Regional Energy Deployment System (ReEDS) Model Documentation: Version 2019

Maxwell Brown, Wesley Cole, Kelly Eurek, Jon Becker, David Bielen, Ilya Chernyakhovskiy, Stuart Cohen, Will Frazier, Pieter Gagnon, Nathaniel Gates, Daniel Greer, Sai Sameera Gudladona, Jonathan Ho, Paige Jadun, Katherine Lamb, Trieu Mai, Matthew Mowers, Caitlin Murphy, Amy Rose, Anna Schleifer, Daniel Steinberg, Yinong Sun, Nina Vincent, Ella Zhou, and Matthew Zwerling

National Renewable Energy Laboratory

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ReEDS Team Members for version 2019

Jon Becker	Pieter Gagnon	Caitlin Murphy
Dave Bielen	Nathaniel Gates	Amy Rose
Maxwell Brown	Danny Greer	Anna Schleifer
Ilya Chernyakhovskiy	Sameera Gudladona	Daniel Steinberg
Stuart Cohen	Jonathan Ho	Yinong Sun
Wesley Cole	Paige Jadun	Nina Vincent
Kelly Eurek	Katie Lamb	Ella Zhou
Will Frazier	Trieu Mai	Matthew Zwerling
Bethany Frew	Matthew Mowers	

List of Abbreviations and Acronyms

AC	alternating current
AEO	Annual Energy Outlook
ATB	Annual Technology Baseline
BA	balancing area
CAES	compressed-air energy storage
CAIR	Clean Air Interstate Rule
CC	combined cycle
CCS	carbon capture and sequestration
CES	clean energy standard
CF	capacity factor
CFL	compact fluorescent lamp
CO_2	carbon dioxide
CMIP	Coupled Model Intercomparison Project
CPP	Clean Power Plan
CPUC	California Public Utilities Commission
CSAPR	Cross-State Air Pollution Rule
CSP	concentrating solar power
CT	combustion turbine
CV	capacity value
DC	direct current
DG	distributed generation
DNI	direct normal insolation
DOE	U.S. Department of Energy
DSIRE	Database of State Incentives for Renewables & Efficiency
DUPV	distribution-side utility-scale photovoltaic
EAC	early action credit
EGR	enhanced gas recovery
EGS	enhanced geothermal system
EIA	U.S. Energy Information Administration
ELCC	effective load carrying capability
EMM	Electricity Market Module
EOR	enhanced oil recovery
EPA	U.S. Environmental Protection Agency
ERC	emission rate credit
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
GCM	general circulation model
GHG	greenhouse gas
GIS	geographic information systems
GW	gigawatt
HMI	U.S. Bureau of Reclamation Hydropower Modernization Initiative
HSIP	Homeland Security Infrastructure Project
HVDC	high-voltage direct current
IGCC	integrated gasification combined cycle
IOU	investor-owned utility

IPM	U.S. Environmental Protection Agency Integrated Planning Model
IPP	independent power producer
ISO	independent system operator
IRS	Internal Revenue Service
ITC	investment tax credit
JEDI	Jobs and Economic Development Impact model
km^2	square kilometer
kV	kilovolt
kW	kilowatt
kWh	kilowatt hour
LCOE	levelized cost of energy
LDC	load-duration curve
LED	light-emitting diode
LOLP	loss of load probability
MACRS	Modified Accelerated Cost Recovery System
MATS	Mercury and Air Toxic Standards
MMBtu	million British thermal units
MPI	materials price index
MW	megawatt
MWh	megawatt hour
NaS	sodium-sulfur
NEB	Canadian National Energy Board
NEMS	National Energy Modeling System
NERC	North American Electric Reliability Corporation
NG	natural gas
NHAAP	National Hydropower Asset Assessment Program
NLDC	net load-duration curve
NO$_x$	nitrogen oxide
NPD	non-powered dam
NRC	Nuclear Regulatory Commission
NREL	National Renewable Energy Lab
NSD	new stream-reach development
NSRDB	National Solar Radiation Database
O&M	operation and maintenance
OGS	oil-gas steam
PCM	production-cost model
PRODESEN	Mexican Programa de Desarrollo del Sistema Eléctrico Nacional
PSH	pumped storage hydropower
PTC	production tax credit
PV	photovoltaic
RCP	representative concentration pathway
REC	renewable energy certificate
ReEDS	Regional Energy Deployment System
reV	Renewable Energy Potential tool
RGGI	Regional Greenhouse Gas Initiative
RLDC	residual load-duration curve

RPS	renewable portfolio standard
RROE	rate of return on equity
RTO	regional transmission organization
SAM	System Advisor Model
SENER	Secretaría de Energía for Mexico
SM	solar multiple
SO_2	sulfur dioxide
T&D	transmission and distribution
TDY	typical direct normal insolation year
TEPPC	Transmission Expansion Planning Policy Committee
TRG	techno-resource group
tCO_2	metric ton of carbon dioxide
TW	terawatt
TWh	terawatt hour
UPV	utility-scale photovoltaic
VRE	variable renewable energy
WACC	weighted average cost of capital
WECC	Western Electricity Coordination Council
WIND	Wind Integration National Dataset
WinDS	Wind Deployment System

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Though the economics literature is replete with estimates of the price elasticity of electricity demand, few studies have attempted to estimate the price elasticity of service demand for specific end uses. This is perhaps due to the substantial data requirements needed to perform such an analysis, specifically household-level information on appliances, electricity consumption for specific end uses, and utility rate schedules. Therefore, we take a conservative approach to parameterizing our energy service demand curves, tending toward lower elasticity values, with the expectation that future work will lend better insight into appropriate elasticity values. Our default elasticity assumptions are presented in Table A-2 122

1 Introduction

This document describes the structure and key data elements of the Regional Energy Deployment System model architecture 2.0 (ReEDS 2.0, or simply ReEDS) version 2019, which is maintained and operated by the National Renewable Energy Laboratory (NREL).[1] ReEDS 2.0 builds upon the original ReEDS model architecture (hereafter, Heritage ReEDS), adding more flexibility and additional capabilities while maintaining the features that have contributed to the model's attractiveness as a decision-support tool. In the past, Heritage ReEDS has been used in support of both public and private sector clients to analyze the evolution of the U.S. (and in some cases, North American) power sector in response to policies and technological change. In this introduction, we provide a high-level overview of ReEDS 2.0 objectives, capabilities, and applications. We also briefly describe the history of the Heritage ReEDS model and discuss major changes introduced by the transition to ReEDS 2.0. Finally, we provide a short discussion of important caveats that apply to any ReEDS analysis.

To access the ReEDS model code and inputs, see https://www.nrel.gov/analysis/reeds/request-access.html.

1.1 Overview

ReEDS is a mathematical programming model of the electric power sector. Given a set of input assumptions, ReEDS models the evolution and operation of generation, transmission, and end-use demand technologies.[2] The results can be used to explore the impacts of a variety of future technological and policy scenarios on, for example, economic and environmental outcomes for the entire power sector or for specific stakeholders. ReEDS employs a modular structure to maximize user flexibility. Currently, the model consists of three separate but interrelated modules: a supply module, which solves a linear program for the cost-minimizing levels of power sector investment and operation; a demand module, which solves a separate linear program for the utility-maximizing levels of end-use device investment and operation; and a variable renewable energy (VRE) module,[3] which calculates key parameters for assessing the value of VRE generators. The modules are executed iteratively until a supply-demand equilibrium for electricity is achieved.

Power markets are represented in the model by separating the continent into model regions, each of which has sources of supply and demand. Regions are connected by a representation of the transmission network, which includes existing transmission capacity and endogenous new capacity. On the supply side, the model represents all existing generating units, planned future builds, and endogenous new capacity within each region. On the demand side, the model represents the existing stock of end-use devices as well as an endogenous composition of new device purchases for residential consumers. The model is intended to solve on the decadal scale, though the time horizon for a particular model run (and the intervening model solve years) can

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[1] "Regional Energy Deployment System Model," NREL, https://www.nrel.gov/analysis/reeds/
[2] Currently, ReEDS only explicitly models end-use device and service demands for the residential buildings sector. Additional work is required to extend this capability to the commercial buildings, industrial, and transportation sectors.
[3] VRE is also sometimes referred to as Variable Renewable Resource

be selected by the user. Within each year, a collection of operation time blocks is used to characterize seasonal and diurnal patterns in supply and demand.

1.2 ReEDS History

The ReEDS model heritage traces back to National Renewable Energy Laboratory's (NREL's) seminal electric sector capacity expansion model, called the Wind Deployment System (WinDS) model. The WinDS model was developed beginning in 2001 to examine long-term market penetration of wind in the electric power sector (Short et al. 2003). From 2003 to 2008, WinDS was used in a variety of wind-related analyses, including the production of hydrogen from wind power, the impacts of state-level policies on wind deployment, the role plug-in hybrid electric vehicles in wind markets, the impacts of high wind penetration on U.S wind manufacturing, the potential for offshore wind, the benefits of storage to wind power, and the feasibility of producing 20% of U.S. electricity from wind power by 2030 (DOE 2008). In 2006, a variation of WinDS was developed to analyze concentrating solar power (CSP) potential and its response to state and federal incentives. In 2009, WinDS was recast as ReEDS—a generalized tool for examining the long-term deployment interactions of multiple technologies in the power sector (Short et al. 2009).

