mandatory standards since Iowa became the first in 1983 [121]. North Carolina's RPS, as discussed in the Existing Energy Policy and Environmental Regulations section, has a nominal target of 12.5% by 2021 and allows 40% of that target to come from energy efficiency measures or out of state renewable generation, resulting in an effective in-state target of 7.5% [46]. To compare proposed RPS policies, this work holds the allowable contribution from energy efficiency to 5% of *total* annual demand in order to maintain approximately the same proportional quantity as the existing RPS. As states have tended to increase their RPS targets over time, the fourth modeled scenario is an expanded RPS. A long-term nominal target of 33.5% by 2050 is proposed, linearly interpolated from 12.5% in 2020. A limitation of the Temoa RPS implementation is that there are no penalties for missing the target or mechanisms to waive the requirement should electricity rates rise beyond a pre-determined limit, as in the existing legislation [114]; the model sets the RPS target as a constraint and the model must meet it.

Carbon Dioxide Regulations

Reducing carbon dioxide emissions over time is of interest to states and citizens concerned about the effects of climate change. Prior to the 2016 presidential election, the Clean Power Plan (CPP) was the first national plan to reduce CO_2 emissions [122]. The proposed rules have been stayed by the Supreme Court and all but abandoned by the new administration, leaving the country without a plan to meet its commitments to combat climate change under the Paris Agreement [123]. Despite federal inaction, the direct regulation of CO_2 is gaining support at the state level, through two pathways: a cap on emissions, and a carbon tax. California began a cap-and-trade program in 2013 [124], joining the Regional Greenhouse Gas Initiative (RGGI), a group of nine northeastern states, in capping total CO_2 emissions from the power sector [125]. The state of Washington put forth a ballot measure creating a state-wide carbon tax in 2015, although it was ultimately defeated over concerns about how the revenue would be spent [126]. In 2017, the governor of Virginia ordered state environmental agencies to draw up regulations to address CO_2 emissions from the power sector [127], and bills in the Massachusetts legislature have proposed carbon prices between $30 and $100 per ton [128]. This analysis explores the effects on North Carolina's electricity sector of both a CO_2 limit and a carbon price. For the carbon limit, the mass-based targets proposed within the CPP are used, allowing 58.5 Mt in 2020, 50.5 Mt in 2025, and 46.5 Mt in 2030 and beyond (see Figure 7) [129]. In the fifth and final policy scenario, a carbon price of $40/ton is imposed on fossil fuel technologies.

Implementing state-level CO_2 regulations makes significant assumptions about whether neighboring states implement similar limits, as leakage of economic activity and emissions can result from local regulations of global pollutants [130]. For the purpose of this thesis, it is assumed that a limit on CO_2 is either imposed on all states through a federal regulatory framework such as the CPP, or is part of a regional effort, thus reducing the effects of leakage.

Table 11: Summary of policy scenarios modeled in this research. Design variations on each policy will be discussed in the results section.

Policy	Description
Renewable Energy Investment Tax Credit (ITC)	35% reduction in investment costs for all non-hydro renewable investments made in periods 2020-2050
Production Incentive (PI)	A reduction in variable costs of 0.03 $/kWh for the first 10 years of operation for all non-hydro renewable sources built in periods 2015-2045. For solar and wind, which have $0 variable costs, this results in a negative variable cost.
Renewable Portfolio Standard (RPS)	A minimum percentage of generation must come from non-hydro renewable sources, increasing linearly from 12% in 2020 to 33.5% in 2050
Clean Power Plan Carbon Cap (CPP)	An upper limit on CO_2 emissions following CPP mass-based limits: 58.5 MT in 2020, 50.5 in 2025, and 46.5 in 2030 and beyond
Carbon Price	A $40/ton cost imposed on the variable costs of all fossil fuel technologies, proportional to their CO_2 emission activity, from 2020-2050

Uncertainty and Stochastic Optimization

Exploring energy futures with energy system models introduces two types of uncertainty: structural and parametric. Structural uncertainty refers to the imperfect means by which the model's equations represent reality. By contrast, parametric uncertainty arises from imperfect assumptions or input data [53]. Ignoring either type of uncertainty can produce misleading policy insights [131]. This paper partially addresses structural uncertainties by introducing three additional constraints that improve the representation of power system operations. Parametric uncertainty is addressed through sensitivity analysis of several critical parameters: natural gas prices, natural gas import constraints, the capacity credit of wind and solar (see the Capacity Credits section for a detailed explanation of the concept), technology-specific interest rates, and end-use demand for electricity. Political uncertainty surrounding the implementation of federal policies is also explored using stochastic optimization.

Sensitivity Analysis

Due to the increasing use of natural gas electricity in the US, developments in the electricity sector are highly influenced by the price of natural gas. While natural gas prices are expected to remain low in the near future, the EIA provides projected prices under various oil and gas sector scenarios in their Annual Energy Outlook [1]. In addition, research has also suggested that natural gas prices projections in the AEO are biased low compared to market prices [132]. Higher natural gas prices drawn from the EIA's Low Oil and Gas Resource and Technology scenario are used to test the model's sensitivity to natural gas prices. Natural gas prices in this scenario are nearly double the reference case by 2050, resulting from lower gas and oil resource availability and higher costs associated with their extraction. The projections are based upon lower estimates of unproved resources and market conditions that discourage domestic crude oil production (which may take the form of regulations targeting the hydraulic fracturing industry), resulting in the US remaining a net importer of crude oil [1]. In addition to prices, constraints on natural gas imports are also explored. As discussed in the DATA section, an upper bound on natural gas imports is used to simulate pipeline constraints in North Carolina. This assumption is tested to observe how the model results are influenced, and explore the implications for future pipeline expansion plans.

The capacity credit of wind and solar – the percent of nameplate capacity that can be counted towards the reserve margin – has been a subject of significant study [81, 82, 88, 133-137] . This research utilized values on the lower end of the range of existing literature. The model sensitivity to this parameter is tested by (1) doubling the nominal capacity credits for both wind and solar, (2) halving the baseline credits, and (3) using the Demand Time Matching method of calculating solar capacity credits [135] (also referred to as the residual load duration curve method [81]), which resulted in a higher value for wind and lower value for solar.

Temoa assumes that capital investments are financed, and an interest rate is specified for each technology. As such, the interest rate can have a significant effect on deployment. In the base case, solar and biomass are assigned favorable interest rates of 6%, which reflect financing terms obtained by solar companies in North Carolina through the Utilities Regulatory Policies Act (PURPA) [111, 112]. These assumptions are tested by increasing solar and biomass interest rates to that of other technologies (10%).

Finally, Temoa specifies fixed electricity demand exogenously, and the electricity demand projections through 2050 are based upon an annual growth rate of 1.2%, drawn from North Carolina utilities' IRPs. Electricity demand projections affect the aggregate amount of electricity generation required, which can significantly affect model results. As it is possible for growth estimates to be either higher or lower than the baseline assumption, annual demand growth is adjusted above and below the baseline estimates by 0.3%.

Stochastic Optimization

Deterministic models such as Temoa assume that – for any given scenario – the future described by the input data is known with certainty. Assuming perfect future knowledge prior to the model run is referred to as a "learn then act" approach [33, 43]. This is often of little use to policy makers who lack perfect foresight, and waiting for perfect information before executing capacity expansion plans can lead to higher costs [138]. Stochastic optimization help redress this model limitation by developing a hedging strategy that can reduce future costs and the risk of stranded assets [33, 54]. For example, stochastic optimization has been used to address capacity expansion under climate policy uncertainty [44, 139]. This technique allows for an "act-then-learn" approach. The modeler must first build a scenario tree: a representation of stages, nodes, and possible outcomes, as shown in Figure 8. Each stage is an optimization period, and each node within a stage has multiple branches, each representing possible outcomes. Each possible outcome is then assigned a subjective probability, and Temoa optimizes over the entire scenario tree. By accounting for future outcomes and optimizing over the whole scenario tree simultaneously, the near-term deployment decisions taken by the model account for potential future recourse action as uncertainty is resolved.

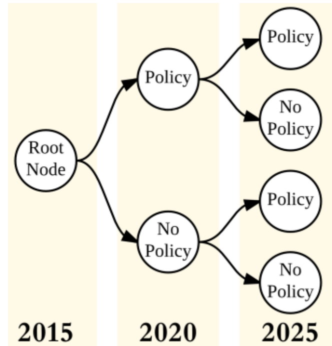


Figure 8: Three-stage scenario tree with two branches per node, denoting the presence of a policy. In this analysis, the Clean Power Plan is the policy under consideration.

The ultimate fate of the Clean Power Plan (CPP), first proposed by President Obama's EPA, is highly uncertain. Currently, the rules have been stayed by the Supreme Court while awaiting a judgement of its legality by the United States Court of Appeals for the District of Columbia Circuit. Depending on their ruling, the stay may be upheld and the rules sent back to President Trump's EPA for modification, or the trial will end in remand, with the stay dissolved and the rule allowed to go into effect [140]. Even if the Supreme Court's stay is dissolved with a remand, there may be additional litigation from coal-friendly states and fossil fuel interests, further tying up enforcement [123]. Compounding this uncertainty is the fact that North Carolina utilities, which have historically been able to shape state-level energy policy [11], are largely powerless to affect the fate of the federal CPP. This can be referred to as *political uncertainty*, as opposed to *impact uncertainty*, which is the uncertainty about how a policy will change business operations [31].

Utilities in North Carolina will need to create a plan to meet the CPP targets in the event they are put into place at some future time, but also want to protect themselves against over-investment in low carbon energy should the rules fall apart. The work presented here includes a 4-stage stochastic optimization (2015 to 2035) to create a hedging strategy for the North Carolina electricity sector under political uncertainty. Each stage has two options: either the CPP is enacted and carbon limits become binding, or no limits are enacted. If the CPP does not come into effect until 2030, the 2030 limit in the original rule is applied – there is no relaxation of the carbon limits based on policy delay. Based upon my belief that the US will eventually join most other countries in reducing carbon dioxide emissions, the probability that a national carbon limit will be enacted increases over time. The full scenario tree is presented in Appendix E – Stochastic Scenario Tree. The assigned probabilities are not based on a rigorous assessment, but rather are meant to be illustrative. The stochastic solution will be compared to both the baseline and the deterministic carbon cap policy scenario described in the Carbon Dioxide Regulations section to see what investment decisions most effectively minimize risk.

RESULTS AND DISCUSSION

Model scenarios were created by modifying the baseline dataset to reflect the impact of proposed energy policies. Each scenario was run with Temoa, producing results over the time horizon 2015-2050. Comparative scenario results are presented for the five state-level energy policies discussed in the ENERGY AND CLIMATE POLICIES section and summarized in Table 11, restated briefly here for convenience: an RPS that increases the share of renewables to 33.5% in 2050 from 4.5% in 2015; a permanent 35% investment tax credit (ITC) for renewable sources (including energy storage but excluding hydro); a production incentive (PI) of 0.03 $/kWh for the first 10 years of operation, for new utility-scale renewable investments (excluding hydro and energy storage) constructed between 2015-2045; a regulatory limit on carbon dioxide emissions, based on CPP targets for North Carolina [116]; and a carbon price of $40/ton imposed on all fossil fuel generation from 2020-2050.

Temoa model optimizes one representative year within each period, and all years within a single period are assumed to produce the same result. Thus, the first period (spanning 2015-2019) is referred to as 2015. The 2015 period result should not be interpreted as historical in this paper, but rather representative of the 2015-2019 period. In addition, the results should not be interpreted as predictions of the future, but rather visions of what the least-cost solution *could* be, if the model assumptions were realized and real-world decision makers behaved in a manner that minimizes social costs [35]. In reality, decisions are made by a range of heterogeneous actors, including developers, consumers, utilities, and regulators. Comparisons across the full suite of model results yield insights that can help planners better understand the potential effects of policy on the future NC electricity sector [35, 109].

To put the comparative scenario analysis in context, results from the baseline scenario are displayed in Figure 9. In terms of installed capacity (Figure 9a), solar is the dominant renewable source of electricity, along with residual hydro and 1 GW of on-shore wind. North Carolina is able to exceed RPS targets of 7.5% until 2025, at which point the RPS becomes binding – indicating that the RPS policy is a vital factor in driving renewable investments in the face of coal retirements and demand growth. As coal, hydro, and nuclear plants are retired, natural gas satisfies the majority of demand beginning in 2035. Although natural gas capacity is split between combustion turbines (NG-CT) and combined cycle (NG-CC), the latter provide more electricity, with an average capacity factor of 65%. Combustion turbines are used to satisfy the reserve margin and provide power during peak demand, as can be seen in the hourly generation profile presented in Figure 10.