Since 2009, ReEDS has been the primary analytical tool in several studies, including the Hydropower Vision (DOE 2016b), Wind Vision (DOE 2015), SunShot Vision (DOE 2012), Geothermal Vision (DOE 2019), and Renewable Electricity Futures (NREL 2012). NREL currently uses ReEDS to publish an annual *Standard Scenarios* report, which provides a U.S. electric sector outlook under a wide range of possible futures (Cole et al. 2019). ReEDS has also been used to examine impacts of a range of existing and proposed energy policies (Lantz et al. 2014; Mai et al. 2015, 2015; Gagnon et al. 2017). Other recent studies have used ReEDS to examine the role of natural gas, high renewable scenarios, and other important issues for the U.S. electricity sector (Mignone et al. 2012; Logan et al. 2013; Clemmer et al. 2013; Mai et al. 2014; Sullivan et al. 2015; Cole et al. 2015; Cole, Lewis, et al. 2016; Richards and Cole 2017; Cole, Frew, et al. 2018). The ReEDS website[4] includes an up-to-date list of publications that use ReEDS.

1.3 Summary of Major Changes

Since the inception of WinDS and ReEDS, NREL has conducted a diverse suite of analyses. Within each analysis, new capabilities were developed, thereby improving the sophistication of the model. The incremental development was often completed by different analysts with unique intentions and coding preferences. Over time, the model became increasingly difficult to maintain. Additionally, as the model evolved, so did the research questions. Therefore, in the fall of 2016, NREL began to rebuild Heritage ReEDS from the ground up. After three years, the resulting product was a cleaner, more flexible, and more advanced tool called ReEDS 2.0. Though ReEDS' fundamental structure and functionality have remained constant, ReEDS 2.0 introduces several changes to the heritage version of the model. The most notable changes include the following:

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[4] "Regional Energy Deployment System Model Publications," NREL, https://www.nrel.gov/analysis/reeds/publications.html

- **Demand-Side Representation:** ReEDS 2.0 includes a representation of consumer demand for energy services. Energy services are provided by end-use devices, which are associated with different efficiency levels. The combination of demand for energy services and efficiency maps to consumer demand for electricity. In ReEDS 2.0, consumer demand for electricity is elastic, responding to changes in prices through both changes in demand for energy services and changes in the composition of end-use devices. In contrast, Heritage ReEDS did not explicitly model the demand for energy services. Moreover, electricity demand was assumed to be inelastic within a given solve year, with a demand elasticity applied for consumption in future years.

- **Model Foresight and Solve Year Flexibility:** ReEDS 2.0 can solve using one of three different types of foresight into future years. As in Heritage ReEDS, the model can be solved sequentially, with decision-making in each model year based on the assumption of static operating conditions for the next 20 years. However, ReEDS 2.0 can also be run as a fully intertemporal model with perfect foresight, or, as a middle ground, with sliding window foresight. Each ReEDS 2.0 model run can also be performed over a fully customizable set of model years. In contrast, Heritage ReEDS could only be solved in two-year time steps.

- **Modular Structure and Iteration:** To address non-linearities introduced by the demand-side representation and the intertemporal optimization option, ReEDS now consists of three stand-alone modules (supply, demand, and VRE). When a model run is launched using both the supply and demand modules, the solution is obtained through an iterative procedure. When a model run includes both the supply and VRE modules and perfect or sliding window foresight, the solution is again obtained through an iterative procedure. However, when a model run includes the supply and VRE modules with a sequential solve, the model does not need to iterate, just as was the case with Heritage ReEDS.

While there are major architectural changes with ReEDS 2.0, many of the incumbent data and methods supporting ReEDS were updated incrementally. This documentation describes the data and methods for the 2019 version of ReEDS. The "Differences from the 2018 Model Version" section of the appendix summarizes more of the specific changes to made to ReEDS since the 2018 version.

1.4 Summary of Caveats

Though ReEDS represents many aspects of the U.S. electricity system, it necessitates simplifications, as all models do. We offer a list of some important limitations and caveats that result from these simplifications.

System-wide optimization: ReEDS takes a system-wide, least-cost perspective that does not necessarily reflect the perspectives of individual decision makers, including specific investors, regional market participants, or corporate or individual consumer choice; nor does it model contractual obligations or noneconomic decisions. In addition, like other optimization models, ReEDS finds the absolute (deterministic) least-cost solution that does not fully reflect real distributions or uncertainties in the parameters; however, the heterogeneity resulting from the high spatial resolution of ReEDS mitigates this effect to some degree.

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- **Resolution:** Though ReEDS has high spatial, temporal, and process resolution for models of its class and scope, it cannot generally represent individual units and transmission lines, and it does not have the temporal resolution to characterize detailed operating behaviors, such as ramp rates and minimum plant runtime. It also does not represent all intra-annual time scales, such as weekly or monthly trends, as ReEDS intra-annual time slices are designed to characterize one day in each season. Many of the time slice shortcomings are addressed by using hourly data in VRE modules, not non-VRE generators do not get that higher resolution.

- **Foresight and behavior:** Except when running with intertemporal optimization, the model has limited foresight and therefore model decision-making does not account for anticipated changes to markets and policies. For example, non-intertemporal runs in ReEDS do not endogenously model banking and borrowing of credits for carbon, renewable, or clean energy policy between solve periods.

- **Project pipeline:** The model incorporates data of planned or under-construction projects, but these data likely do not include *all* projects in progress.

- **Manufacturing, supply chain, and siting:** The model does not explicitly simulate manufacturing, supply chain, or siting and permitting processes. Potential bottlenecks or delays in project development stages for new generation or transmission are not fully reflected in the results. All technologies are assumed to be available at their defined capital cost in any quantity up to their technical resource potential. Penalties for rapid growth are applied in ReEDS; however, these do not fully consider all potential manufacturing or deployment limits. Dates associated with cost inputs in the model reflect project costs for the commercial operation date but not necessarily when equipment is ordered.

- **Financing:** Though the model can use annually varying financing parameters to capture near-term market conditions and technology-specific financing to account for differences in typical investment strategies across technologies, ReEDS cannot fully represent differences in project financing terms across markets or ownership types and thus does not allow multiple financing options for a given technology.

- **Technology learning:** Future technology improvements are considered exogenously and thus are not a function of deployment in each scenario.

- **Power sector:** ReEDS models only the power sector within its defined regional scope (contiguous United States or United States with Canada and/or Mexico), and it does not represent the broader U.S. or global energy economy. For example, competing uses of resources (e.g., natural gas) across sectors are not dynamically represented in ReEDS, and end-use electricity demand is exogenously input into ReEDS.

Notwithstanding these limitations—many of which exist in other similar tools—the modeling approach considers complex interactions among numerous policies and technologies while ensuring electric system reliability requirements are maintained within the resolution and scope of the model. In doing so, ReEDS can comprehensively estimate the system cost and value of a wide range of technology options given a set of assumptions, and we can use the model to generate self-consistent future deployment portfolios.

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A comparison against historical data using ReEDS was completed by Cole and Vincent (2019) and is useful for providing context for how ReEDS can perform relative to what actually occurred in historical years.

2 Modeling Framework

In this section, we describe the modeling framework underlying ReEDS, including the modular structure of the model (and how outputs are passed between modules and convergence is achieved), spatial resolution, temporal resolution, technology represented, and the model formulations.

2.1 Model Structure

ReEDS combines two optimization modules with a simulation module. One the two optimization modules represents electricity supply, and the other represents end-use energy service demand. The simulation model uses a dispatch algorithm to estimate the contribution of storage and VRE units to capacity (see Section 7.2) and a statistical calculation to estimate the level of curtailment for VRE units (see Section 0). Though both optimization modules are described here, only the supply module is used for most ReEDS analysis (i.e., the demand module is typically turned off for most runs).

The model can be run sequentially, intertemporally, or using a sliding window. Figure 1 illustrates how the modules interact when the model is run in sequential solve mode. Within an iteration, the supply and VRE modules are run in sequence for each model solve year. For a given model year t, the supply module, which has been provided with a set of inputs dependent on the results from previous model years, is solved and a subset of the outputs are passed along to the VRE and storage module. Using these inputs, the module then calculates the capacity value of VRE and storage, and curtailment rates for VRE units, which are then applied to the next model year solve (t+1).[5] After this recursive procedure is executed for all model years, the resulting electricity prices for all model years are passed to the demand module. Based on those prices, the demand module solves and exports new values for load, which the supply module then uses the in the next iteration. This process repeats until convergence (i.e., until the results of successive iterations are sufficiently close)

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[5] Here, the t+1 notation is used heuristically, as the model year subsequent to t can be *t+1, t+2, t+3,* etc.

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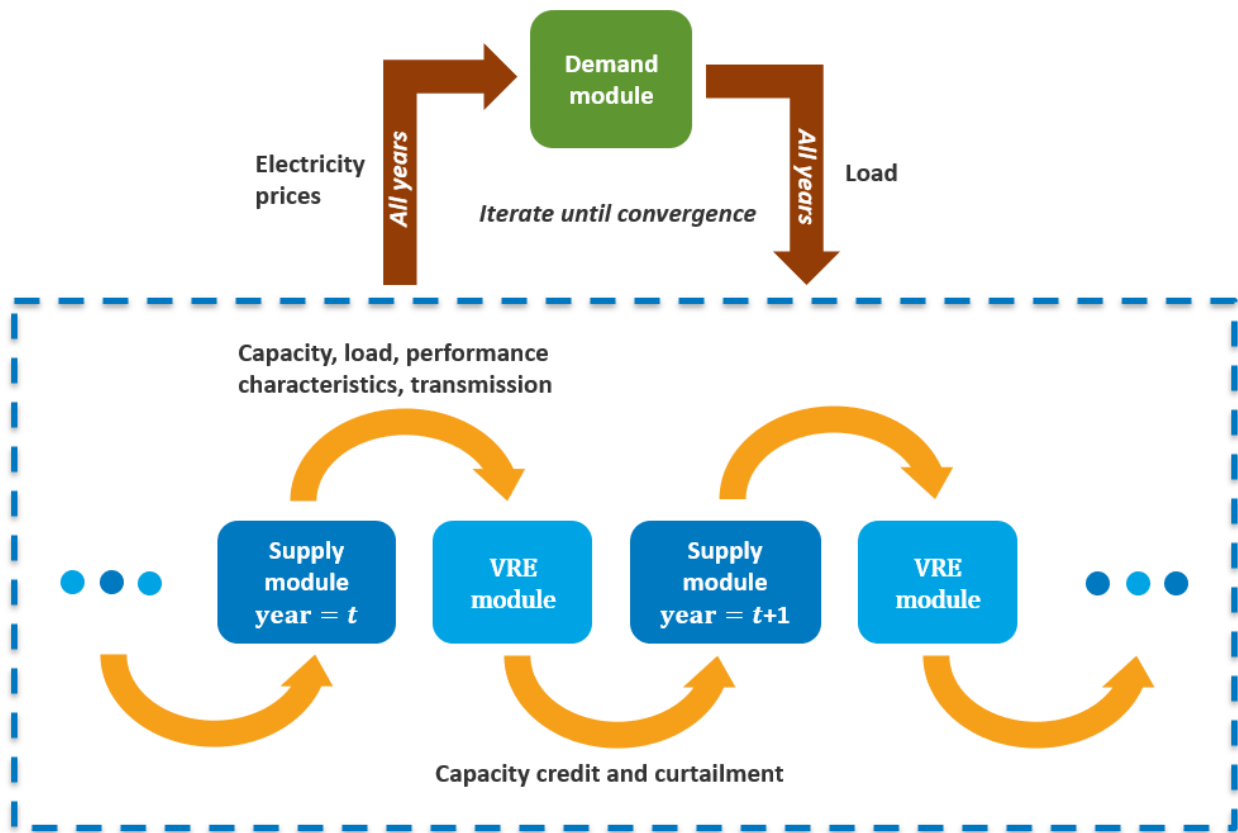
Figure 1. Schematic illustrating the ReEDS structure with a sequential solve

Figure 2 illustrates how the core modules interact when the model is run with sliding window or perfect foresight. Each iteration begins with an execution of the supply module for all model years. The outer cycle (red arrows) illustrates the order in which the modules are executed: after the supply module, the VRE module is executed, followed by the demand module. After the demand module is executed, the next iteration begins with the supply module. This process is repeated until convergence. The inner cycles (orange arrows) illustrate how information is shared by the modules. The types of information shared by the three modules is the same as for the sequential solve mode. The major difference is that the supply module passes information for all model years to the VRE and storage module (and vice versa), and that an iterative process occurs between the two modules. Note also that the VRE and demand modules are still only indirectly linked by way of the supply module.

Regardless of which foresight mode is chosen, the modular structure allows each part of the model to be executed independently. However, the supply and VRE and storage modules are unlikely to be executed without each other, except for testing purposes. This is because one of the key strengths of ReEDS resides in its detailed representation of VRE integration and valuation.
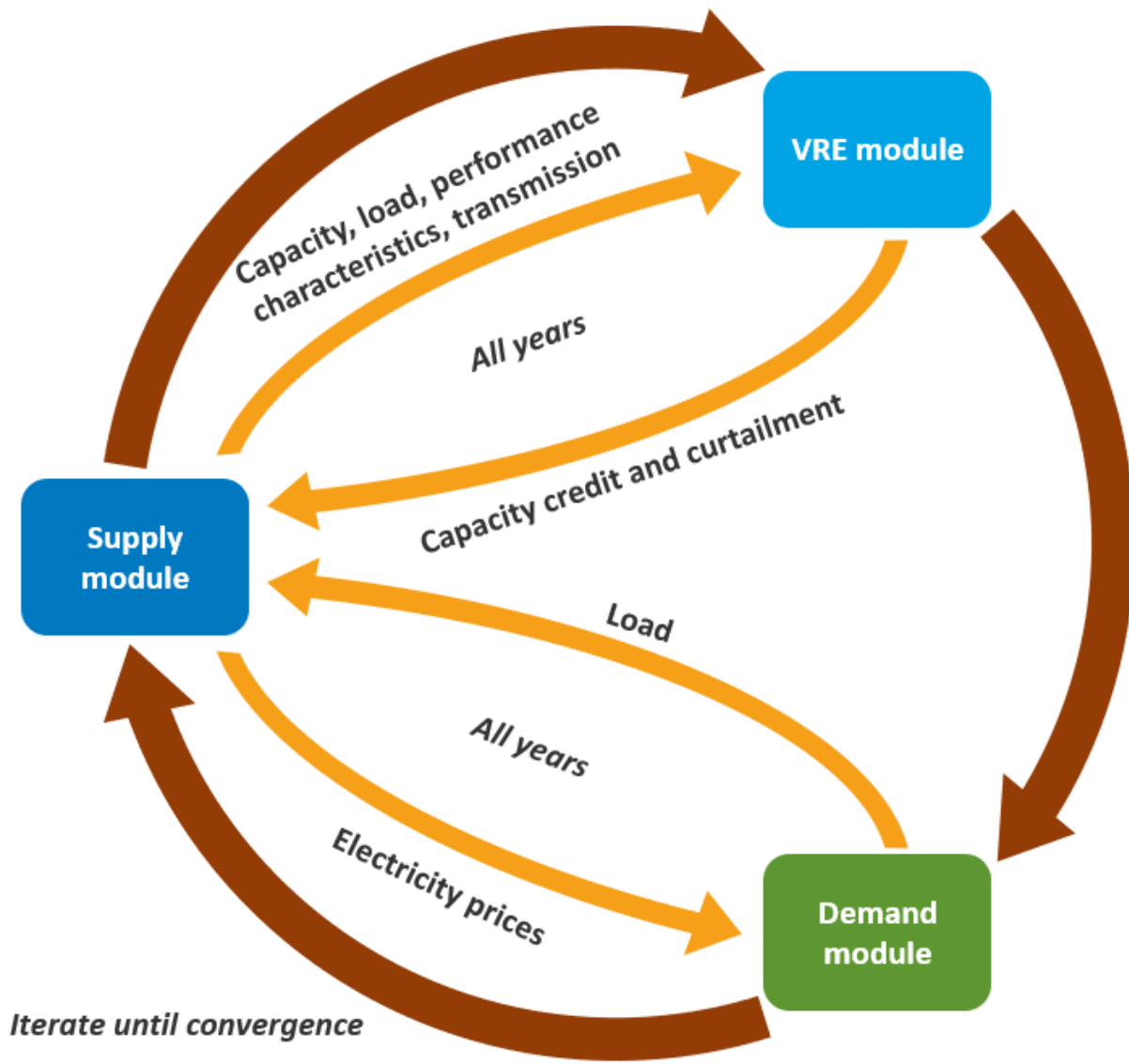
Figure 2. Schematic illustrating the ReEDS structure with sliding window or perfect foresight

2.2 Model Formulations

The supply and demand modules are both cast as linear programs, and each can be described by its objective function, decision variables, and constraints. This section describes each of these elements for both modules.

2.2.1 Supply Module

The supply module is a linear program that governs the evolution and operation of the generation and transmission system. This module seeks to minimize power sector costs as it makes various operational and investment decisions, subject to a set of constraints on those decisions.

The objective function is a minimization of both capital and operating costs for the U.S. electric sector, including:

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- The net present value of the cost of adding new generation, storage, and transmission capacity (including project financing)

- The present value of operating expenses over the evaluation period[6] (e.g., expenditures for fuel and operation and maintenance [O&M]) for all installed capacity

- The cost of several categories of ancillary services and storage

- The cost or incentive applied by any policies that directly charge or credit generation or capacity

- Penalties for rapid capacity growth as a proxy for manufacturing, supply chain, and siting/permitting limitations.

By minimizing these costs and meeting the system constraints (discussed below), the linear program determines the types of new capacity to construct in each region during each model year to minimize systemwide cost. Simultaneously, the linear program determines how generation and storage capacity should be dispatched to provide the necessary grid services in each of the 17 time-slices. The capacity factor for each dispatchable technology therefore is an output of the model and not an input assumption.

The constraints that govern how ReEDS builds and operates capacity fall into several main categories:

- **Load Balance Constraints**: Sufficient power must be generated within or imported by the transmission system to meet the projected load in each of the 134 balancing areas (BAs) in each of the 17 time-slices. The annual demand and the time-slice-specific electricity demand in future years are scaled based on load growth inputs.

- **Planning Reserve Constraints**: Each region must have sufficient available capacity to meet the forecasted peak demand as well as an additional planning reserve margin (NERC 2018). Dispatchable technologies contribute their full capacity toward planning reserves. For variable renewable energy (VRE) technologies, ReEDS uses a load-duration curve (LDC) approximation to estimate the effective load-carrying capacity of both existing capacity and potential capacity additions to determine their contribution to meeting the reserve margin. For storage, a chronological simulation using hourly data is used to assess its contribution. Planning reserve capacity can also be traded between regions if transmission capacity is available.[7]

- **Operating Reserve Constraints:** These constraints ensure enough capacity is available to meet unexpected changes in generation and load in each reserve-sharing group (Section 7.3) and time-slice. ReEDS accounts for the following operating reserve requirements: regulation reserves, spinning reserves, and flexibility reserves.

- **Generator Operating Constraints:** Technology-specific constraints bound the minimum and maximum power production and capacity commitment based on physical limitations and assumed average outage rates.

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[6] The current default is 20 years but it can be adjusted by the user.
[7] Hydropower's contribution to planning reserves depends on its categorization as dispatchable or non-dispatchable, which is discussed in Section 3.1.6.

- **Transmission Constraints:** Power transfers among regions are constrained by the nominal carrying capacity of transmission corridors that connect the regions. Transfers of planning reserves are also subject to transmission limits. A detailed description of the transmission constraints can be found in Section 6.

- **Resource Constraints:** Many renewable technologies, including wind, solar, geothermal, biopower, and hydropower, are spatially heterogeneous and constrained by the quantity available at each location. Several of the technologies include cost- and resource-quality considerations in resource supply curves to account for depletion, transmission, and competition effects. The resource assessments that seed the supply curves come from various sources; these are discussed in Section 3, where characteristics of each technology are also provided.