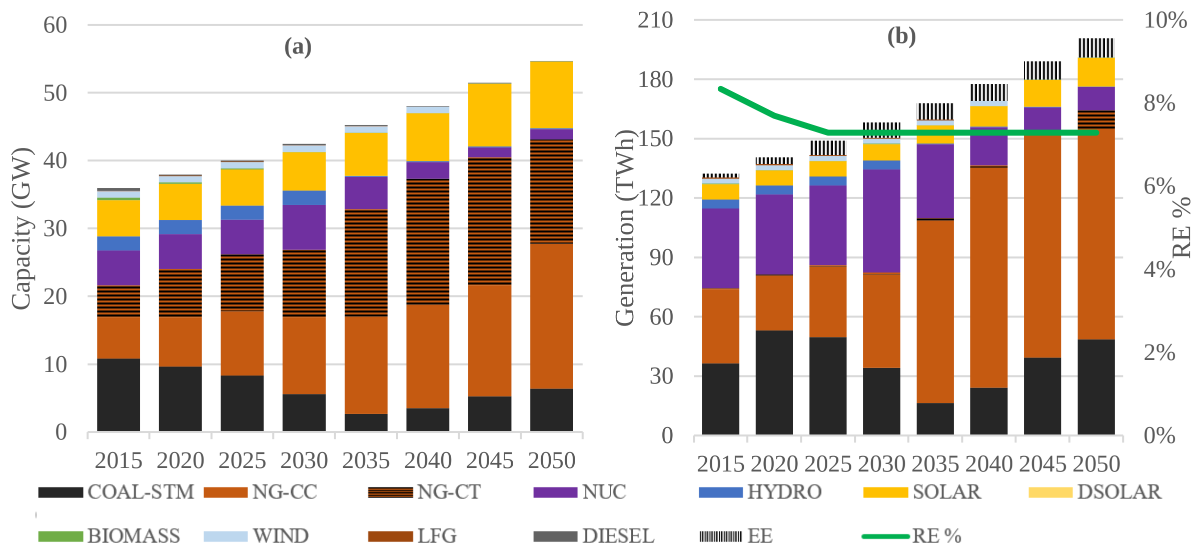


*Figure 9: **(a)** Capacity available per period and **(b)** net generation and renewable share (green line) for the baseline scenario. EE is energy efficiency, and DSOLAR is distributed solar generation.*

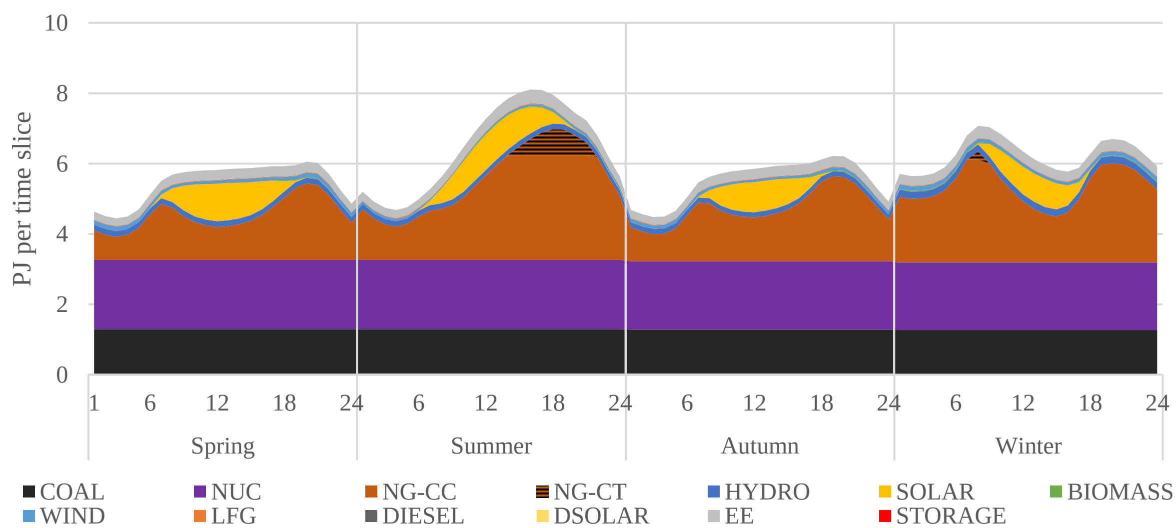


Figure 10: Hourly generation profile in the baseline scenario for each season in the 2030 time period. Each time slice represents approximately 91 hours. Note that 'SOLAR' denotes utility-scale solar, 'DSOLAR' represents distributed solar, and 'EE' represents energy efficiency and conservation.

It should be noted that coal capacity, which declines steadily through 2035, experiences a resurgence in later periods as demand growth outpaces the static RPS requirement and the natural gas import constraint becomes binding in 2040. This results in significant increases in CO_2 emissions and spending on pollution control devices, such as flue gas desulfurization and low-NO_X burners, to meet the CSAPR limits on SO_2 and NO_X. As the comparative scenario results will demonstrate, new energy policy could play an important role in increasing the renewables share and preventing long-term increases in emissions.

Investment and Generation Decisions

Figure 11 displays the net additions and retirements of capacity by fuel source in each period, and total new investment is summarized in Figure 12. Under each policy, natural gas and solar PV comprise the majority of new capacity additions over the model time horizon. Natural gas is added consistently in each scenario, although the carbon tax favors combined cycle over combustion turbines. Coal declines through 2035 for all scenarios, and continues to decline throughout the time horizon for all scenarios except for the baseline and, to a lesser extent, the production incentive. The deployment of significant coal capacity in these two scenarios can be explained largely by the natural gas import restriction, the lack of regulations or costs associated with CO_2 emissions (as in the CPP and carbon price scenarios), and low minimum renewable generation requirements (as in the RPS). As coal is not deployed in the ITC scenario, the production incentive appears to be a less significant a driver of renewable deployment than the ITC.

On-shore wind capacity is deployed in 2015, with the largest quantities found in the RPS and carbon tax scenarios, although solar dominates the renewable field due to its relatively high capacity credit, low investment costs, and favorable loan rates enabled by PURPA standard contract terms. The highest solar PV deployment occurs in the ITC scenario, primarily displacing coal and natural gas. A "winner take all" effect that has been observed in linear programming models may contribute to the dominance of solar over wind [35]. Because the least-cost option is always chosen in Temoa, there is no value to a diverse energy portfolio, leading to highly competitive technologies not being deployed in the model results. Distributed (rooftop) solar PV (DSOLAR in results graphs) is not deployed, as its higher investment cost compared to utility-scale solar PV outweighs its reduction in transmission losses and the lack of transmission investment costs that are required for utility-scale solar PV. The large addition of solar in 2020 under the ITC scenario is explained by the timing of the tax credit. The federal ITC is 26% in 2020 and reduces to 10% by 2025, while the 35% state ITC begins in 2020 – thus, the 2015 investments in utility-scale solar seen in other scenarios instead takes place in 2020. This represents approximately 2.6 GW of additional solar capacity added each year between 2020 and 2025. This level of growth in solar is ambitious, but not outside the realm of possibility: the nascent solar industry in North Carolina added 1.1 GW of utility-scale solar between 2014 and 2015 [74].

Biomass (modeled as CO_2 neutral) is only deployed in the RPS, CPP, and carbon price scenarios. Biomass deployment in the CPP and carbon price scenarios occurs largely because it can follow load and is dispatchable – that is, its capacity credit towards the reserve margin is 100%. It can replace natural gas and coal to meet CO_2 goals or minimize carbon taxes paid. Within the RPS scenario, 23% of electricity is generated from solar in 2050; however, biomass is added as a renewable source to replace the wind resources retired in 2045, and as a dispatchable source to replace the combined cycle natural gas that retires in 2050. Had biomass capacity been replaced by solar PV in the RPS scenario, the resultant high production during the mid-afternoon may have required solar PV curtailment or a reduction of nuclear output. This issue is discussed in more detail in The "Duck Curve" Problem subsection. Dispatchable biomass thus gives flexibility while still meeting the RPS requirement.

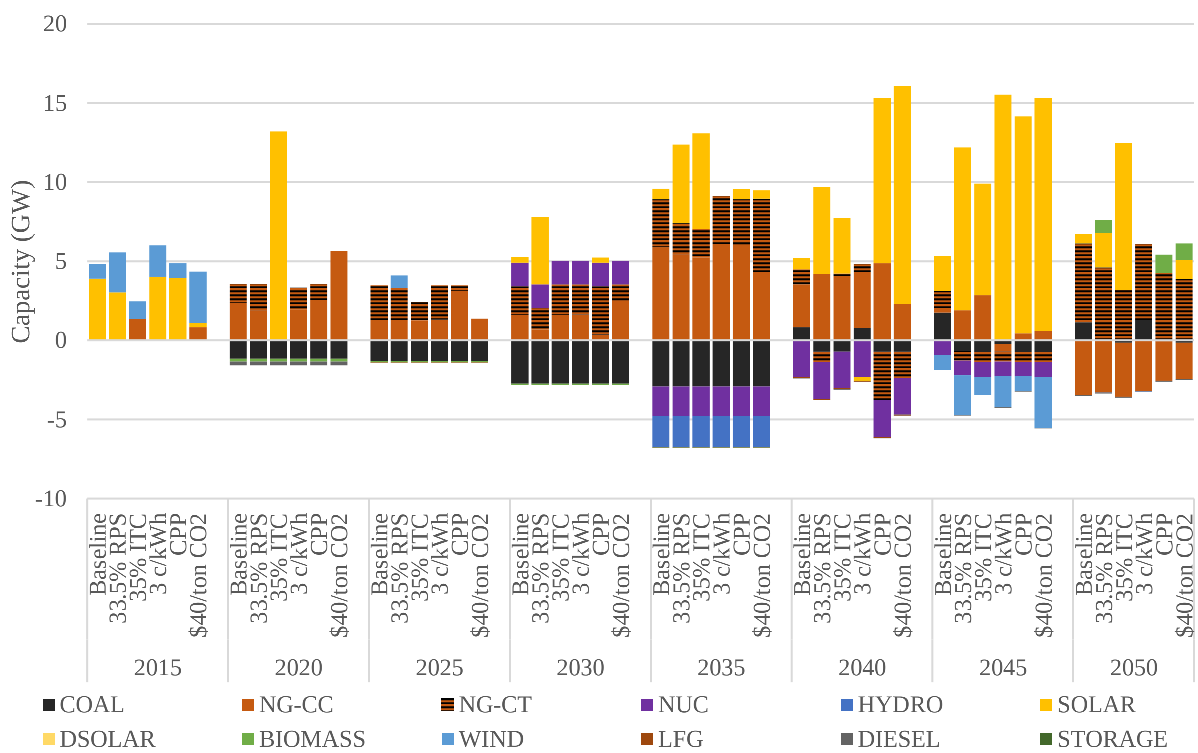
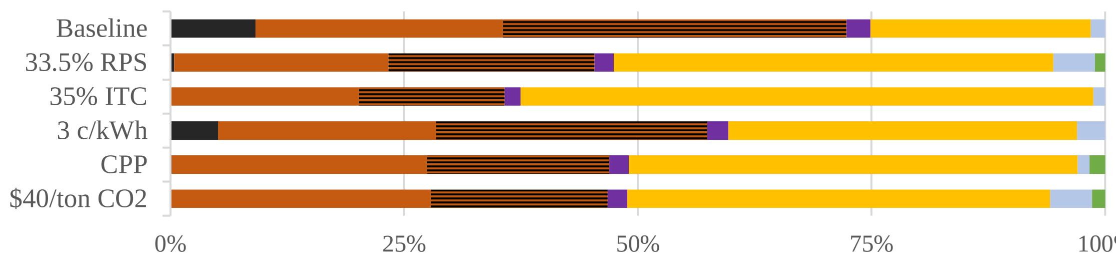


Figure 11: Net capacity additions (if positive) and retirements (if negative) per period by fuel type. Model runs are, left to right: baseline, 33.5% RPS, 35% ITC, 0.03 $/kWh PI, CPP carbon cap, and $40/ton carbon price.

There are over twenty new technologies for Temoa to invest in, yet only about half of these are deployed in any given scenario. How close a technology is to deployment can be measured by the *breakeven cost ratio*, which is the investment cost at which the technology *would* have been deployed, divided by the baseline investment cost. This metric is derived from the reduced costs generated by the linear programming model. The breakeven ratio for distributed solar PV does not vary significantly between scenarios, averaging 55%. This seems to indicate that from the central planner's perspective, the less expensive utility-scale solar is always the preferred choice over distributed solar. The fact that we see deployment of rooftop solar in reality and not the model is likely due to consumers motivated by economic and environmental reasons not captured by Temoa. On-shore wind is only slightly dominated by utility-scale solar PV, with an average breakeven ratio above 83% cost for all scenarios. Breakeven ratios for biomass primarily reside between 50% and 85%, with the higher values found in the CPP, carbon price, and RPS scenarios, indicating that biomass is more valuable when natural gas emissions are regulated or renewable generation is mandated. Off-shore wind is prohibitively expensive, with breakeven ratios never reaching above 50%, despite its higher availability factor than on-shore wind. Because on-shore dominates off-shore wind, the "winner take all" effect of the model tends to decrease the energy portfolio diversity that is often valued by utilities and governments.



	$40/ton CO2	CPP	3 c/kWh	35% ITC	33.5% RPS	Baseline
COAL-STM	0	0.1	3.4	0	0.3	5.3
NG-CC	19.9	19.6	15.5	17.7	16.9	15.4
NG-CT	13.5	14	19.3	13.7	16.3	21.4
NUC	1.5	1.5	1.5	1.5	1.5	1.5
SOLAR	32.3	34.5	24.8	53.8	34.7	13.7
WIND	3.2	0.9	2	1.1	3.3	0.9
BIOMASS	1	1.2	0	0	0.8	0

Figure 12: Cumulative new capacity (in GW) built in each scenario over the model time horizon (2015-2050), for all technologies with some positive level of deployment.

Two technologies, nuclear and energy storage, see little deployment in the model. The breakeven investment ratio for each is displayed in Figure 13. We see that breakeven ratio of nuclear rises from about 65% in all scenarios to 100% in 2030, when 1.5 GW is deployed in accordance with Duke Progress' IRP [59]. This 1.5 GW deployment was forced via a minimum capacity constraint, to reflect major investments in the state utility's long-term plans. Afterwards, the breakeven ratio drops to about 45% for all scenarios, except for the CPP and carbon price. Under those policies, due to the restrictions on coal and natural gas, the nuclear breakeven ratio is 20% higher. This indicates that policies which regulate CO_2 emissions without setting generation mandates or offering incentives for renewables appear to be more favorable to nuclear energy, bringing the breakeven price closer to the actual investment cost.

The breakeven prices for energy storage increase over time, with little variation between scenarios. The model results do not support the hypothesis that storage is more economically competitive in scenarios with higher levels of intermittent renewables. The use of a limited number of time slices does not fully capture the hourly variability in wind and solar, which may contribute to the weak correlation between deployment of intermittent renewable capacity and energy storage. As discussed later in this section, at very high levels of solar generation and discounted storage investment costs, lithium ion batteries act to shift excess solar PV generation from peak production to early evening peak load. Temoa does not capture value streams associated with energy storage, such as taking advantage of tiered energy prices to charge during low rates and sell during high rates, or providing frequency regulation services. These are value streams that might be represented in future work, which would better represent reality and perhaps trigger deployment of energy storage.