- **Emissions Constraints:** ReEDS can limit or cap the emissions from fossil-fueled generators for sulfur dioxide (SO_2), nitrogen oxide (NO_x), and carbon dioxide (CO_2). The emission limit and the emission per megawatt-hour by fuel and plant type are inputs to the model. Emissions can be either capped or taxed, with flexibility for applying either. Alternatively, emissions intensities can also be limited to certain bounds in ReEDS.

- **Renewable Portfolio Standards or Clean Electricity Standards:** ReEDS can represent renewable portfolio standards (RPSs) and clean electricity standards constraints at the national and state levels. All renewable generation is considered eligible under a national RPS requirement. The renewable generation sources include hydropower, wind, CSP, geothermal, PV, and biopower (including the biomass fraction of cofiring plants). The eligibility of technologies for state RPSs depends on the state's specific requirements and thus varies by state. RPS targets over time are based on an externally defined profile. Penalties for noncompliance can be imposed for each megawatt-hour shortfall occurring in the country or a given state. In the same way, a clean energy standard constraint can be implemented to include non-renewable clean energy resources, such as nuclear, fossil fuels with carbon capture and sequestration (CCS), or natural gas.

2.2.2 Demand Module

The demand module represents demand for energy services (e.g., lumens for lighting) for different customer classes. In the residential buildings sector, customer classes are defined on the basis of income. Services are provided by end-use devices, which are associated with different efficiency levels. The desirability of different device efficiency levels depends in part on the subjective discount rates for each customer class, with higher income customers being associated with lower discount rates. Over time, the stock of devices evolves according to the costs and benefits associated with new technologies.

The objective function for the demand module represents the net present value of total consumer welfare over the model horizon. The function has three components: one corresponding to the capital investment and two for the use of devices. For the latter two, the components are illustrated in Figure 3 (page 11) for a low-efficiency device (equilibrium point E_{low}) and a high-efficiency device (E_{high}). The letters in the figure (A, B, C, D, and E) denote the area of the associated region.

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- **Consumer benefit** corresponds to the area under the energy service demand curve. It captures the difference between customer willingness to pay (reflected in points along the demand curve) and the equilibrium price paid for the consumption of service below the equilibrium level. In Figure 3, these benefits are equal to A+B+C for a low-efficiency device and A+B+C+D+E for a high-efficiency device. For a given device purchase in the model, consumer benefits are summed over the entire lifetime of the device.

- **Operational costs** represent the price paid for the electricity required to achieve a given level of service. In Figure 3, these costs are equal to B+C for a low-efficiency device and C+E for a high-efficiency device. Like consumer benefits, for a given device purchase, operational costs are summed over the entire lifetime of the device.[8]

- **Capital costs** represent the purchase price of a new device. We assume this is a one-time payment for customers that does not depend on the level of service consumed. Because they do not depend on service levels, capital costs are not explicitly captured in Figure 3. However, they relate to the figure in the following way: if the figure represents operations for a device with a one-year lifetime, the consumer will choose the low-efficiency device if the net operational benefit (consumer benefit less operational cost, or A) less the capital cost of the device is greater than the net operational benefit (A+B+D) less the capital cost of the high-efficiency device. Thus, the choice of device will depend on the magnitude of the increased operational benefit of the high-efficiency device (B+D) versus its (presumably) higher capital cost.

Details about the demand module are in the Demand Module section of the appendix. The demand module is typically not used in ReEDS runs, and therefore it is given less emphasis in this documentation.

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[8] For devices that remain in the capital stock in the terminal model year, both consumer benefits and operational costs are weighted by an end-of-horizon factor based on the expected remaining lifespan of the device
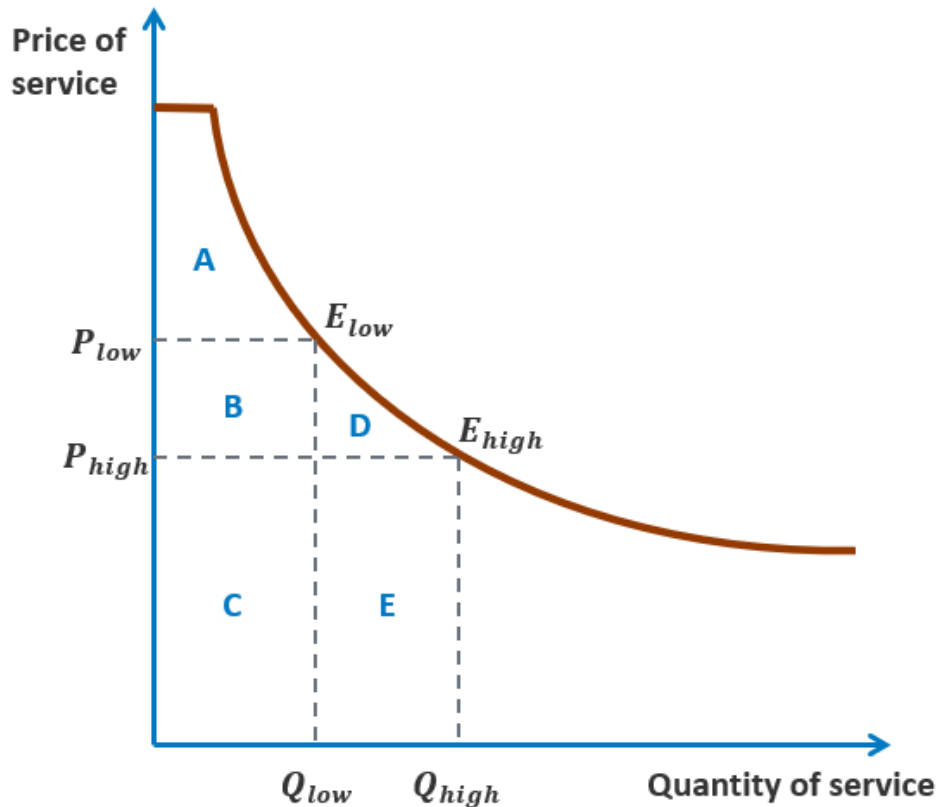
Figure 3. Energy service consumption equilibrium for two different device efficiency levels

2.3 Supply and Demand Module Integration

After each supply module solve, the model passes retail electricity prices to the demand module to inform consumers' purchase and use decisions about devices. The calculation of retail electricity prices for this supply-to-demand module interaction is different from the supply-side reported electricity prices that are discussed in Section 10.2.2. To obtain retail electricity prices that can be fed into the demand module, regional and sector-specific transmission and distribution (T&D) adders are applied to the wholesale electricity prices. The adders are constructed by combining state-wide historical retail electricity sales data from EIA(EIA 2016a) with T&D price component data from the Annual Energy Outlook (AEO) (EIA 2017a), using 2016 data for each. The process that we use is as follows:

1. Sum the National Energy Modeling System (NEMS) T&D price components: Because we treat both the T&D components of electricity prices as exogenous, we create an aggregated T&D factor to represent both. The end result is a single factor for each NEMS Electricity Market Module (EMM) region.

2. Map ReEDS BAs to states and EMM regions: To calculate adders at the ReEDS BA, we define the mapping between each BA and its state and EMM region. As is the case for states, there is a one-to-many relationship between EMM regions and ReEDS BAs.

3. Remove the wholesale electricity price component from retail prices: To calculate sector-specific adders, we make two assumptions: first, each sector-specific retail price from the

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EIA historical data has two components, a generation component that is common to all sectors and a T&D component that is sector-specific; and second, the aggregated T&D factor from AEO is a sales-weighted average of the sector-specific adders. Combining these assumptions, we can calculate expressions for sector specific adders by calculating and removing the wholesale price component from the sector-specific retail prices.

Our assumptions can be formalized by the following set of equations:

$$r_i = p + a_i$$

$$\overline{a} = \sum_i a_i q_i \Big/ \sum_i q_i$$

where i indexes sectors, r denotes retail a price, p denotes a wholesale electricity price, a denotes a T&D adder, $\overline{a}$ denotes a sales-weighted average adder across sectors, and q denotes electricity sales. The only unknown quantities in these equations are the wholesale electricity price and the sector-specific adders. Solving this set of linear equations for the adders yields:

$$a_i = r_i - \sum_i r_i q_i \Big/ \left(\overline{a} \sum_i q_i \right)$$

This adder is used to adjust supply-side wholesale prices into retail prices that can be used by the demand module.

2.4 Spatial Resolution

ReEDS can model the contiguous United States, Canada, and Mexico, though the model is typically used to study the contiguous United States.[9] In Section 11, we discuss the model and data requirements for continental optimization. Within the contiguous United States, ReEDS models capacity expansion and grid service requirements in 134 model BAs, shown in Figure 4. The model BAs are not designed to represent or align perfectly with real balancing authority areas; they are county aggregates intended to represent model nodes where electricity supply and demand is balanced. The model's synthetic transmission network connects the BAs and is composed of roughly 300 representative corridors across the three asynchronous interconnections: the Western Interconnection, the Eastern Interconnection, and Electric Reliability Council of Texas (ERCOT). The BAs also respect state boundaries, allowing the model to represent individual state regulations and incentives. The BAs are further subdivided into 356 resource supply regions that describe wind and CSP resource supply (both quality and quantity) to have more spatial granularity for these resources. Resource supply regions also consist of one or more counties. All other renewable resources are represented at the BA level of spatial resolution. Additional geographical layers used for defining model characteristics include 3 electricity interconnects, 18 model regional transmission operators designed after existing

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[9] A ReEDS-India model version has also been developed. Details of the implementation are not discussed here.

regional transmission operators, 19 North American Electric Reliability Corporation (NERC) reliability subregions, 9 census divisions as defined by the U.S. Census Bureau, and 48 states.[10]
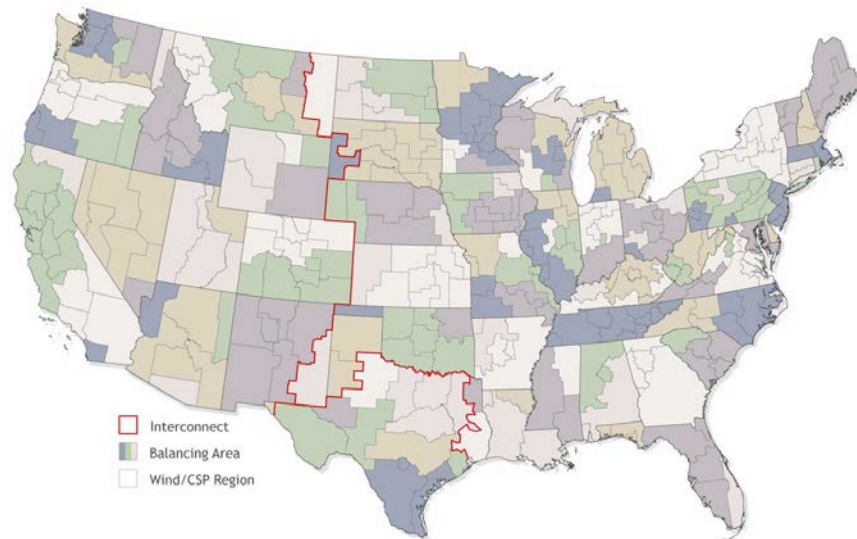
Figure 4. Map showing the ReEDS regional structure

ReEDS includes 3 interconnections, 134 model BAs, and 356 wind and CSP resource regions.

2.5 Temporal Resolution

ReEDS serves load and maintains operational reliability using a reduced-order dispatch in 17 time-slices within each model year, as defined in Table 1. Each of the four seasons is modeled with four time blocks of non-chronological aggregate hours, organized by when they occur: overnight, morning, afternoon, and evening.[11] The 17th time-slice is a summer "superpeak" representing the top 40 hours of summer load. Though this schedule does allow the model to capture seasonal and diurnal variations in demand, wind, and solar profiles, it is insufficient to address some of the shorter time-scale challenges associated with unit commitment and economic dispatch, especially under scenarios with high penetration of variable generation (e.g., wind and solar). To more accurately represent how renewable grid integration might affect investment and dispatch decisions, the ReEDS model includes parameters designed to address intra-time-slice variability and uncertainty of wind, solar, and other variable renewable resources. These parameters are derived from 8,760 hourly data and updated between each solve year. These parameters include capacity credit for resource adequacy and curtailment estimates, and are discussed in detail in Section 7.

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[10] These additional geographical layers defined in ReEDS do not necessarily align perfectly with the actual regions, except for state boundaries, which are accurately represented.

[11] The modeled load for each time-slice is an average of all hours represented by that time-slice. Therefore, the representative days are non-chronological across seasons. However, for the purposes of storage charging and discharging, we assume that time-slices within a season *are* chronological.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Table 1. Definition of ReEDS Time-Slice

Time-Slice	Hours/Year	Season	Time of Day	Period
H1	736	Summer	Overnight	10 p.m. to 6 a.m.
H2	644	Summer	Morning	6 a.m. to 1 p.m.
H3	328	Summer	Afternoon	1 p.m. to 5 p.m.
H4	460	Summer	Evening	5 p.m. to 10 p.m.
H5	488	Fall	Overnight	10 p.m. to 6 a.m.
H6	427	Fall	Morning	6 a.m. to 1 p.m.
H7	244	Fall	Afternoon	1 p.m. to 5 p.m.
H8	305	Fall	Evening	5 p.m. to 10 p.m.
H9	960	Winter	Overnight	10 p.m. to 6 a.m.
H10	840	Winter	Morning	6 a.m. to 1 p.m.
H11	480	Winter	Afternoon	1 p.m. to 5 p.m.
H12	600	Winter	Evening	5 p.m. to 10 p.m.
H13	736	Spring	Overnight	10 p.m. to 6 a.m.
H14	644	Spring	Morning	6 a.m. to 1 p.m.
H15	368	Spring	Afternoon	1 p.m. to 5 p.m.
H16	460	Spring	Evening	5 p.m. to 10 p.m.
H17	40	Summer	Peak	40 highest demand hours of H3

3 Technology Descriptions

This section describes the electricity generating technologies included in ReEDS. Cost and performance assumptions for these technologies are not included in this report but are taken directly from the 2019 Annual Technology Baseline (ATB) (NREL 2019).

3.1 Renewable Energy Resources and Technologies

Because renewable energy technologies are a primary focus area of the ReEDS model, they are characterized in detail. Their characterization encompasses resource assessments,[12] projected technology improvements, grid interconnection costs, and operational implications of integration. Renewable energy technologies modeled include land-based and offshore wind power, solar PV (both distributed and utility-scale), CSP with and without thermal storage,[13] hydrothermal geothermal, near-field enhanced geothermal systems (EGS), deep EGS, run-of-the-river and traditional hydropower (including upgrades and non-powered dams), dedicated biomass, cofired biomass, land-fill gas, and marine hydrokinetic wave technologies. The input assumptions, data sources, and treatments of these technologies are discussed in the following sections. Transmission considerations for renewable energy technologies are discussed in Section 6.3.[14]

3.1.1 Land-Based Wind

Wind technologies are modeled using representative turbine technologies by region depending on wind resource quality. Details of the wind resource data and technology representation can be found in Appendix H of the Wind Vision study (DOE 2015). In the current version of ReEDS, we have relied on the same data sources and approach; however, we extend the wind resource data to lower-quality wind sites.

Wind turbine models can be classified into three different International Electrotechnical Commission turbine ratings (I–III), which are designed for a range of annual average wind speeds.[15] The Class I turbines have smaller rotors relative to the size of the generator, or a higher specific power (watts per meter squared, or W/m^2), and they are therefore rated to withstand higher winds. In the lowest-speed wind resources, Class III turbines are primarily used to gain the highest capacity factor possible in lower wind speeds. Interpolating cost and performance across the three International Electrotechnical Commission classes allows monotonic functions

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[12] All renewable resource assessments are independent and mutually exclusive of each other due to their unique nature and to allow ReEDS to dynamically evaluate cost-optimal capacity expansion without any upstream ranking of which technologies would be preferred at a given site. This implementation ignores any possible land-use conflicts between multiple technologies at the same site, but spatial aggregation and resource heterogeneity is expected to alleviate this limitation.

[13] CSP refers to solar thermal power and not concentrating PV.

[14] Where given in the sections below, renewable energy resource potential values refer to the resource potential represented in ReEDS and not the total technical resource potential. The renewable potential capacity modeled in ReEDS includes exclusions in the pre-processing steps for the model, such as site exclusions, assumed transmission access limits, or a narrower set of technologies considered. Lopez et al. (2012) present renewable technical potential for the United States.

[15] International Electrotechnical Commission Class I turbines are used with an annual average wind speeds of 10 meters/second (m/s) and higher; Class III are used with an annual average wind speed of 7.5 m/s and lower. A blend of Class II and Class III turbines is used at annual average wind speeds of 7.5–8.5 m/s; while a blend of Class II and Class I turbines is used at annual average wind speeds of 8.5–10 m/s.

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of cost and performance by annual average wind speed. Cost and performance assumptions for land-based wind plants are based on expected cost and performance for a turbine (representative or interpolated) appropriate for the average annual wind speed at the site and are based on a representative system size of 100 MW.

The resource assessment for land-based wind starts with a resource map of hourly wind speeds for the United States and offshore areas (for offshore wind, see Section 3.1.2). Land area is filtered to exclude a standard set of areas considered unlikely to be developed for environmental or technical reasons: federal and state protected areas (e.g., parks, wilderness areas, and wildlife sanctuaries), areas covered by water, urban areas, wetlands, airports, and rough terrain. Areas classified as non-ridge-crest forest, non-ridge-crest U.S. Forest Service and U.S. Department of Defense lands, and state forests (where available in geographic information systems [GIS]) are 50% excluded. The remaining resource totals more than 12,000 gigawatts (GW).

Individual wind sites are grouped into ten resource classes (a.k.a., techno-resource groups or TRGs) for ReEDS, based on estimated levelized cost of energy for present-day technology (

Table 2).[16] The modeling and assessment of individual wind sites was facilitated using NREL's Renewable Energy Potential (reV) tool (Maclaurin et al. 2019). The meteorological data for onshore wind are from the Wind Integration National Dataset (WIND) Toolkit, using long-term average data for the resource assessment. Each class includes representative costs (capital and O&M) and expected output (capacity factor) along with cost and performance improvements over time. Figure 5 shows the land-based wind resource data modeled in ReEDS for all 10 TRGs, where the highest-quality wind resources belong to TRG 1 and the lowest to TRG 10. Each TRG is then further differentiated by a supply curve for grid interconnection costs in each region. See Section 6.3 for a discussion of interconnection supply curves for accessing the wind resource.

Distinct wind production profiles are also modeled for each TRG and wind resource region. In addition, to inform the statistical parameterizations for capacity value and curtailment, we use hourly production data and correlations between regions and TRGs. A 2012 weather year is used for the generation of the hourly onshore wind profile data.

Table 2. Characteristics of Land-Based Wind TRGs

Techno-Resource Group (TRG)	Wind Speed Range (m/s)	Weighted Average Wind Speed (m/s)	Weighted Average Net CF (%)	Potential Wind Plant Capacity (GW)
TRG1	8.2–13.5	8.7	47.4	100
TRG2	8.0–10.9	8.4	46.2	200
TRG3	7.7–11.1	8.2	45.0	400
TRG4	7.5–13.1	7.9	43.5	800
TRG5	6.9–11.1	7.5	40.7	1,600

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[16] The wind resource is not evenly binned into the 10 TRGs. The best resource sites (TRGs 1–4) are grouped into smaller bins to improve resolution for sites that are likely to be most competitive.