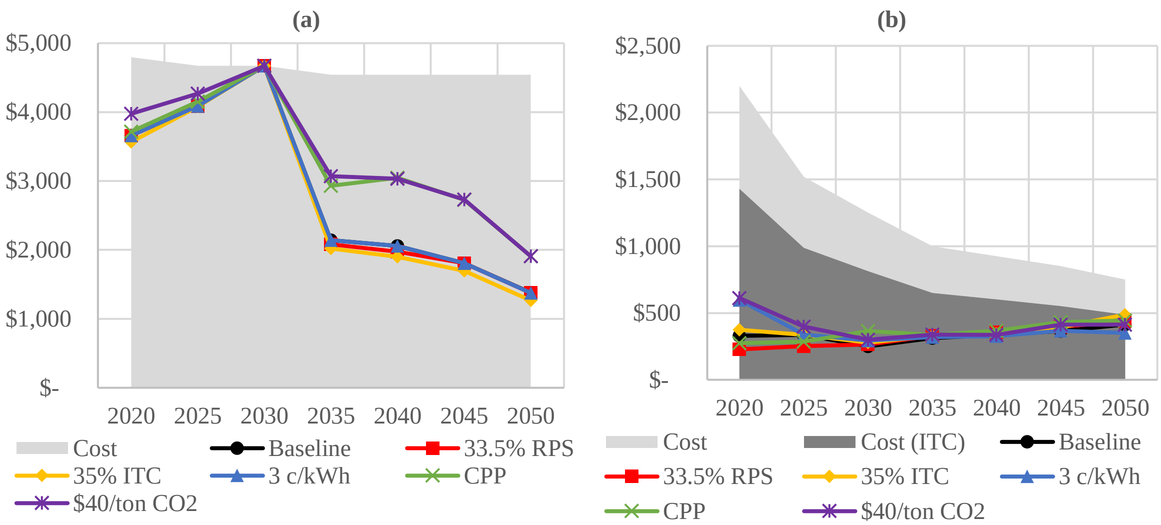


Figure 13: Breakeven prices in $/kW for ***(a)*** *nuclear capacity and* ***(b)*** *utility-scale lithium ion battery storage (8 hours of storage capacity). The light grey area indicates the baseline investment cost, and the dark grey area indicates the investment cost after the 35% ITC (not applicable to nuclear).*

Figure 14 displays electricity generation by fuel source for each policy scenario, as well as the percentage of total generation that is derived from non-hydro renewable sources. With some exceptions discussed here, trends in generation and capacity are closely linked. Sources with low or zero marginal costs, such as solar, wind, hydro, and nuclear, reach maximum utilization over other technologies. For example, the sudden jump in the renewables share in the ITC scenario in 2020 reduces the capacity factor of both natural gas and coal relative to the baseline (see Figure 15 for coal and combined cycle natural gas capacity factors).

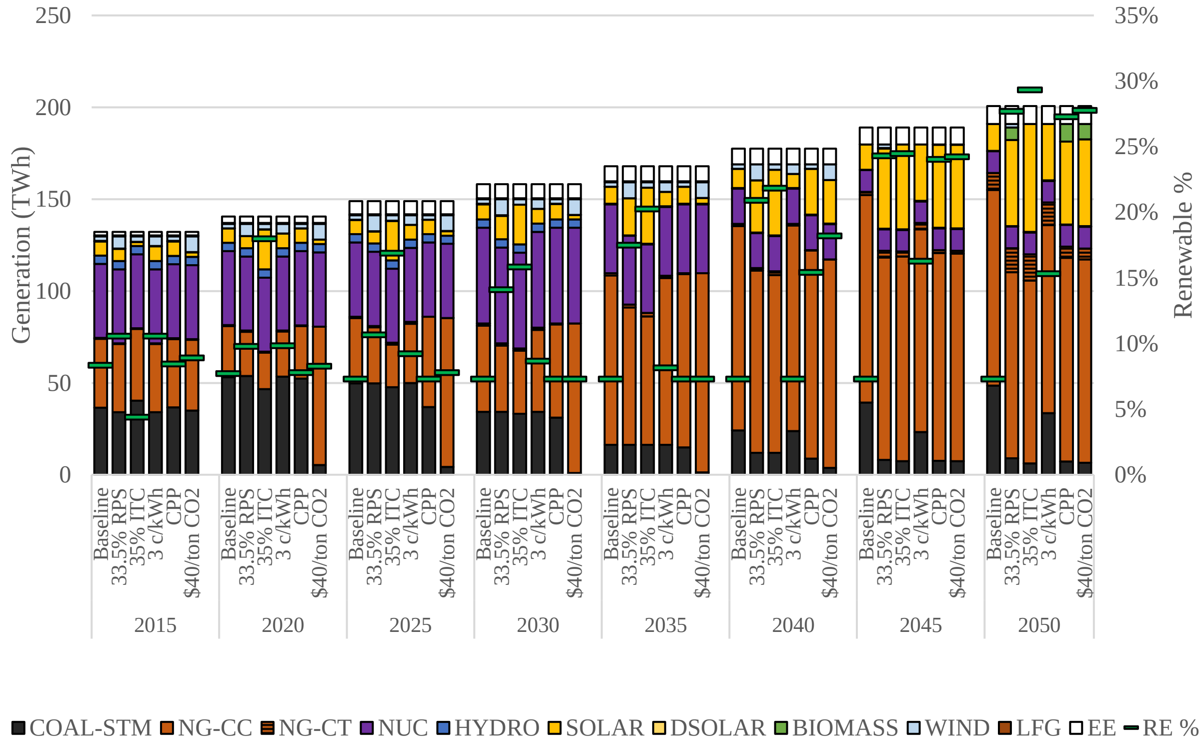


Figure 14: Generation by fuel source per period. Policy scenarios are, from left to right: baseline, 33.5% RPS, 35% ITC, 0.03 $/kWh PI, CPP-based CO_2 limit, and $40/ton carbon price. The green marker corresponds to the right hand vertical axis, and represents the renewable share in each period.

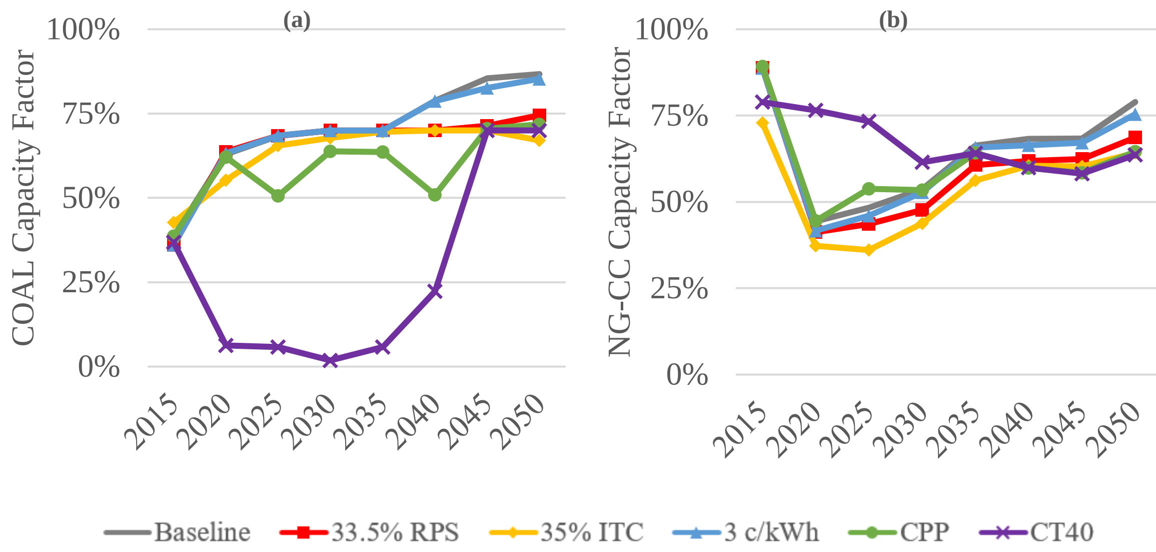


*Figure 15: Capacity factors throughout the time horizon in each policy scenario for **(a)** coal steam and **(b)** combined cycle natural gas.*

Coal, with one of the least expensive marginal costs of generation, is utilized with an average 65% capacity factor in all scenarios except the one with a carbon price. A $40 per ton CO_2 price on generators drives the average coal capacity factor to 28%, which is also responsible for significant decreases in CO_2, SO_2, and NO_X emissions (discussed in detail within the Emissions section). This capacity factor includes the 40% of residual coal classified as baseload, which demonstrates an extremely low utilization that might result in early plant retirements in the real world. Coal utilization increases in later periods (2040-2050), as only 1 GW of residual capacity remains, reducing the scale of the carbon price penalty. This also has the effect of increasing the capacity factor of combined cycle natural gas, which averages 67% in the carbon price scenario, compared to a 60% average over all other scenarios. The CPP emissions cap also restricts the coal capacity factor, but only as much as needed to meet emission limits. This implies that a carbon price may reduce pollution from coal generation to a greater degree than a simple limit on CO_2, leading to additional environmental benefits. While this may be an artifact of the specific carbon price and limit chosen for this study, the carbon price penalizes all fossil fuel generation, particularly coal due to its high CO_2 emission rates, while the carbon cap does not penalize fossil fuel generation until the cap is reached. Thus, any fossil fuel generation under the carbon limit is unaffected by the limit, resulting in higher SO_2 and NO_X emissions compared to the carbon price. In addition, the marginal price advantage of coal over natural gas is erased when the carbon price is applied, indicating that such a policy may result in significant stranded coal assets (defined here as generation capacity that is retired before its useful life is reached). While Temoa only retires a plant when its lifetime is reached, it is unlikely that utility companies would keep a coal plant open if the capacity factor dropped to below 20%, as observed in the carbon price scenario.

In terms of renewable generation, model results indicate that financial incentives such as the ITC, as well as aggressive measures to reduce CO_2, produce a high renewable share without a mandatory RPS. However, increasing the share of renewables is simply a means to an end – it reduces local and global pollutants associated with fossil fuel combustion. As will be discussed in the next subsections, the policies that achieve greater than a 25% renewable share (RPS, ITC, CPP, and carbon price) have quite different emissions and cost characteristics.

The "Duck Curve" Problem

The large increase in renewables observed in some policy scenarios may lead to grid reliability challenges. Figure 16 displays 2050 hourly generation profiles for three scenarios: carbon price, 35% ITC, and 40% ITC, with 32, 40, and 44 GW of utility-scale solar PV capacity, respectively. As solar generation begins to decrease in the early evening hours, a rapid ramp up in generation from natural gas is required to meet demand. This phenomenon leads to the "duck curve", which refers to the duck-like shape of solar generation within the diurnal load pattern [141]. The duck belly is "fatter" in the carbon price scenario than in the baseline scenario (see Figure 10) given the higher deployment of solar. This leads to the “minimum load” problem, where the net load (load minus solar PV production) is less than the full output level of resources that cannot easily ramp down, such as nuclear. This issue is now emerging as a technical challenge in California, with more flexible generation options, energy storage, retail tariffs, and a larger balancing network being proposed as components of a possible solution [142]. Future high levels of renewable penetration could lead to similar effects in North Carolina.

The curtailment predicted by high levels of solar capacity is observed in the 35% ITC scenario (Figure 16b). At midday in spring, the net load after solar generation is less than safe nuclear output levels, resulting in a curtailment of 1.2 TWh of solar output. This phenomenon was explored by increasing the ITC: an incentive of 40% (Figure 16c) deployed energy storage in order to increase the solar capacity to 44 GW. The 4 GW of utility-scale lithium ion batteries store excess generation during peak solar PV production (the ‘hump’ evident in the Figure 16c generation profile at midday in spring) and discharge it in the late evening (red storage generation), as solar output ramps down and load ramps up. Compared to the 35% ITC, energy storage enables 4 GW of additional solar PV capacity in 2050. This result indicates that solar PV production at capacities beyond 40 GW begin to affect baseload nuclear power, and that energy storage may become a necessity to avoid curtailment of either solar PV or nuclear within North Carolina.

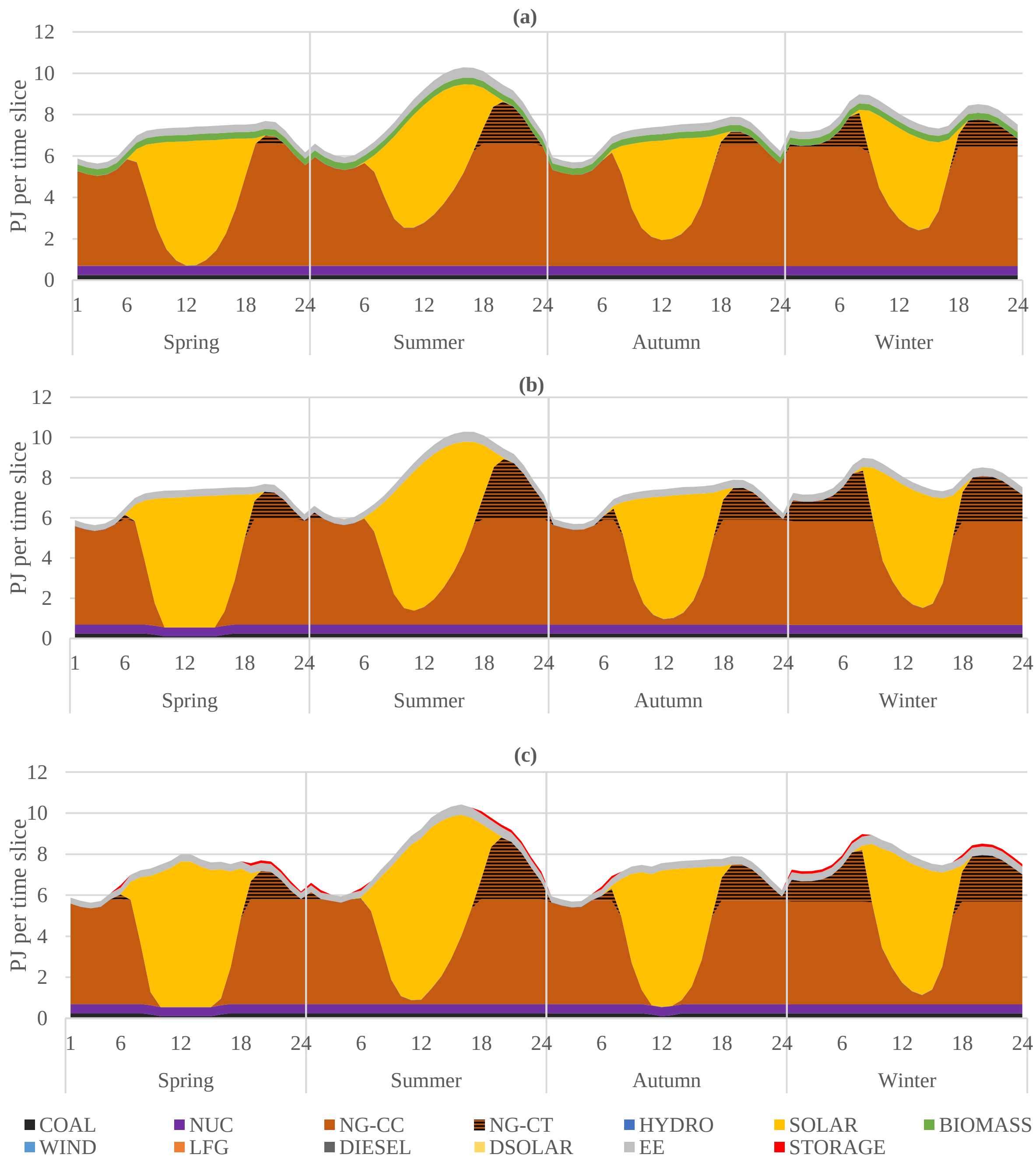


*Figure 16: Hourly generation profiles in 2050 for **(a)** carbon price scenario (32 GW solar), demonstrating no solar curtailment, **(b)** the 35% ITC scenario (40 GW solar), demonstrating 1.2 TWh of solar curtailment, and **(c)** the 40% ITC scenario (44 GW solar), demonstrating how energy storage can shift excess solar PV output. The "duck curve" refers to the shape of the utility-scale solar PV generation area within the load curve.*

Emissions

Due to the limits on SO_2 and NO_X emissions imposed by the Cross-State Air Pollution Rule (described in the Existing Energy Policy and Environmental Regulations section), there is little variation in emission profiles for each scenario until later periods, except for the carbon price (Figure 17). A price on CO_2 emissions sharply reduces coal generation, which explains the drop in cumulative SO_2 (Figure 17a) and NO_X (Figure 17b) emissions: 74% and 47%, respectively. These reductions are accompanied by a 75% decrease in spending on pollution control relative to the baseline, further evidence that a carbon price may result in stranded coal assets.

The ITC, RPS and PI policies result in cumulative SO_2 emission reductions of approximately 20%, while the CPP only sees a 3% reduction. The primary driver of the reductions is a lack of new coal compared to the 5.3 GW in the baseline, although the sulfur content of coal and biomass capacity also plays a role. The reduction in SO_2 observed in the ITC and RPS policies is explained by the deployment of zero and 500 MW of new coal capacity, respectively. However, the PI scenario deploys 3.4 GW of coal capacity, but still reduces SO_2 by 20% below the baseline scenario by shifting to 100% low-sulfur coal by 2045, compared to only 23% in the baseline. This highlights the impact the sulfur content of coal can have on local emissions. The environmental consequence of biomass generation is observed in the CPP scenario: despite only deploying 100 MW of new coal (98% less than the baseline), the CPP only sees a 3% reduction in cumulative SO_2. The cap on CO_2 restricts the amount of natural gas that can be used, so the CPP scenario relies on 1.2 GW of biomass capacity, which is responsible for the increase in SO_2 despite the steep reduction in coal capacity.

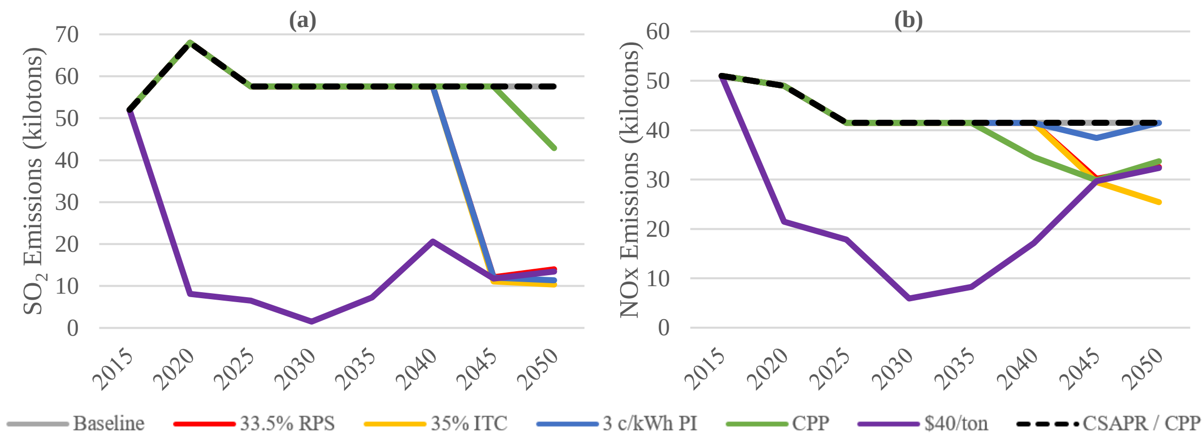


Figure 17: Electricity sector emission profiles for ***(a)*** *SO_2 and* ***(b)*** *NO_X. Dashed black lines indicate emission limits from the EPA's CSAPR limits on SO_2 and NO_X [117].*

The RPS, ITC, and CPP policies see a similar reduction in NO_X emissions, shown in Figure 17b, primarily due to avoiding late-term coal investments. The 2050 uptick in NO_X observed in the RPS and CPP scenarios is due to the deployment of biomass. The consistently binding nature of the CSAPR constraint suggests that without it, both NO_X and SO_2 emissions would increase relative to the baseline. A model run eliminating both emission constraints found a 173% increase in cumulative NO_X emissions and a 211% increase in cumulative SO_2 emissions. This was driven by three primary factors: the capacity factor of residual coal rose to 66% from 39% in the baseline scenario, indicating increased utilization of coal capacity at the expense of natural gas; low-sulfur coal comprised only 21% of all coal consumed, down from 71% in the baseline scenario; and the use of flue gas desulfurization, low-NO_X burners, and selective catalytic reduction to reduce emissions was eliminated.

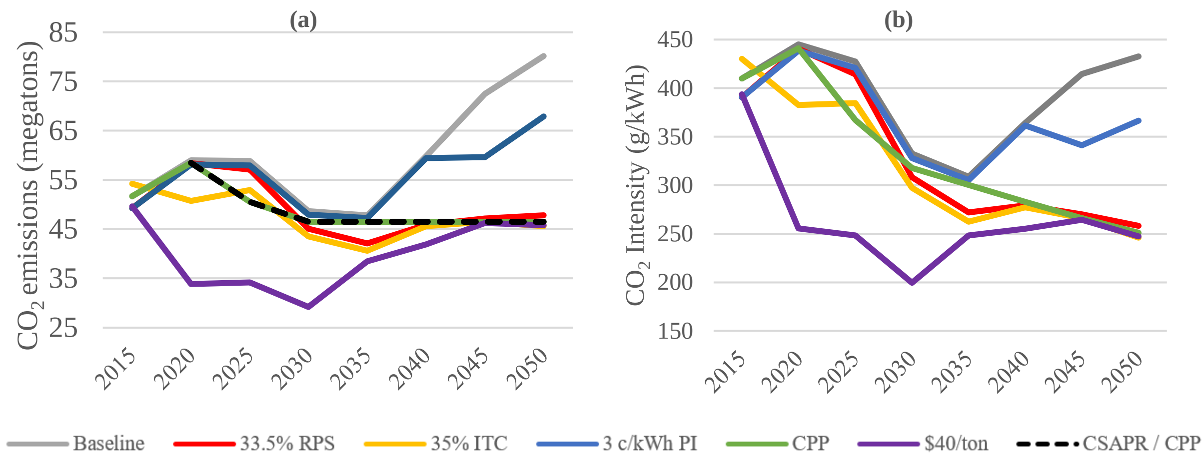


*Figure 18: **(a)** Emission profiles for CO_2 and CPP mass-based caps [116], and **(b)** displays power sector CO_2 intensity in grams CO_2 per kWh of electricity delivered.*

CO_2 emissions from the electricity sector account for roughly 35% of national emissions [74], although this proportion is falling as the national carbon intensity of power plants, defined as CO_2 emissions divided by delivered power, declines [143]. Since 2007, North Carolina has experienced a similar decarbonization of its power sector, declining to 405 gCO_2/kWh in 2015 from 600 gCO_2/kWh, a level maintained between 1997 and 2006 [70, 74]. Despite this progress in decarbonizing its electricity supply, CO_2 results shown in Figure 18 indicate it is possible that North Carolina may reverse these gains. The baseline scenario, with no expanded energy policy, shows an initial decline in both absolute emissions and emissions intensity through 2035, and then both begin to rise as natural gas combustion turbines and coal plants are deployed to replace over 6.5 GW of retired solar and nuclear plants. This is not likely to happen in the real world due to environmental considerations and the possibility of future climate policies. However, observing coal deployed in the baseline model results is an indicator that despite the recent solar boom in North Carolina, there are still a variety of policies that underpin this progress and action is needed in the future to continue driving renewable deployment. A similar trend exists under a production incentive, although the increase is slightly blunted as the emissions intensity levels off between 2040-2050. The PI scenario demonstrates less of an increase in emission intensity compared to the baseline by replacing 2 GW each of coal and NG-CT with 12 GW solar PV between 2040-2050. For North Carolina to sustain its decarbonization efforts in the face of rising demand and retiring capacity, policy measures are likely needed.

In this analysis, a policy is determined to meet the CPP requirements if the following two conditions are met: cumulative CO_2 emissions from 2020-2050 cannot exceed the cumulative mass based limits by more than 1%, and for any given year, and annual emissions cannot exceed the annual mass based limit by more than 5%. Figure 18a displays the emission profiles for each scenario. The carbon price and ITC policies are both able to satisfy both the cumulative and annual conditions without direct regulation (the CPP profile is exactly equal to the CPP limit), while the RPS only violates the annual condition in 2025. The ability to meet CPP goals by tweaking policy design characteristics is explored in more detail below, but it is an interesting insight that should the CPP not survive its legal challenges, there are several policy mechanisms by which North Carolina can meet those goals without simply imposing statutory caps on CO_2. The carbon price produces an immediate drop in CO_2 emissions and intensity as coal plants sit idle and combined cycle natural gas is heavily utilized. This 33% reduction in cumulative CO_2 emissions relative to the baseline is the largest such decline, but comes at a cost, which will be discussed in the next section. Compared to the baseline, the CPP, RPS, and ITC each achieve approximately 20% reduction in cumulative CO_2.

One way to measure the cost-effectiveness of a policy in terms of CO_2 reduction is the abatement cost, or average cost per unit of carbon avoided. Table 12 displays this metric for each scenario relative to the baseline, as well as the baseline relative to a scenario without any RPS. The most cost-effective method of removing CO_2 is the carbon price policy, followed closely by the CPP and the baseline RPS of 7.5%. The expanded RPS of 33.5% is more expensive per ton of CO_2 removed, which follows from the economic theory of diminishing marginal returns. Increasing the RPS from 0% to 7.5% will avoid the CO_2 that is least expensive to remove, such as shifting capacity from coal to natural gas. After a certain point, those measures will not be sufficient to meet a higher RPS target, and more expensive solutions must be deployed, such as increased renewables or carbon capture and sequestration. Both the ITC and PI reduce the total supply cost by decreasing investment and variable costs, respectively. However, the tax credits and production incentives are funded by state governments through tax revenue, and this incentive cost is included in the abatement cost, making them less efficient than other policies in terms of reducing CO_2.

Table 12: Changes in discounted total solution cost and taxpayer-borne price (or revenue) of incentives, in millions of dollars, and CO_2 abatement cost for each scenario.

Policy Scenario	Solution Cost Δ (*M$*)	Incentive Cost *(M$)*	Total Net Cost *Δ (M$)*	Avoided CO_2 *(Mt)*	Abatement Cost *($/ton)*
$40/ton	$26,480	$(19,539) [b]	$6,941	159	$43
CPP	$3,766	-	$3,766	85	$44
Baseline RPS [a]	$(2,404)	-	$(2,404)	51	$47
3 c/kWh PI	$(3,180)	$4,808 [c]	$1,628	31	$53
33.5% RPS	$4,560	-	$4,560	86	$53
35% ITC	$(4,504)	$10,555 [d]	$6,051	99	$61

[a] *The baseline scenario (with currently enacted RPS) was compared to a model run with the RPS removed*
[b] *Represents total discounted carbon prices paid by generators*
[c] *Represents total discounted production incentives awarded to renewable generation*
[d] *Represents total discounted tax credits awarded to renewable developers*

These results suggest that direct regulations on CO_2, SO_2, or NO_X emissions tend to initially lead to increased spending on pollution control technologies to maximize generation from existing coal assets, but more aggressive policies can lead to under-utilization or early retirements of coal capacity along with increased deployment of renewable energy. Decarbonization of the electricity sector is critical to mitigate the effects of climate change, and these results indicate that there are many policy tools that can achieve large reductions in CO_2. This research does not consider the environmental and health benefits from a reduction in local pollutants such as SO_2 and NO_X, nor does it explore possible future tightening of emission caps. The CSAPR regulations placed lower limits on SO_2 and NO_X than North Carolina's Clean Smokestacks Act [144], and the possibility of future state or federal regulations that push these limits down further plays into expansion planning uncertainty. The model results suggest that energy policies targeting renewable energy growth could lead to decreases in SO_2 and NO_X.

Policy Design Variations

To illustrate how CO_2 emissions are affected by minor modifications in policy design, Figure 19 presents emission profiles for the RPS, ITC, and PI scenarios with design variations. The nominal policy designs discussed throughout this paper are indicated by circular markers, and the baseline scenario (grey solid line) is shown on each subplot. Figure 19b shows four PIs with different values and end dates. We see that some PI variations are capable of meeting CPP limits, if it is increased to 4 c/kWh and open to all new renewable capacity built through period 2045. Extending the duration of the PI appears to be a stronger driver of emissions reduction than simply increasing the incentive – even a 6 c/kWh PI does not avoid the baseline trend upwards.