Techno-Resource Group (TRG)	Wind Speed Range (m/s)	Weighted Average Wind Speed (m/s)	Weighted Average Net CF (%)	Potential Wind Plant Capacity (GW)
TRG6	6.1–9.4	6.9	36.4	1,600
TRG7	5.4–8.3	6.2	30.8	1,600
TRG8	4.7–6.9	5.5	24.6	1,600
TRG9	4.0–6.0	4.8	18.3	1,600
TRG10	1.0–5.3	4.0	11.1	2,132

More information can be found in the NREL Annual Technology Baseline (NREL 2019).
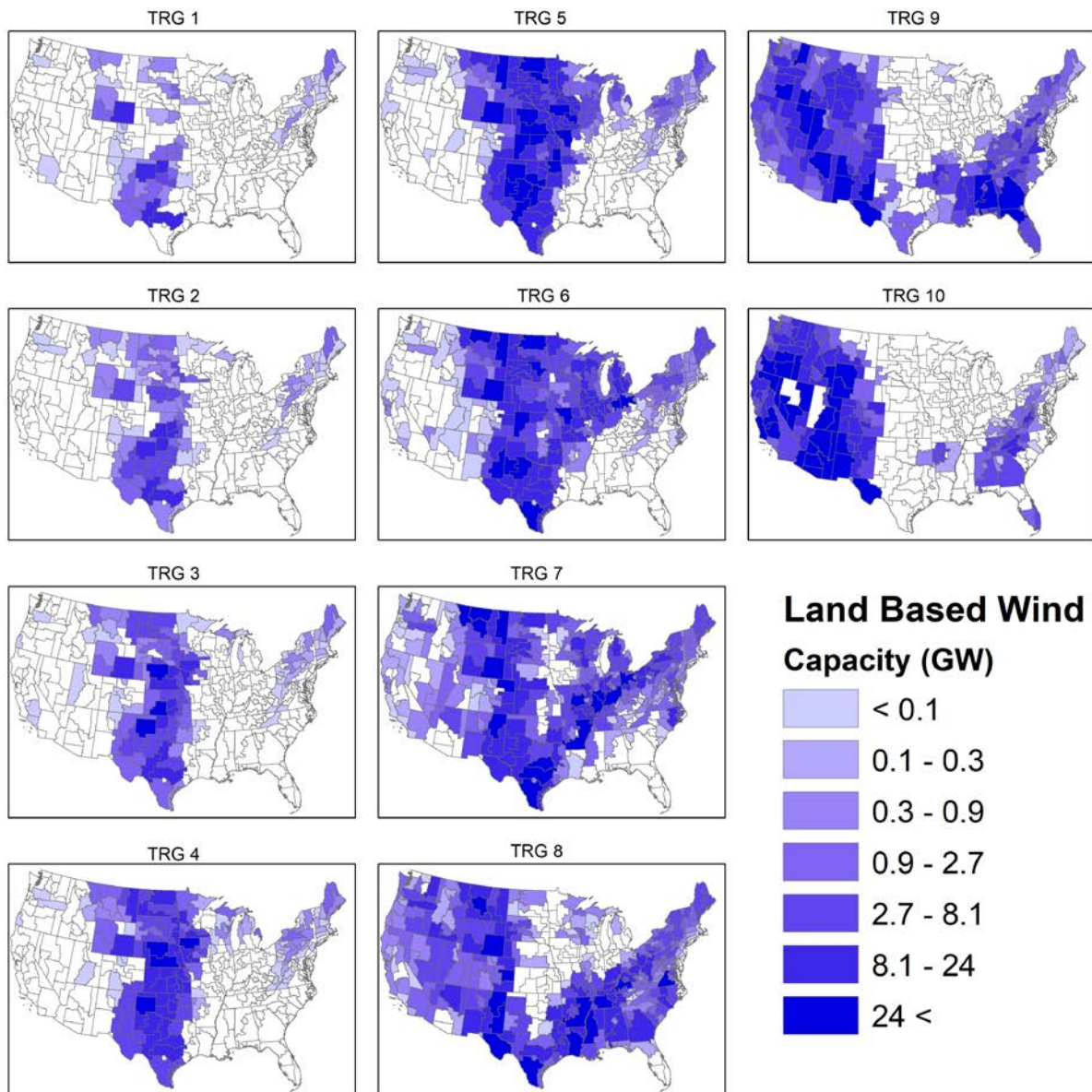
Figure 5. Land-based wind resource map for the contiguous United States

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3.1.2 Offshore Wind

There is substantial diversity in offshore wind generators, in distance from shore, water depth, and resource quality. ReEDS subdivides offshore wind potential into fifteen resource classes: five for fixed-bottom turbine designs and ten for floating designs. Fixed bottom offshore wind development is limited to resources < 60 meters [m] in depth using either current-technology monopile foundations (0–30 m); or jacket (truss-style) foundations (30–60 m). Offshore wind using a floating anchorage could be developed for greater depths and are assumed the only feasible technology for development for resource deeper than 60 m. Within each category, the classes are distinguished by resource quality, and then supply curves differentiate resource by cost of accessing transmission in a similar fashion as land-based wind.

Eligible offshore area for wind development includes open water within the U.S.-exclusive economic zone having a water depth less than 1,000 m, including the Great Lakes. As with land-based resource, offshore zones are filtered to remove areas considered unsuitable for development, including national marine sanctuaries, marine protected areas, wildlife refuges, shipping and towing lanes, offshore platforms, and ocean pipelines. The offshore technology selection is made using the Offshore Wind Cost Model, which selects the most economically feasible technology for developing a wind resource (Beiter and Stehly 2016). More than 2,000 GW of technical offshore wind potential remain after applying the exclusions.

Current-day cost data are derived from the published data of the global offshore wind industry as well as estimates from recent development activity on the Atlantic Coast of the United States (Musial et al. 2019; NREL 2019). These data are coupled with engineering assessments and distance-based cost functions (specific to the offshore export cable and incremental construction cost associated with moving farther from shore) to determine expected site-specific costs for technology across a broad range of water depths and distances from shore (Beiter et al. 2017). Cost and performance for offshore wind plants are based on assuming a representative plant size of 600 MW.

Other aspects of our model representations for offshore wind follow the same methods as those for land-based wind (see Appendix H of the Wind Vision study [DOE 2015]). Figure 6 shows the offshore wind resource potential modeled in ReEDS using the 15 TRGs. The first five TRGs represent fixed-bottom offshore wind resources with TRG 1 representing the lowest-cost resource based on levelized cost of energy (LCOE). TRGs 6–15 represent floating offshore wind resources with TRG 6 being the lowest cost based on LCOE. The three lowest cost TRGs, for both fixed-bottom and floating-bottom turbines, have smaller bin sizes to capture the highest quality resources with greater resolution.

Table 3. Characteristics of Offshore Wind TRGs

TRG		Wind Speed Range (m/s)	Weighted Average Wind Speed (m/s)	Weighted Water Depth (m)	Weighted Distance Site to Cable Landfall (km)	Weighted Average Net CF (%)	Potential Wind Plant Capacity (GW)
Fixed-Bottom	TRG 1	8.5–9.0	8.6	13	6	45	12
	TRG 2	8.0–8.5	8.4	16	9	43	25
	TRG 3	8.0–8.5	8.3	19	15	42	50
	TRG 4	8.0–8.5	8.3	26	36	41	320
	TRG 5	7.5–8.0	7.9	36	72	37	320
Floating	TRG 6	9.5–10	9.7	130	24	51	12
	TRG 7	9.5–10	9.7	145	40	50	25
	TRG 8	9.5–10	9.5	139	50	49	50
	TRG 9	9.0–9.5	9.4	136	70	48	100
	TRG 10	9.0–9.5	9.1	140	94	45	200
	TRG 11	8.5–9.0	8.7	323	118	42	200
	TRG 12	8.0–8.5	8.1	404	123	37	200
	TRG 13	7.5–8.0	7.8	474	138	35	200
	TRG 14	7.0–7.5	7.4	615	130	33	200
	TRG 15	7.5–8.0	7.5	797	199	31	143

More information can be found in the NREL Annual Technology Baseline (NREL 2019).