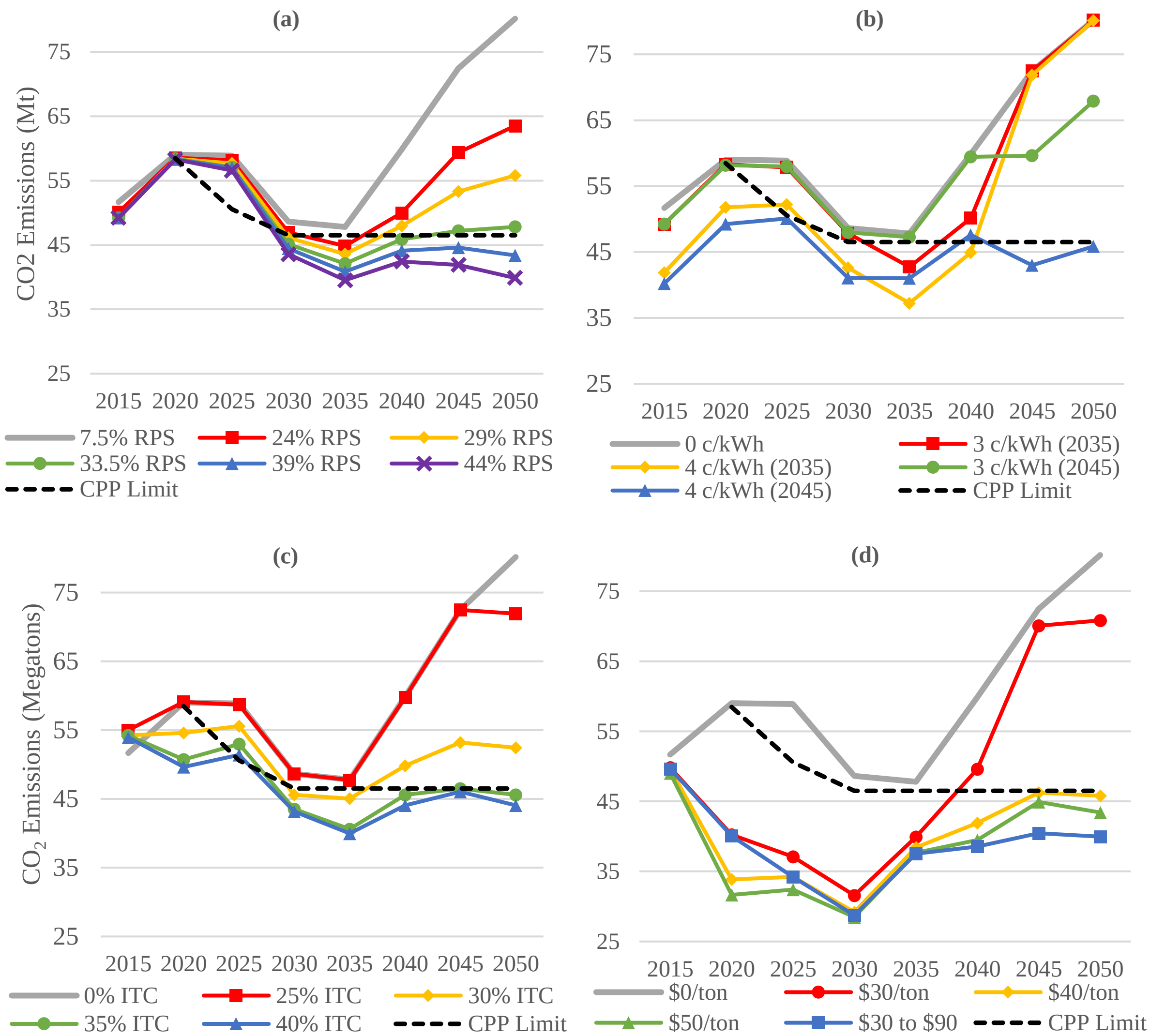


Figure 19: CO_2 emission profiles for
(a)** variations in the RPS 2050 targets, from 7.5% (baseline) to 40% (n**ominal policy is 33.5%);
(b)** production incentive with variations in payout, from $0/kWh (baseline) to $0.04/kWh, with the last period in which new qualified investments are eligible in parenthesis (2035 or 2045) (n**ominal policy is $0.03/kWh, ending in 2045);
(c)** investment tax credit variations from 0% (baseline) to 40%. **(nominal policy is 35%); and
(d)** carbon price variations, flat price of $0/ton (baseline) to $50/ton, including an increasing price design of $30/ton in 2020 to $90/ton in 2050 **(nominal policy is $40/ton)

If a reduction in CO_2 emissions is the policy goal, the most effective policy mechanism may be a carbon price, and the least effective appears to be a production incentive, although there are diminishing marginal returns to more aggressive policies. We see in Figure 19c that increasing the ITC to 30% from 25% leads to a dramatic reduction in CO_2 emissions, but increasing to 40% from 35% has much less of an effect. In North Carolina, there appears to be a ITC "sweet spot" between 30% and 35%, which yields the greatest emission reductions at the least cost. A similar effect is present in the carbon price scenario in Figure 19d: the \$40/ton policy meets CPP goals and is a marked reduction over the \$30/ton policy. Increasing to \$50/ton, however, does not produce the same significant drop seen between \$30/ton and \$40/ton. The effects of increasing the RPS are more linear, although a slight decline in marginal CO_2 abatement is observed at higher targets. For example, increasing the renewable share from 24% to 29% reduces cumulative CO_2 by an additional 4%, while increasing from 39% to 44% only reduces cumulative CO_2 by an additional 2%. Depending on policy makers' goals, these insights may help design policies that have the greatest chance of success.

Electricity Cost

The levelized cost of electricity (LCOE) for each period is calculated by summing up the total electricity supply costs attributed to each period and dividing by the total amount of electricity generated, resulting in an average cost per MWh. This figure is used as a proxy for electricity rates, as investment in new capacity is a contributing factor in utility rate cases in North Carolina [145]. The LCOE for the modeled baseline scenario is \$65 per MWh in 2015, escalating to \$115 per MWh by 2050, shown in the dotted line in Figure 20. Also displayed is the LCOE of each scenario relative to the baseline. It is important to note that the ITC and PI results do not include the taxpayer-borne costs of tax and production incentives. For this analysis, those costs are not included under the assumption that changes in state tax revenue do not directly affect the electricity rates imposed by the public utility.

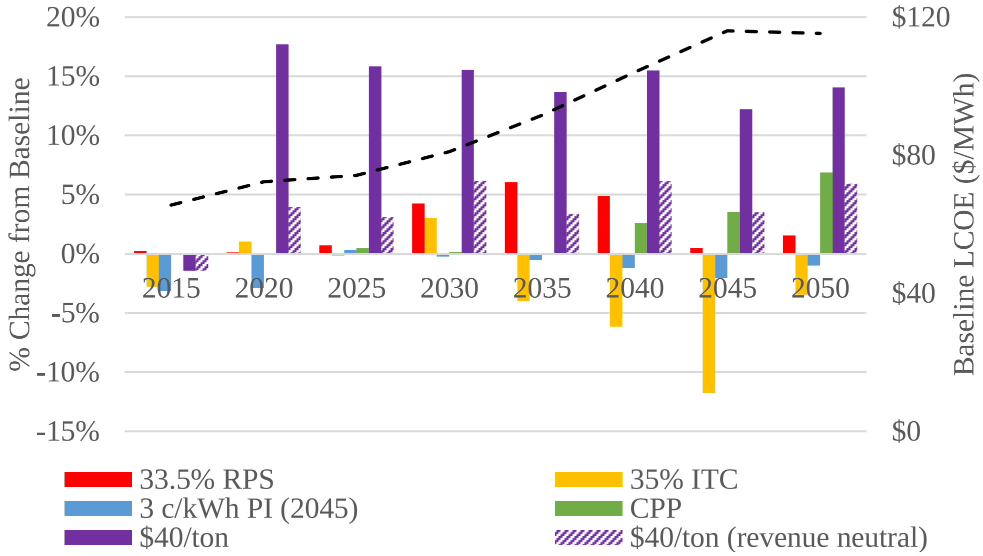


Figure 20: Change in each scenario's LCOE relative to the baseline. Baseline LCOE in $/MWh is shown as a dotted line mapped to the right-hand axis.

The expanded RPS increases cost between 4.2% and 6% in periods 2030-2040, driven by large investments in utility scale solar to overcome retirements of residual solar capacity in 2030. Based on the model results, compliance with an expanded RPS would increase supply costs by $4.5 billion (in present dollars) over the baseline scenario through the next 35 years. This represents approximately 1.0% of North Carolina's 2015 gross domestic product (GDP) of $439 billion [146], and about one third of the $13 billion Duke Energy plans to spend on grid upgrades over the next ten years in their Power Forward program, unveiled in 2016 [147]. These results are in line with cost-benefit analyses that have looked at enacted RPS and found an impact between 1% and 5% of electricity prices [21, 26, 27]. Generally, the increase in investment costs from an expanded RPS is partially or completely offset by reductions in future fossil fuel variable costs, which is shown by the expanded RPS costs' return to baseline in 2045 and 2050.

The CPP policy has little impact on electricity cost until 2040, with expected cost increases between 3% and 7%. The delay of CPP compliance costs is supported by estimates that place North Carolina on track to meet the CPP targets through 2030, due to the growth of solar, natural gas, and the impact of the existing RPS [148, 149]. Instead of deploying coal and natural gas in 2040-2045 as in the baseline, the CPP drives large investments in solar PV. While not deployed, carbon capture and sequestration (CCS) becomes more economically attractive under these constraints: the breakeven ratio for coal CCS reaches a maximum of 74% in the CCP scenario, up from 59% in the baseline. The increase in total solution cost associated with CPP compliance is $3.7 billion over the next 35 years, 0.9% of North Carolina's state GDP.

Both the ITC and the PI tend to reduce electricity costs by an average of 3% and 1.4%, respectively. However, reduction in electricity generation cost are not always reflected in consumer rates. Utilities would need to present the savings to the North Carolina Utilities Commission during a rate case. If these costs are accurately reflected in electricity rates, however, the ITC has the largest potential to reduce consumer electricity costs in future years, as significant solar PV assets bring down the LCOE compared to the baseline. In addition, the tax credits and production incentives are assumed paid out by the government, which do not impact the electricity rates, but may affect other aspects of state operations. The tax incentive is estimated to cost the state $10.6 billion (present dollars) from 2020-2050, and total production incentives distributed to renewable energy facilities between 2015-2045 total $4.8 billion (present dollars).

The largest increase in electricity prices is observed in the carbon price policy scenario. The $40/ton of CO_2 price imposed on electricity producers will be passed through in the form of increased electricity rates, making this perhaps the most politically unattractive policy. While this policy does drive additional renewable development and higher utilization of combined cycle natural gas over coal and combustion turbine natural gas, it comes at a high cost to ratepayers. On average, the cost of generating electricity increases by 15% over the baseline once the carbon price is imposed. The impact of this cost increase to ratepayers can be mitigated by designating the carbon price "revenue neutral", and returning revenues to taxpayers through a monthly subsidy, as is done in British Columbia [150]. Revenue neutrality limits price increases to less than 7%, as seen in Figure 20. However, voters in Washington State rejected a revenue neutral carbon tax proposal, with environmental groups that opposed the policy arguing that the carbon revenue should be used for green energy and infrastructure projects [151]. A price on carbon is the policy most recommended by economists for achieving a "first best" solution, yet is often the most politically difficult due to the adverse impact on ratepayers [152-155]. Successful carbon price policies must first set the price at the correct level, and then determine how the revenue will be distributed. The effects of specifying demand exogenously are likely most acute under the carbon price scenario, as the significant price increases would likely decrease demand.

Sensitivity Analysis Results

Key model results from the sensitivity analysis are presented in Table 13 for demand fluctuations (High and Low Demand), natural gas price uncertainty (High NG Prices), unlimited natural gas imports (Unlimited NG Imports), capacity credit variations for wind and solar (CC LDC, High CC, and Low CC), and equal interest rates for all technologies (10% INT). We see that total solution cost is most sensitive to fluctuations in natural gas prices (5.8% increase over baseline), and that LCOE is most sensitive to the pipeline constraint. The 23% reduction in cumulative natural gas capacity caused by the increase in natural gas prices results in the deployment of coal-based integrated gasification combined-cycle (IGCC), which has higher ramp rates than steam coal and is a suitable, if more expensive, substitute for natural gas. This shift towards coal from natural gas suggests that a large increase in CO_2 emissions is possible if natural gas prices rise significantly over current baseline projections. The model results indicate that IGCC could be relied upon in the future as a load following alternative.

Removing the natural gas import constraint has two major effects on the model. First, no new coal is deployed, indicating that the constraint (which becomes binding in 2040) is at least partially responsible for the late-term coal investments. Coal investments can also be avoided with an expanded RPS, a 35% ITC, or a carbon price policy. The 5.3 GW of coal in the baseline scenario is entirely replaced with natural gas, with no significant change in renewables deployment. Without any restriction on natural gas imports, Temoa relies on natural gas to generate 80% of its electricity in 2050, up from 58% in the baseline scenario. This increased natural gas use reduces the LCOE of delivered electricity by 2% and cumulative CO_2 by 8.6%, suggesting that increasing pipeline capacity is one way for North Carolina to keep electricity rates low and avoid growth in CO_2 emissions. However methane leaks from the extraction, transmission, and distribution of natural gas contribute to climate change, and research has estimated leakage rates as high as 8% over the lifetime of a single well [156, 157]. The leakage rate of natural gas is not captured within the NC dataset.

Among the scenarios tested, the low demand scenario leads to the lowest cost solution and the least CO_2 emissions as well as a lower LCOE than the baseline scenario. Coal deployment is highly sensitive to demand: the high demand scenario increases cumulative new coal capacity by 46%, and the low demand scenario decreases it by 43%. Renewables are relatively insensitive to demand, with high demand increasing solar and wind by 8% and 12%, respectively, and low demand decreasing solar and wind by 7% and 12%, respectively. This reinforces the importance of North Carolina's RPS as demand grows over time, and suggests that future demand-side management tactics to reduce electricity demand may have a significant effect on reducing coal and CO_2 emissions, if coal is not used as baseload electricity.

Solar and wind deployment is highly sensitive to the capacity credit parameter. When wind is assigned a higher capacity credit than solar (in the LDC capacity credit scenario), wind and biomass increase, while solar capacity drops significantly. When both wind and solar capacity credits are doubled, intermittent renewable deployment increases by 70%; when both are halved, intermittent deployment decreases by 57%. This highlights the need to accurately quantify the capacity credits for solar and wind in any energy model with a reserve margin constraint. Capacity credits tend to decrease non-linearly as renewable penetration increases. The scalar capacity credit values assumed in this analysis likely overstate the true values associated with high levels of renewable deployment. Natural gas capacity, particularly simple cycle combustion turbines, are used to satisfy the reserve margin constraint in the baseline scenario. When the capacity credit for wind and solar is increased, cumulative natural gas capacity drops by 25%, and is largely replaced by renewables. This leads to the largest decrease in LCOE, indicating that electricity costs are also sensitive to the capacity credit given to wind and solar.

Renewable deployment is also highly sensitive to the interest rates assumed for each technology. When all technologies are assigned the same interest rate, solar deployment is nearly eliminated, and is replaced with wind and natural gas. This result highlights to the importance of the financing terms obtained by solar developers through PURPA standard contract terms. If North Carolina's PURPA standard contracts were reduced without a replacement mechanism to encourage solar development, financiers may not be willing to provide low interest rates to capital-intensive solar projects. The sensitivity analysis suggests that this would be detrimental to the solar industry in North Carolina. The reduction of maximum system size and contract length for PURPA qualified facilities proposed in North Carolina House Bill 589 will likely not have this effect, as it creates a competitive bidding process for renewable energy resources, with minimum annual procurement requirements [158].

Table 13: Sensitivity analysis results for five four parameters over eight scenarios. Capacity Credit is abbreviated as CC.

	Baseline	**High Demand**	**Low Demand**	**High NG Prices**	**Unlimited NG Imports**	**LDC Method CC**	**High CC**	**Low CC**	**10% INT**
Total Cost *(M$)*	$220,300	$231,500	$209,300	$233,000	$219,800	$220,800	$218,000	$221,400	$218,800
Average LCOE *($/MWh)*	$89.99	$90.78	$89.12	$95.89	$88.45	$90.40	$89.09	$90.61	$89.23
Cumulative CO_2 *(Mt)*	2392.6	2616.5	2181	3070.5	2187.7	2381.6	2367.4	2379.2	2387.1
Average Renewable %, 2015-2050	7.5%	7.5%	7.5%	8.1%	7.4%	7.5%	8.5%	7.5%	7.5%

Cumulative New Capacity, 2015-2050 (GW)

	Baseline	**High Demand**	**Low Demand**	**High NG Prices**	**Unlimited NG Imports**	**CC LDC**	**High CC**	**Low CC**	**10% INT**
Coal Steam	5.34	7.78	3.04	5.23	0	5.36	4.07	5.36	5.38
Coal IGCC	0	0	0	7.12	0	0	0	0	0
Coal w/ CCS	0	0	0	0	0	0	0	0	0
NG CC	15.41	15.63	15.34	9.03	19.91	14.98	15.21	14.96	14.84
NG CT	21.36	23.54	19.2	19.23	22.19	23.55	12.3	23.43	23.7
NG w/ CCS	0	0	0	0	0	0	0	0	0
Solar	13.69	14.78	12.73	17.88	13.63	2.02	24.62	3.16	0.26
Wind	0.93	1.04	0.82	1.01	0.96	3.69	0.17	3.11	4.75
Biomass	0	0	0	0	0	1.26	0	1.23	1.16

Stochastic Optimization Results

Policy uncertainty around the Clean Power Plan was explored by applying stochastic optimization to the Temoa NC model. The probability that the CPP carbon limits would be enforced is increased over time, and the results are compared to deterministic models with and without the CPP limits. The differences can be interpreted as a hedging strategy – an "act then learn" approach which can be useful to policy makers. There are only two areas of significant difference found in the model results: the types of natural gas and the deployment of utility-scale solar PV.

Compared to the no carbon limit baseline scenario, the hedging strategy replaces 100 MW of combustion turbine capacity with combined cycle in 2015 – less than the 600 MW of capacity shifted in the deterministic carbon limit scenario. Combustion turbines have a lower investment cost than combined cycle, but have higher operations costs, higher CO_2 emissions rate, and are less efficient. The uncertainty of the carbon limit reduces the shift towards the more expensive but cleaner combined cycle compared to the deterministic carbon limit scenario. The stochastic solution is reducing the risk of building the more expensive combined cycle plants that could become underutilized or stranded if CO_2 limits are enacted in later periods.

Compared with the deterministic baseline scenario results, CPP uncertainty also leads to delayed investment in solar, albeit by a small quantity (less than 50 MW difference). The stochastic solution increased output from existing coal and natural gas capacity to compensate for the reduction in renewable electricity. This led to a small rise in pollution control costs associated with the increased coal consumption. This supports the hedging strategy's general "wait and see" approach, particularly when considering expensive investments in solar PV and natural gas combined cycle.

Figure 21 presents the total solution costs for the deterministic and stochastic solutions. Of the 16 possible end nodes in the scenario tree, only the ones which exhibit policy consistency are shown –

that is, the 'CPP in 2025' scenario indicates that there is no carbon limit until 2025, and from 2025 to the end of the time horizon, the CPP remains in effect. The stochastic costs reflect the changes in capacity investments and generation that are necessary to respond to the potential implementation of a future carbon limit, which is not revealed until the beginning of each period. Thus, the hedging strategy is likely to reduce total costs, but only if the CPP is not enacted until 2030. For example, if carbon limits are enacted in 2020 and remain in place, the hedging strategy would end up increasing total costs by almost $200 million. However, if carbon limit is delayed until 2030, total costs are reduced by $100 million.

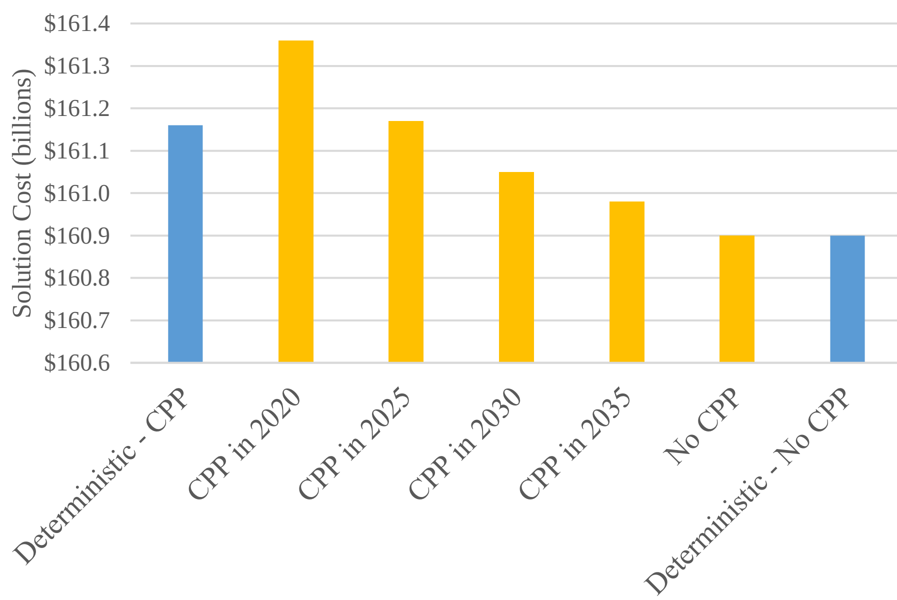


Figure 21: Total solution cost for deterministic (blue) and stochastic (yellow) solutions. The stochastic costs represent the total solution cost depending on what year the CPP is enacted. The costs are presented only for those stochastic scenarios which enact the CPP and do not repeal it in later periods.

The stochastic optimization strategies applied to the Temoa model are highly influenced by the probabilities assigned to each node. Future work could perform a more detailed analysis of the probabilities in the scenario tree, possibly using 2020 as the initial period, which may suggest new ways to minimize the cost of future policy uncertainty. These results are illustrative and demonstrate how energy models can help craft hedging planning strategies.

Limitations and Future Work

Research using energy economy optimization models to explore the effect of policy should clearly state the assumptions and limitations of their work to avoid an appearance of certainty that can confound policy makers [109]. Temoa, like all models, represents a simplification of reality, where complex markets are reduced to representative equations and constraints. Some caveats to this research are expressed here, with possible future work identified to address them.

First, the representation of renewable variability was simplified by using hourly average capacity factors to create a representative diurnal pattern for each season. This representation also lacks spatial differentiation – there is no difference in solar PV output between a solar farm in eastern and western areas of the state as clouds pass overhead. In addition, solar PV may generate larger than average output during full sun, and lower than average output during overcast days.

Second, Temoa solves with perfect foresight, unlike system operators who must make forecasts of solar PV and wind output which are imperfect, resulting in load corrections. Future work may improve this aspect of the model by creating additional time segments and by creating probability distributions to represent solar and wind output under uncertainty, following the example of other researchers [32]. The spatial differences could also be addressed by creating multiple technologies for solar and wind, indexed by region, with slightly varying technical characteristics and costs.

Third, Temoa also does not capture all value streams that may motivate energy storage deployment in reality; for example, taking advantage of tiered electricity rates to charge during low price periods, and discharging during high price periods, or providing frequency regulation and serving as a component in resilient microgrids [67, 159]. In addition, the model may see less solar and wind deployment due to their discounted contribution towards the reserve margin constraint. Energy storage could be deployed on-site with utility-scale solar PV and wind, potentially increasing their contribution to peak demand through a higher capacity credit. While results suggest that scenarios with discounted storage costs and very high levels of renewable penetration will deploy storage to shift excess renewable output to other time periods, the inclusion of on-site storage may lower these barriers to entry. Future work could improve Temoa's storage representation by capturing revenue streams associated with temporal price differences or creating hybrid intermittent renewable and energy storage technologies with higher capacity credits.

Fourth, the exogenous assumption regarding the natural gas pipeline capacity in North Carolina has a significant effect on the deployment of natural gas in later periods. The expansion of natural gas pipeline capacity could be modeled endogenously within Temoa, using pipeline expansion costs. Methane leaks from natural gas transmission and distribution could also be modeled to represent the true greenhouse gas emissions associated with natural gas. To a lesser extent, this applies to the lack of spatial representation of the expansion of transmission and distribution resources. While the NC dataset included average transmission connection costs embedded within the investment costs, it does not explicitly allow for varying costs for transmission and distribution due to different distances from the grid or the need for specific distribution upgrades.

Fifth, the RPS and CO_2 emission limit in this work did not explicitly represent renewable energy certificates (RECs) or emission permit trading, in- or out-of-state. Instead, the RPS and carbon cap are treated as state wide mandates with no market for allowances. As real-world policies often have such trading mechanisms, this is a limitation of the model that may be addressed in future work by building a set of technologies and commodities which represent the REC and emissions allowance trading markets. This lack of a permit market is likely to lead to greater in-state renewable deployment and lower emissions in the model. For example, real-world in-state generators with high marginal abatement costs could buy permits from out-of-state firms with lower abatement costs, thus potentially increasing in-state emissions relative to model results. The same effect is possible with renewable deployment: in-state utilities subject to an RPS could choose to purchase RECs from out-of-state renewable generators instead of deploying renewable capacity in North Carolina.

Finally, the Temoa structure assumes one state-wide decision maker who is driven solely by cost minimization. The reality is far more complex, with thousands of individuals and firms each making decisions that maximize their own profit, rather than that of the entire state's. The actual future energy portfolio of North Carolina may differ significantly from these model results due to this interplay between actors, yet valuable insights can still be gained by interpreting the results with full understanding of assumptions and model limitations. These results are prescriptive, as they propose courses of action that should be taken to meet future demand, under environmental and operational constraints, if cost minimization is the objective.

CONCLUSIONS

This research has demonstrated how Temoa, an open source energy economy optimization model, can be used to explore possible effects of new energy policies in North Carolina. The publicly available data and source code are a key feature of this work, and can hopefully serve as the basis for further efforts in North Carolina. In addition, the input dataset is based on publicly available data and can be replicated for other states. The increasing awareness of states and citizens regarding the threats posed by climate change and the role renewable energy can play in decarbonizing the electricity supply has driven the adoption of hundreds of state-level policies over the years. Rigorous, open source modeling efforts can help inform the accelerating state-level debates over new energy and climate policy.

The objective of this thesis was to examine the effects of state-level energy policy on electricity costs, renewable generation, and emissions in North Carolina. The results are highly dependent on the policy chosen, its design characteristics, and the underlying model assumptions. The results presented here suggest that energy policies still play an important role in the large-scale deployment of renewables in North Carolina, and that new or expanded policies are likely needed to continue the electric sector's recent decarbonization trend. The new coal deployments observed in the baseline scenario are not likely to actually occur given the likelihood of future climate policy; however, it is an indication that ongoing support for renewables may be required to push their deployment.

The first significant energy policy enacted by North Carolina was the RPS in 2007. For a decade prior, the electric sector CO_2 intensity was largely unchanged; since 2007, it has dropped by nearly 30%, driven by the RPS and low natural gas prices. Future demand growth and projected retirements of nuclear baseload capacity cast doubt on whether this progress can be sustained. This work suggests that at least 35% of North Carolina's future electricity should be produced by zero-carbon energy sources to sustain and build upon the decarbonization efforts of the last ten years. This can be done through careful policy design, as demonstrated in the Policy Design Variations section. Future decarbonization is not a trivial goal; the current RPS only requires a 7.5% renewable share, so a 35% share represents a significant increase. Scheduled nuclear retirements makes this goal harder to reach, but it is not impossible – and future nuclear investment may be needed to get there. Directly regulating CO_2 through a carbon price or emission limit appears to increase the economic competitiveness of nuclear relative to scenarios that only promoted renewables. Carbon policies, combined with financial and political support for nuclear, might lead to future reactor construction.

Despite valid concerns that high levels of renewables could lead to sharp increases in electricity prices, the model results indicate that sustaining the electric sector decarbonization by increasing zero-carbon electricity sources is not likely to result in significant cost increases for ratepayers in North

Carolina. For example, implementation of the Clean Power Plan did not have a significant impact on the LCOE. While the effect of a carbon price on electricity cost was substantial, a revenue neutral design could mitigate most of the electricity rate impacts consumers may face. Cost increases from an expanded RPS were also minimal; this result is supported by real-world experience with North Carolina's existing RPS: utilities have thus far stayed well under the cost caps that were designed as a relief valve should renewable energy prove too expensive for ratepayers. In addition, at high levels of solar penetration, the well-documented duck curve effect was observed in North Carolina, with some scenarios exhibiting solar curtailment. The deployment of energy storage as a countermeasure is an interesting result of the model, and speaks to the reliability challenges faced by intermittent renewables and how they might be resolved without fossil fuels.