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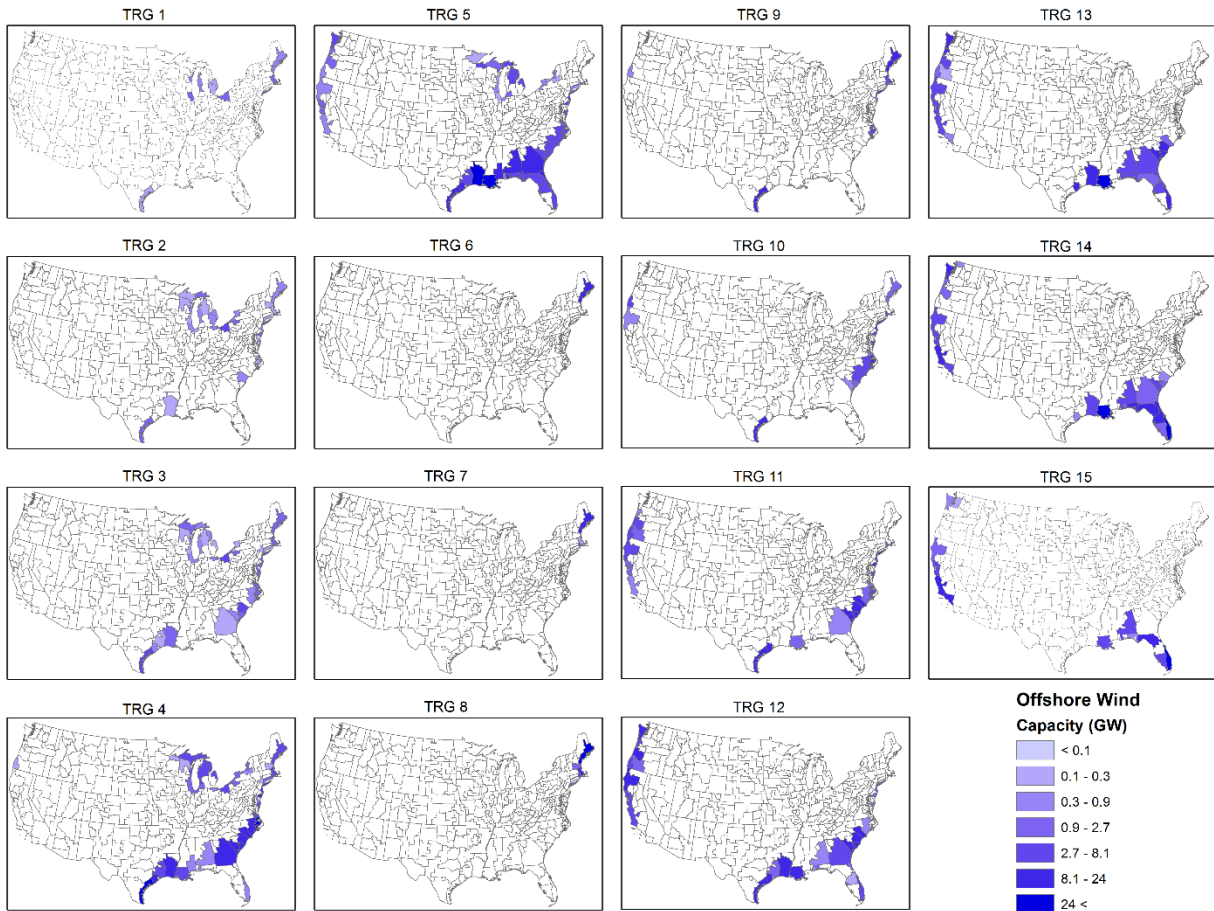
Figure 6. Offshore wind resource map for the contiguous United States

3.1.3 Solar Photovoltaics

ReEDS differentiates between three solar photovoltaic technologies: large-scale utility PV (UPV), distribution-side utility-scale PV (DUPV), and rooftop PV. Investments in UPV and DUPV are evaluated directly in ReEDS, while rooftop PV deployment and performance are exogenously input into ReEDS from the dGen model.

UPV in ReEDS represents utility-scale single-axis-tracking PV systems with a representative size of 100 megawatts (MW) and an array density of 39 MW per square kilometer (km^2) with an inverter loading ratio of 1.3. Resource potential is assumed to be located on large parcels outside urban boundaries, excluding federally protected lands, inventoried "roadless" areas, U.S. Bureau of Land Management areas of critical environmental concern, and areas with slope greater than 5%. Each eligible UPV site is characterized by a raw hourly (8,760) irradiance profile that is representative of the solar resource within a 10 km2 contiguous area. Each of these UPV sites are compiled into supply curves for each of the 134 ReEDS BAs with 7 PV resource classes, which are further differentiated by cost to connect to the transmission network (process described in Section 6.3). The nine resource classes reflect different resource qualities based on the annual average global horizontal irradiance (GHI) reported by the latest National Solar Radiation Database (NSRDB), assuming a tilt angle equal to the latitude (Table 4). The UPV supply curves

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input into ReEDS include 117 terawatts (TW) of potential, which is shown by resource class in Figure 8.

Table 4. Characteristics of UPV and DUPV Resource Classes

Class	GHI (kWh/m2/day)	Potential UPV Capacity (GW)	Weighted Average UPV Capacity Factor (%)	Potential DUPV Capacity (GW)	Weighted Average DUPV Capacity Factor (%)
1	3.0–3.5	167	12.2	14	12.6
2	3.5–4.0	16,870	16.8	184	16.7
3	4.0–4.5	30,238	18.6	434	17.9
4	4.5–5.0	37,438	19.6	511	19.1
5	5.0–5.5	20,372	21.8	222	21.1
6	5.5–6.0	11,868	23.9	116	23.8
7	6.0–6.5	332	24.4	4	24.8
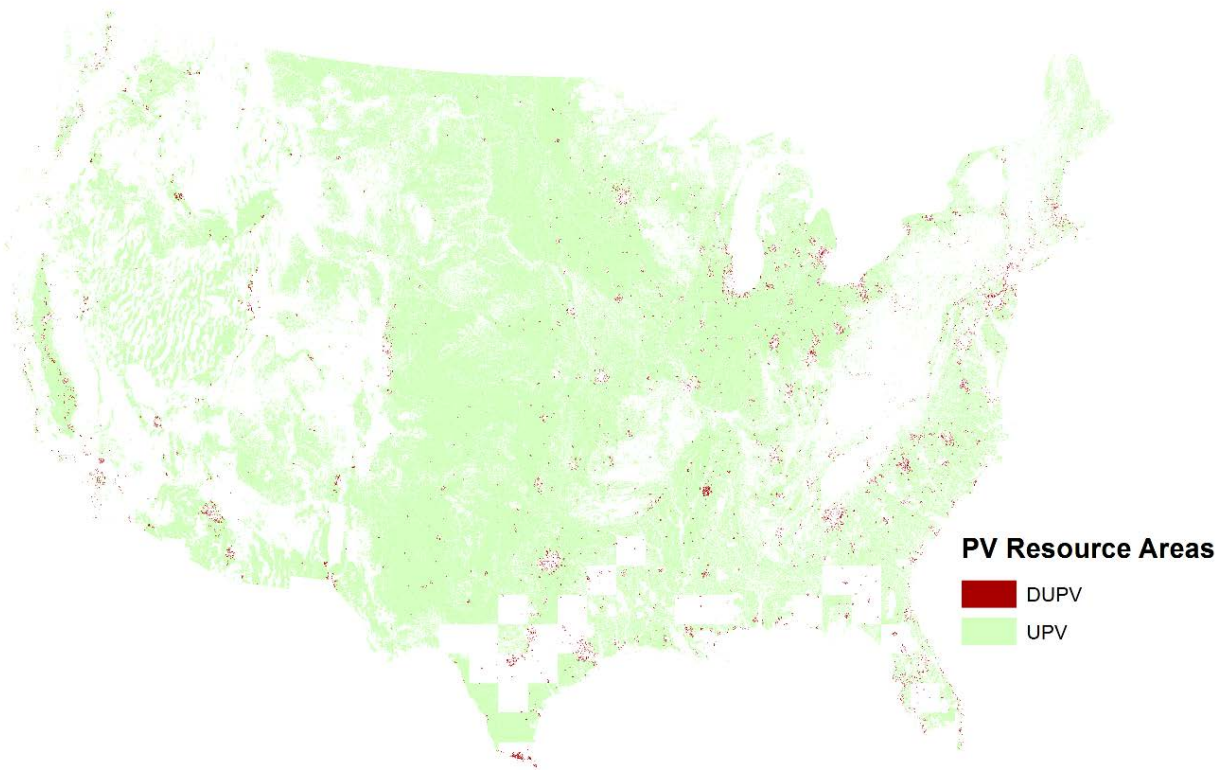
Figure 7. UPV and DUPV resource areas available for development considering land use exclusions
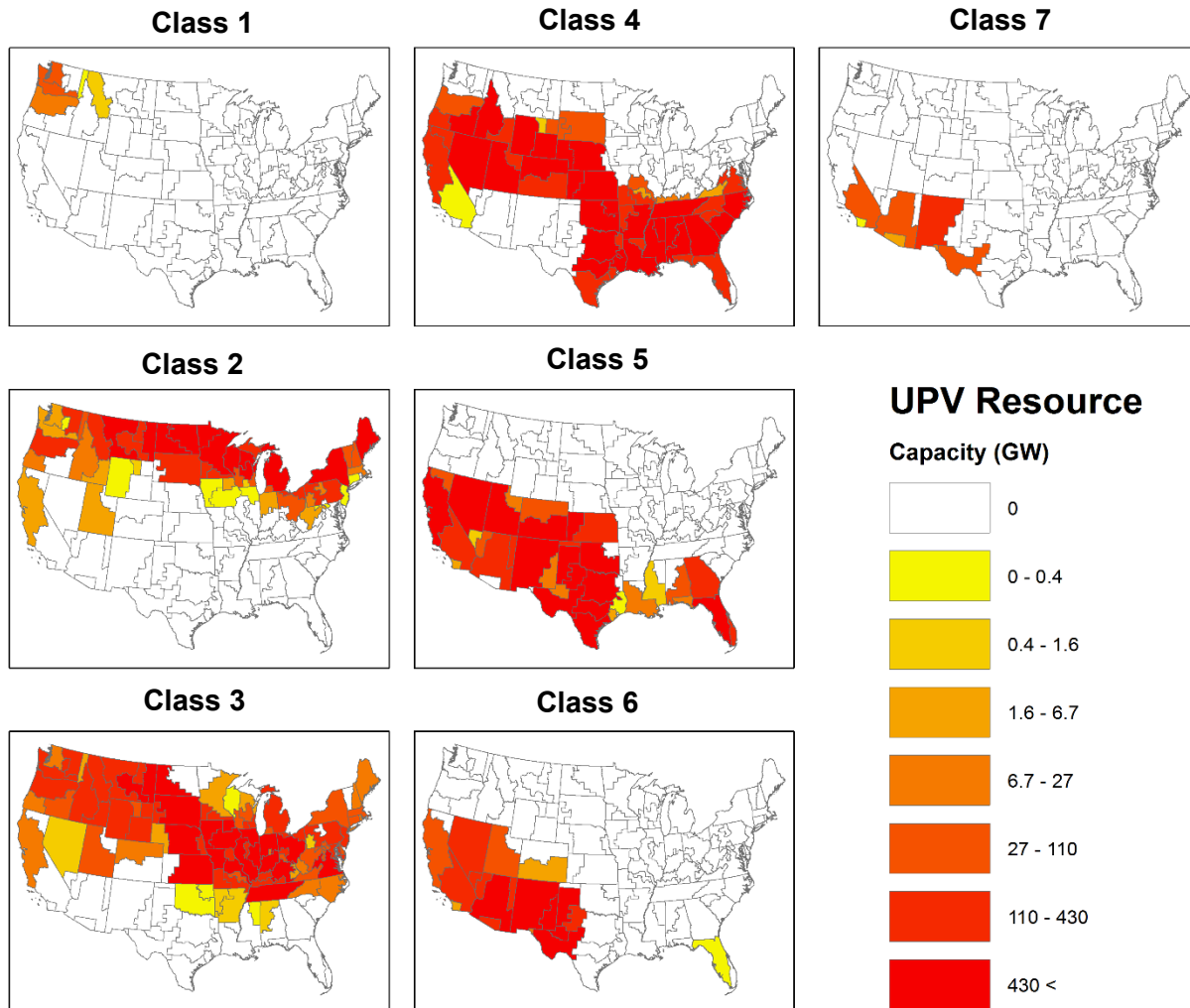
Figure 8. UPV resource availability by ReEDS BA region and resource class