The policies chosen for study in this thesis are only a small subset of the tools available to policy makers, and results from the sensitivity analysis highlight other policies that warrant further study. The results were highly sensitive to interest rates, suggesting that a public benefit fund set up to provide low-interest rates to renewable energy investments could prove to be a powerful policy tool. The model's sensitivity to the capacity credit of intermittent renewables could inspire additional policy ideas, such as requiring on-site energy storage at wind and solar farms to provide peaking power at the utilities' request. The growth rate of electricity demand had a significant effect on emissions, so a policy designed to decrease projected growth through energy efficiency and demand side management techniques is of interest. The high breakeven ratio of on-shore wind suggests that a policy allowing residents, businesses, institutions, and the state government to sign purchase power agreements directly with wind generators, might be enough to increase wind investment and further diversify North Carolina's energy portfolio. There are many different pathways for North Carolina to realize a future electric sector that is reliable, affordable, and low-carbon.

Whatever pathway chosen by policy makers and stakeholders, it is important to consider the role that energy models play in crafting policy, particularly when considering unexpected consequences. For example, model results presented here suggested that an unanticipated resurgence of coal might result from natural gas price increases and supply restrictions. Energy models can help policy makers in determining the appropriate RPS target or tax incentive to offer, but they also provide valuable insight into the electric sector's potential response under various conditions. The complex interconnections of the electric power sector, compounded by the intricacies of policy design, can be illuminated through detailed energy modeling. Latent consequences, particularly those that increase electricity rates, can quickly lead to an erosion of public support for clean energy policies. Many state governments share the goal of implementing efficient policies to reduce pollution and promote clean energy industries. Rigorous policy analysis, utilizing open source energy models operated by knowledgeable professionals, can provide decision makers the insights and tools they need to implement policies that minimize the unintended consequences.

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APPENDICIES

Appendix A – Additional Constraint Formulations

Appendix A1: Reserve Margin

The reserve margin constraint is defined as shown in Equation 2. Each period, the available capacity over all technologies that is available in the season and day of highest demand ($s^*$and d^*) is first discounted by the capacity credit (cc_t), converted to activity by the capacity to activity factor ($C2A_t$), and then summed. The concept of a capacity credit will be discussed in more detail in the Technical Parameters section of this report. This quantity must be larger than the demand during that same season and time of day, multiplied by the reserve margin (RES_c). It is important to note that the NERC specified reserve margin of 15% cannot be applied here. This is due to the representation of hourly demand in Temoa. Due to computational constraints, Temoa represents 8,760 actual hourly demand slices with 96 representative season and time of day slices, which serves to reduce the maximum demand seen by the model. To correct for this, a reserve margin of 60% is applied in Temoa, which accounts for the difference between the real-world and representative peak loads.

$$\sum_{t \in \mathbf{T}^{res}} cc_t \cdot \mathbf{CAPAVL}_{p,t} \cdot SEG_{s^*,d^*} \cdot C2A_t \geq DEM_{p,c} \cdot DSD_{s^*,d^*,c} \cdot (1 + RES_c), \forall p \in \mathbf{P}^O, c \in \mathbf{C}^{res}$$

Equation 2

Appendix A2: Ramp Rate

The ramp rate constraints are utilized to limit the electricity generation increase and decrease between two neighboring time slices. The formulation is given below in Equation 3.

$$-r_t \cdot \mathbf{CAPAVL}_{p,t} \leq \frac{\mathbf{ACT}_{p,s,d+1}}{SEG_{s,d+1} \cdot C2A_t} - \frac{\mathbf{ACT}_{p,s,d}}{SEG_{s,d} \cdot C2A_t} \leq r_t \cdot \mathbf{CAPAVL}_{p,t}$$
$$\forall p \in \mathbf{P}^{\mathrm{O}}, s \in \mathbf{S}, d, d+1 \in \boldsymbol{D}, t \in \mathbf{T}^{\mathrm{ramp}}$$

Equation 3

In the above equation, r_t represents the ramping rate limits in percentage for those technologies defined as ramping technologies ($\boldsymbol{T}^{ramp}$). It is assumed that the ramping rate of a technology is not affected by its vintage. In Temoa, r_t governs the amount of electricity generated in neighboring time slices ($\mathbf{ACT}_{p,s,d}$), and is expressed as a fraction of available capacity ($\mathbf{CAPAVL}_{p,t}$).

Appendix A3: Hourly Energy Storage

The hourly energy storage constraint created a new decision variable, $\mathbf{HS}_{p,s,d,t}$, which represents the amount of energy stored in a battery technology t in each time slice. Several constraints were necessary to link storage between subsequent time of day (Equation 4) and seasons (Equation 5). The amount of electricity flowing in or out of the battery, $\mathbf{FI}_{p,s,d,i,t,v,o}$ and $\mathbf{FO}_{p,s,d,i,t,v,o}$, respectively, is discounted by the $SEG_{p,d}$ to account for the fact that Temoa represents 8760 hours in a year with only 96 time slices.

$$\mathbf{HS}_{\mathrm{p,s,d,t}} = \mathbf{HS}_{\mathrm{p,s,d-1,t}} + \sum_{i,v,o}\left[\left(EFF_{i,t,v,o} \cdot \mathbf{FI}_{p,s,d,i,t,v,o}\right) - \mathbf{FO}_{p,s,d,i,t,v,o}\right] \cdot SEG_{p,d}$$

$$\forall\, p \in \mathbf{P};\ s, \in \mathbf{S};\ d, d-1 \in \mathbf{D} - \mathbf{D}^f;\ v \in \mathbf{V};\ i, o = ELC;\ t \in \mathbf{T}^{\mathrm{hourlystorage}}$$

Equation 4

$$\mathbf{HS}_{\mathrm{p,s,d^0,t}} = \mathbf{HS}_{\mathrm{p,s-1,d^f,t}} + \sum_{i,v,o}\left[\left(EFF_{i,t,v,o} \cdot \mathbf{FI}_{p,s,d^0,i,t,v,o}\right) - \mathbf{FO}_{p,s,d^0,i,t,v,o}\right] \cdot SEG_{p,d}$$

$$\forall\, p \in \mathbf{P};\ s, s-1 \in \mathbf{S} - \mathbf{S}^f;\ d^0, d^f \in \mathbf{D};\ v \in \mathbf{V};\ i, o = ELC;\ t \in \mathbf{T}^{\mathrm{hourlystorage}}$$

Equation 5

As previously stated, stored energy must zero out at the end of each period, which prohibits storage technologies from carrying over a charge from period to period (an unrealistic scenario). Equation 6 accomplishes this by imposing a constraint on the storage decision variable in the final season and day (s^f and d^f) which forces it to empty all stored energy.

$$\mathbf{HS}_{\mathrm{p,s^f,d^f,t}} = \mathbf{HS}_{\mathrm{p,s,d^f-1,t}} + \sum_{i,v,o}\left[\left(EFF_{i,t,v,o}\cdot \mathbf{FI}_{p,s^f,d^f,i,t,v,o}\right) - \mathbf{FO}_{p,s^f,d^f,i,t,v,o}\right]\cdot SEG_{p,d} = 0$$

$$\forall\, p \in \mathbf{P};\ s, s^f \in \mathbf{S};\ d^f, d^f - 1 \in \mathbf{D};\ v \in \mathbf{V};\ i, o = ELC;\ t \in \mathbf{T}^{\text{hourlystorage}}$$

Equation 6

Energy storage technologies cannot charge or discharge at an infinite rate. Storage capacity, $\mathbf{CAPAVL}_{p,t}$, is installed in GW (GJ/s), and energy exchanges occur in PJ. Therefore, the total energy in or out of a storage technology in a single time slice is limited by the installed capacity, converted from GJ per second to PJ per hour ($C2A_t$), in Equation 7. Finally, it should be noted that battery capacity has two parameters: GW of installed capacity and hours of storage, yielding an upper limit on energy stored in GWh. Based upon the assumption that all storage technologies installed have 8 hours of capacity, the total stored energy is limited by the capacity in GWh converted to PJ in Equation 8.

$$\sum_{i,v,o}\left[\left(EFF_{i,t,v,o}\cdot \mathbf{FI}_{p,s^f,d^f,i,t,v,o}\right)\right]\cdot SEG_{p,d} \le \mathbf{CAPAVL}_{p,t}\cdot C2A_t$$

$$\sum_{i,v,o}\left[\mathbf{FO}_{p,s^f,d^f,i,t,v,o}\right]\cdot SEG_{p,d} \le \mathbf{CAPAVL}_{p,t}\cdot C2A_t$$

$$\forall\, p \in \mathbf{P};\ s, \in \mathbf{S};\ d \in \mathbf{D};\ v \in \mathbf{V};\ i, o = ELC;\ t \in \mathbf{T}^{\text{hourlystorage}}$$

Equation 7

$$0 \le \mathbf{HS}_{\mathrm{p,s,d,t}} \le \mathbf{CAPAVL}_{p,t}\cdot C2A_t \cdot 8\ hrs$$

$$\forall\, p \in \mathbf{P};\ s, \in \mathbf{S};\ d \in \mathbf{D};\ t \in \mathbf{T}^{\text{hourlystorage}}$$

Equation 8

Appendix B – EIA to Temoa Mapping

Table 14 presents all existing electricity generation technologies currently in use in North Carolina as of 2015 [74]. Based on the EIA-specified technology, prime mover and energy source, all existing capacity is aggregated into a single representative technology to be used in Temoa. Approximately 0.5% of existing capacity was not mapped from EIA to Temoa – this is primarily small generation facilities that did not have technical data readily available (such as burning tire derived fuels [TDF]). This existing capacity was small enough to be neglected with no impact on overall findings.

Table 14: A mapping of all residual technologies in North Carolina to Temoa

Technology	Prime Mover	Energy Source 1	Energy Source 2	TEMOA Tech	Existing Capacity (MW)
All Other	ST	TDF	WDS	unknown	107
All Other	ST	WH	OTH	unknown	54
Conventional Hydroelectric	HY	WAT		EHYDCONR	2004.1
Conventional Steam Coal	ST	BIT		ECOASTMR	7625.6
Conventional Steam Coal	ST	BIT	DFO	ECOASTMR	3064
Conventional Steam Coal	ST	BIT	TDF	ECOASTMR	32
Conventional Steam Coal	ST	BIT	BLQ	ECOASTMR	52.5
Conventional Steam Coal	ST	BIT	NG	ECOASTMR	28.7
Hydroelectric Pumped Storage	PS	WAT		EHYDREVR	86
Landfill Gas	FC	LFG		unknown	10
Landfill Gas	GT	LFG		ELFGGTR	3.3
Landfill Gas	GT	LFG	DFO	ELFGGTR	12.1

Table 14 continued

Technology	Prime Mover	Energy Source 1	Energy Source 2	TEMOA Tech	Existing Capacity (MW)
Landfill Gas	IC	LFG	DFO	ELFGICER	11.1
Landfill Gas	IC	LFG		ELFGICER	48.8
Natural Gas Fired Combined Cycle	CA	NG	DFO	ENGACCR	761
Natural Gas Fired Combined Cycle	CA	NG		ENGACCR	1051.8
Natural Gas Fired Combined Cycle	CT	NG	DFO	ENGACCR	2953.2
Natural Gas Fired Combined Cycle	CT	NG		ENGACCR	0
Natural Gas Fired Combustion Turbine	GT	NG	DFO	ENGACTR	6049.7
Nuclear	ST	NUC		EURNALWR	5113.6
Other Waste Biomass	ST	SLW		EBIOSTMR	0.8
Petroleum Liquids	GT	DFO		EDSLCTR	241
Petroleum Liquids	IC	DFO		EDSLCTR	160
Petroleum Liquids	IC	DFO	NG	EDSLCTR	1.8
Solar Photovoltaic	PV	SUN		ESOLPVR	1436.8
Wood/Wood Waste Biomass	ST	WDS	TDF	EBIOSTMR	47
Wood/Wood Waste Biomass	ST	WDS	OBS	EBIOSTMR	81.7
Wood/Wood Waste Biomass	ST	BLQ	NG	EBIOSTMR	89.6
Wood/Wood Waste Biomass	ST	WDS	NG	EBIOSTMR	74
Wood/Wood Waste Biomass	ST	BLQ	WDS	EBIOSTMR	31.3
Wood/Wood Waste Biomass	ST	BLQ	DFO	EBIOSTMR	40.8
Wood/Wood Waste Biomass	ST	BLQ	BIT	EBIOSTMR	30
Wood/Wood Waste Biomass	ST	WDS	BIT	EBIOSTMR	7

Appendix C – Commodities

Table 15: Full listing of all commodities used in NC dataset

Commodity	Sector p = physical e = emissions	Description
Ethos	p	Dummy commodity to supply inputs
COALSTMCC	p	Coal
COALIGCCCC	p	Coal
COALIGCC	p	Coal
COALSTM	p	Coal
ELCNGAEA	p	Natural Gas
ELCDSLEA	p	Diesel
LFGICEEA	p	Landfill gas to ICE
LFGGTREA	p	Landfill gas to gas turbines
URNA	p	Uranium
ELCBIGCCEA	p	Biomass to IGCC
ELCBIOSTM	p	Biomass to steam
ELCGEO	p	Geothermal
SOL	p	Solar
WND	p	Wind
ELCHYD	p	Hydro
ELCRNWB	p	Electricity, physical, from renewables
ELC	p	Electricity, physical, to transmission
ELCDIS	p	Electricity, physical, to distribution
ELCDMD	d	Electricity, from distribution, final end-use demand
co2	e	CO_2 emissions
so2_ELC	e	SO_2 emissions from the electric sector
nox_ELC	e	NO_X emissions from the electric sector
so2_SUP	e	SO_2 emissions from the supply sector
nox_SUP	e	NO_X emissions from the supply sector
COALSTM_R_B	p	Existing BIT coal steam to the blending tech
COAB_R	p	Existing BIT coal after SCR/SNCR or SCR PT to the bit blending technology for existing coal steam
COAB_R_SCR_PT	p	Existing bituminous coal after LNB retrofit or passthrough to the SCR SNCSR NO_X retrofit or passthrough
COAB_R_LNB	p	Existing bituminous coal after CO_2 capture to the LNB retrofit
COAB_R_LNB_PT	p	Existing bituminous coal after SO_2 or CO_2 passthrough to the LNB NOx retrofit or passthrough
COAB_R_CC	p	Existing bituminous coal after SO_2 removal to the CO_2 capture retrofit or passthrough

Table 15 continued

Commodity	**Sector** p = physical e = emissions	Description
COABH_R	p	Bituminous high sulfur to the blending tech then existing coal plant
COABM_R	p	Bituminous medium sulfur to the blending tech then existing coal plant
COABL_R	p	Bituminous low sulfur to the blending tech then existing coal plant
COAB_EA	p	Bituminous coal to CO_2 emission accounting tech
COALIGCC_N_CC	p	Coal IGCC to CO_2 emission capture retrofit
COALIGCC_N_B	p	Bituminous new coal IGCC to the blending tech
COABH_IGCC_N	p	Bituminous high sulfur to the blending tech then new coal IGCC plant
COABM_IGCC_N	p	Bituminous medium sulfur to the blending tech then new coal IGCC plant
COABL_IGCC_N	p	Bituminous low sulfur to the blending tech then new coal IGCC plant
COALSTM_N_CC	p	New coal to CO_2 emission capture retrofit
COALSTM_N_B	p	Bituminous new coal steam to the blending tech
COABH_N	p	Bituminous high sulfur to the blending tech then new coal steam plant
COABL_N	p	Bituminous low sulfur to the blending tech then new coal steam plant
COABM_N	p	Bituminous medium sulfur to the blending tech then new coal steam plant

Appendix D – Cost Figures

Table 16: Investment costs for new electricity generation technologies used in the NC dataset

Technology	Overnight Investment Costs (M$/GW)							
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
EBIOIGCC	3805	3657	3582	3582	3508	3508	3508	3508
ECOALIGCC	3736	3590	3518	3518	3445	3445	3445	3445
ECOALIGCCS	6494	6121	5747	5747	5747	5747	5747	5747
ECOALSTM	2898	2825	2789	2789	2753	2753	2753	2753
EGEOBCFS	2517	2391	2328	2328	2266	2266	2266	2266
ENGAACC	1002	969	953	953	936	936	936	936
ENGAACT	679	654	641	641	628	628	628	628
ENGACC05	923	923	923	923	923	923	923	923
ENGACCCCS	2023	1902	1780	1780	1780	1780	1780	1780
ENGACT05	979	979	979	979	979	979	979	979
ESOLPVCEN	1199.1	1505.9	1735.2	1638	1541.7	1541.7	1541.7	1541.7
ESOLPVDIS	1575	2856.4	3320	3080	2850	2650	2650	2650
ESOLSTCEN	2788	2758	3417	3337	3178	3178	3178	3178
EURNALWR15	5048	4796	4670	4670	4543	4543	4543	4543
EWNDOFS	3843.7	5216	4942	4667	4393	4393	4393	4393
EWNDON	1292.9	1842	1838	1833	1829	1829	1829	1829
ESLION	3888	2200	1520	1250	1000	925	850	750
ESFLOW	2976	2143	1309	1232	1155	1110	1065	971
ESCAIR	1576	1497	1422	1351	1297	1258	1233	1221
ESZINC	2160	1987	1868	1756	1651	1568	1505	1460

Table 17: Fixed Costs for electricity generation technologies by vintage and period used in the NC dataset

		Fixed Costs (M$/GW)							
Technology	**Vintage**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
EBIOIGCC	ALL	112	112	112	112	112	112	112	112
EBIOSTMR	ALL	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5
ECOALIGCC	ALL	54.5	54.5	54.5	54.5	54.5	54.5	54.5	54.5
ECOALIGCCS	ALL	79.4	79.4	79.4	79.4	79.4	79.4	79.4	79.4
ECOALSTM	ALL	33	33	33	33	33	33	33	33
ECOASTMR	ALL	33	33	33	33	33	33	33	33
EDSLCTR	ALL	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8
EGEOBCFS	ALL	119.7	119.7	119.7	119.7	119.7	119.7	119.7	119.7
EHYDCONR	ALL	9.7	9.7	9.7	9.7	9.7	9.7	9.7	9.7
EHYDREVR	ALL	14.4	14.4	14.4	14.4	14.4	14.4	14.4	14.4
ELFGGTR	ALL	159.2	159.2	159.2	159.2	159.2	159.2	159.2	159.2
ELFGICER	ALL	197.5	197.5	197.5	197.5	197.5	197.5	197.5	197.5
ELFGICER	ALL	197.5	197.5	197.5	197.5	197.5	197.5	197.5	197.5
ENGAACC	ALL	16.3	16.3	16.3	16.3	16.3	16.3	16.3	16.3
ENGAACT	ALL	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
ENGACC05	ALL	14	14	14	14	14	14	14	14
ENGACCCCS	ALL	34.7	34.7	34.7	34.7	34.7	34.7	34.7	34.7
ENGACCR	ALL	4.6	4.6	4.6	4.6	4.6	4.6	4.6	4.6
ENGACT05	ALL	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8
ENGACTR	ALL	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8
ESOLPVCEN	ALL	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4
ESOLPVDIS	ALL	0	0	0	0	0	0	0	0
ESOLPVR	ALL	20	20	20	20	20	20	20	20
ESOLSTCEN	ALL	63	63	63	63	63	63	63	63
EURNALWR	ALL	83.4	83.4	83.4	83.4	83.4	83.4	83.4	83.4
EURNALWR15	ALL	98.9	98.9	98.9	98.9	98.9	98.9	98.9	98.9
EWNDOFS	ALL	66.5	66.5	66.5	66.5	66.5	66.5	66.5	66.5
EWNDON	2015-2020	23.5	23.5	23.5	23.5	23.5	23.5	23.5	23.5
EWNDON	2025	n/a	n/a	22.5	22.5	22.5	22.5	22.5	22.5
EWNDON	2030-2050	n/a	n/a	n/a	21.4	21.4	21.4	21.4	21.4
ESLION	ALL	56	40	25	23	22	21	20	18
ESFLOW	ALL	24	17	11	10	9	9	8	8
ESCAIR	ALL	32	30	29	27	26	26	25	25
ESZINC	ALL	32	29	28	26	24	23	22	22

Table 18: Investment costs for new pollution control technologies used in the NC dataset

Technology	Overnight Investment Costs (M$/GW)							
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
E_LNBSCR_COAB_N	1.535	1.535	1.535	1.535	1.535	1.535	1.535	1.535
E_LNBSNCR_COAB_N	0.786	0.786	0.786	0.786	0.786	0.786	0.786	0.786
E_SNCR_COAB_N	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544
E_SCR_COAB_N	1.284	1.284	1.284	1.284	1.284	1.284	1.284	1.284
E_LNB_COAB_N	0.252	0.252	0.252	0.252	0.252	0.252	0.252	0.252
E_CCR_COAB	15.11	15.11	15.11	15.11	15.11	15.11	15.11	15.11
E_FGD_COABH_N	3.184	3.184	3.184	3.184	3.184	3.184	3.184	3.184
E_FGD_COABM_N	2.347	2.347	2.347	2.347	2.347	2.347	2.347	2.347
E_FGD_COABL_N	3.797	3.797	3.797	3.797	3.797	3.797	3.797	3.797
E_CCR_COALIGCC_N	14.52	14.52	14.52	14.52	14.52	14.52	14.52	14.52
E_CCR_COALSTM_N	20	20	20	20	20	20	20	20

Table 19: Fixed costs for pollution control retrofit technologies by vintage and period used in NC dataset.

		Fixed Costs (M$/GW)							
Technology	**Vintage**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
E_CCR_COAB	ALL	0.264	0.264	0.264	0.264	0.264	0.264	0.264	0.264
E_CCR_COALIGCC_N	ALL	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435
E_CCR_COALSTM_N	ALL	0.346	0.346	0.346	0.346	0.346	0.346	0.346	0.346
E_LNBSCR_COAB	ALL	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
E_LNBSNCR_COAB	ALL	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
E_SCR_COAB_N	ALL	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
E_SNCR_COAB	ALL	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008

Table 20: Variable costs of electricity generation technologies by period and vintage used in the NC dataset

		Variable Costs (M$/PJ)							
Technology	**Vintage**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
EBIOIGCC	ALL	1.549	1.549	1.549	1.549	1.549	1.549	1.549	1.549
EBIOSTMR	ALL	5.909	5.909	5.909	5.909	5.909	5.909	5.909	5.909
ECOALIGCC	ALL	2.126	2.126	2.126	2.126	2.126	2.126	2.126	2.126
ECOALIGCCS	ALL	2.559	2.559	2.559	2.559	2.559	2.559	2.559	2.559
ECOALSTM	ALL	1.316	1.316	1.316	1.316	1.316	1.316	1.316	1.316
ECOASTMR	ALL	1.316	1.316	1.316	1.316	1.316	1.316	1.316	1.316
EDSLCTR	ALL	10.233	10.233	10.233	10.233	10.233	10.233	10.233	10.233
EGEOBCFS	ALL	0	0	0	0	0	0	0	0
EHYDCONR	ALL	5.244	5.244	5.244	5.244	5.244	5.244	5.244	5.244
EHYDREVR	ALL	6.124	6.124	6.124	6.124	6.124	6.124	6.124	6.124
ELFGGTR	ALL	0	0	0	0	0	0	0	0
ELFGICER	ALL	0	0	0	0	0	0	0	0
ENGAACC	ALL	0.963	0.963	0.963	0.963	0.963	0.963	0.963	0.963
ENGAACT	ALL	3.053	3.053	3.053	3.053	3.053	3.053	3.053	3.053
ENGACC05	ALL	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
ENGACCCCS	ALL	2.053	2.053	2.053	2.053	2.053	2.053	2.053	2.053
ENGACCR	ALL	1.426	1.426	1.426	1.426	1.426	1.426	1.426	1.426
ENGACT05	ALL	4.549	4.549	4.549	4.549	4.549	4.549	4.549	4.549
ENGACTR	ALL	9.314	9.314	9.314	9.314	9.314	9.314	9.314	9.314
ESOLPVCEN	ALL	0	0	0	0	0	0	0	0
ESOLPVDIS	ALL	0	0	0	0	0	0	0	0
ESOLPVR	ALL	0	0	0	0	0	0	0	0
ESOLSTCEN	ALL	0	0	0	0	0	0	0	0
EURNALWR	ALL	0.459	0.459	0.459	0.459	0.459	0.459	0.459	0.459
EURNALWR15	ALL	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
EWNDOFS	ALL	0	0	0	0	0	0	0	0
EWNDON	ALL	0	0	0	0	0	0	0	0
ESLION	ALL	0	0	0	0	0	0	0	0
ESFLOW	ALL	0	0	0	0	0	0	0	0
ESCAIR	ALL	0	0	0	0	0	0	0	0
ESZINC	ALL	0	0	0	0	0	0	0	0
EE	ALL	11.94	12.54	13.17	13.83	14.52	15.24	16.01	16.81
EDISTR	ALL	6.407	7.018	7.188	7.348	7.585	7.781	8	8.1
ETRANS	ALL	1.935	2.389	2.547	2.735	2.953	3.121	3.235	3.28

Appendix E – Stochastic Scenario Tree

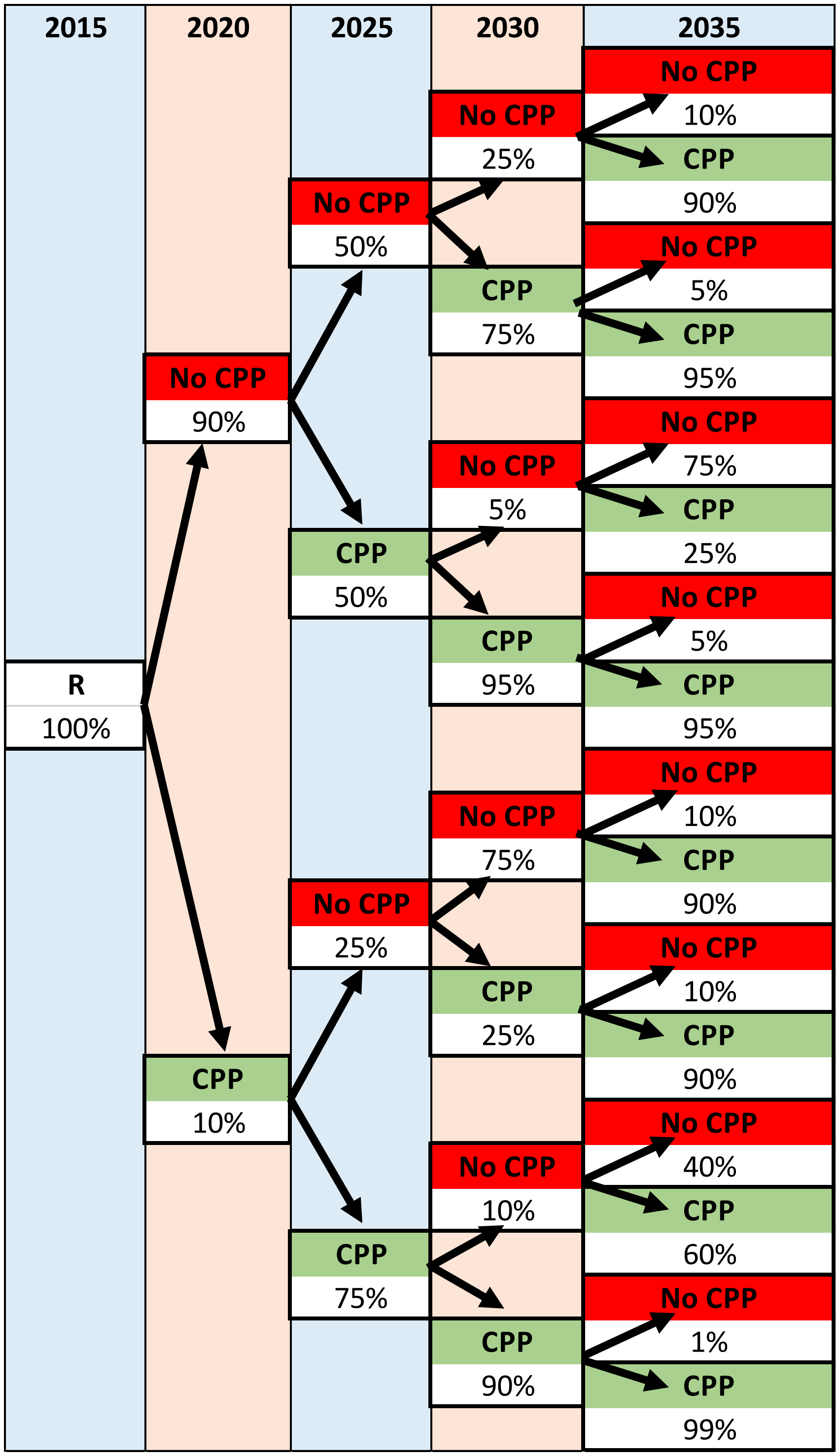

Figure 22: Scenario tree for stochastic optimization of CPP political uncertainty