DUPV in ReEDS assumes utility-scale single-axis-tracking systems with a representative size of 1 MW and an array density of 39 MW/km^2 with an inverter loading ratio of 1.3. These systems are located within or are directly connected to distribution networks in urban areas. Resource potential estimates for DUPV are made by defining the eligible area as open space within urban areas and near existing distribution substations. Parking lots, roads, and urbanized areas are excluded by identifying areas with imperviousness greater than or equal to 1% (Fry et al. 2011). Additional exclusions for landmarks, parks, and water further exclude areas deemed unlikely for development. Each DUPV site within the resulting eligible rural land areas is characterized by a raw hourly (8,760) irradiance profile that is representative of the solar resource within a 10 km^2 contiguous area. This process returns an urban DUPV potential of nearly 1.48 TW across the contiguous United States (see Figure 9), with resource potential generally correlated with region size and population, and with higher-quality potential in the Southwest. The two order-of-magnitude difference in resource capacity relative to UPV is a result of the significantly smaller land area with access to the distribution networks. Similar to UPV, these values are input into ReEDS as supply curves by BA region and the nine PV resource classes from Table 4.

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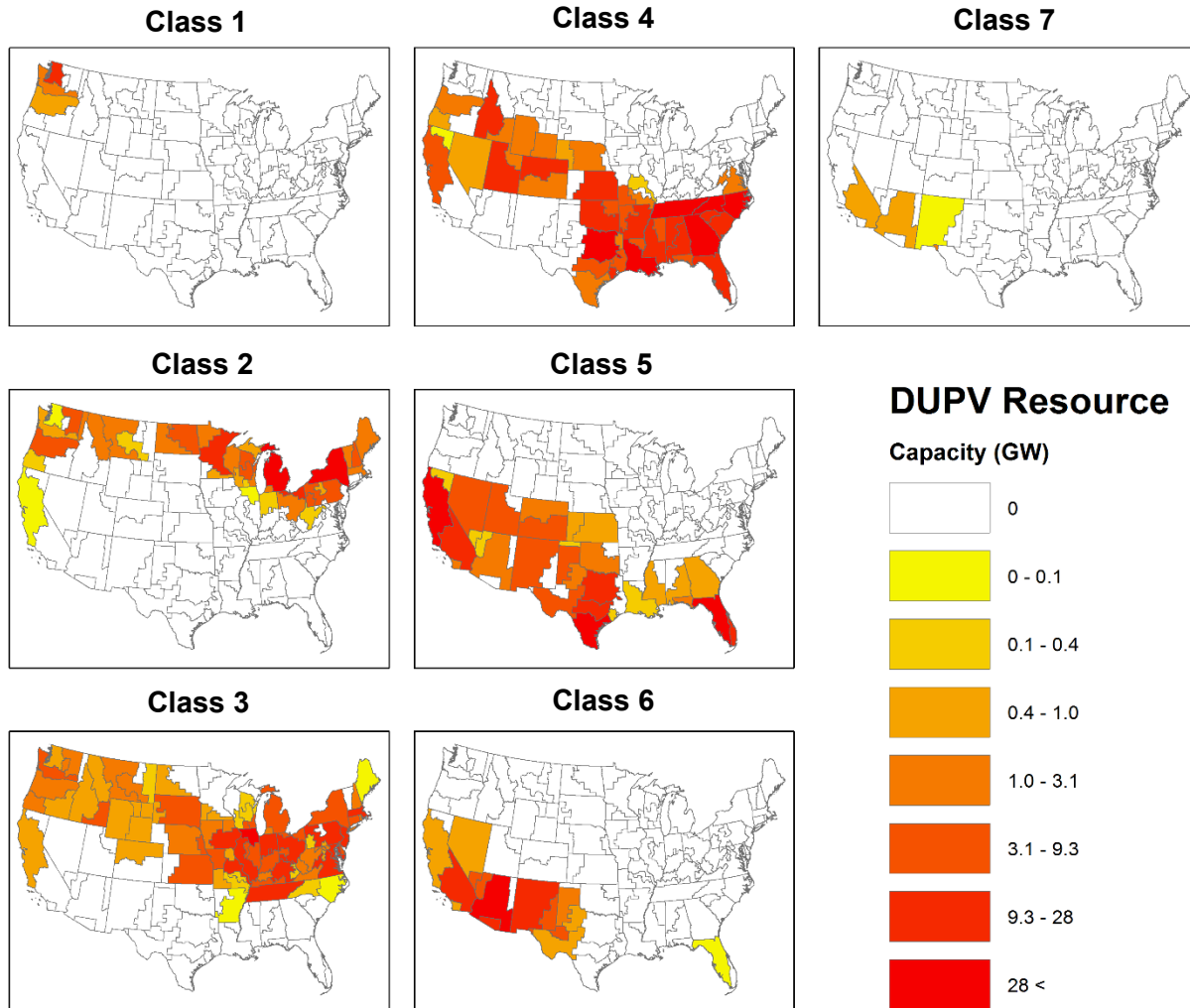
Figure 9. DUPV resource availability in each ReEDS region by resource class

DUPV systems have lower infrastructure requirements than large-scale rural UPV systems; we assume they connect to existing nearby distribution substations at about 13 kilovolts (kV), whereas the representative UPV system connects to a high-voltage bus at 230 kV and may require a spur line several miles long to reach that connection point. The cost of the spur line is handled separately in the accessibility supply curve (Section 6.3), but the additional transformers and power electronics associated with the larger systems and higher-voltage interconnections add cost and losses to the UPV systems. On the other hand, the larger UPV systems benefit from economies of scale. On balance, we assume a per-kW capital cost penalty of 8.7%[17] and 5.3% higher delivered energy (i.e., reduced losses) for DUPV relative to UPV.

Performance characteristics for UPV and DUPV were developed using NREL's reV Tool, using multiyear hourly weather files from the National Solar Radiation Database[18] at 4-km by 4-km parcels throughout the contiguous United States from 1998 to 2016. No changes or

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[17] Represents the average of union and non-union total system cost without transmission between a 10MW (proxy for DUPV) and 100MW (UPV) system (Fu et al. 2015).
[18] https://nsrdb.nrel.gov/

improvements in capacity factor over time are assumed for PV technologies. For each ReEDS BA region, resource quality classifications were made by averaging across the 1998–2016 period for all available parcels. Hourly generation profiles were taken from 2012. The generation profiles from all the regions in a BA for each resource class were averaged to provide ReEDS with average capacity factors by time-slice and resource class.

To mitigate excessive wheeling of distributed PV generation, ReEDS assumes all power generated by both DUPV and rooftop PV systems is permitted to be exported to neighboring BAs only when total generation in the source region exceeds the load for a given time-slice. UPV-generated electricity, in contrast, can be exported in all time-slices and regions.

Degradation of the efficiency of solar PV capacity over time is also modeled at 0.5%/year (Jordan and Kurtz 2013). This degradation is modeled by reducing the capacity of PV that generates energy by 0.5%/year.

Rooftop PV includes commercial, industrial, and residential systems. These systems are assumed to have an inverter loading ratio of 1.1. The Distributed Generation Market Demand model (dGen), a consumer adoption model for the contiguous U.S. rooftop PV market, is used to develop future scenarios for rooftop PV capacity, including the capacity deployed by BA and the pre-curtailment energy production by that capacity (Sigrin et al. 2016). The default dGen trajectories used in this version of ReEDS are based on the residential and commercial PV cost projections as described in the 2019 ATB (NREL 2019). There are 12 unique rooftop PV trajectories available in ReEDS that are from the 2019 Standard Scenarios report (Cole et al. 2019). These trajectories were created by running a ReEDS scenario and feeding the electricity price outputs from ReEDS back into dGen. The trajectories incorporate existing net metering policy as of spring 2019, and they include the investment tax credit (ITC) as discussed in Section 9.2.

Assumptions for each dGen scenario are made consistent with the ReEDS scenario assumptions as much as is possible. For example, the Tax Credit Extension scenario also includes an extension of the ITC in dGen, and the Low PV Cost scenario uses low trajectory from ATB for commercial and rooftop PV costs.

3.1.4 Concentrating Solar Power

Concentrating solar power (CSP) technology options in ReEDS encompass a subset of possible thermal system configurations, with and without thermal storage, as shown in Table 5. The two system types access the same resource potential, which is divided into 12 resource classes based on direct normal insolation (DNI) (Table 6). The CSP resource and technical potential are based on the latest version of NSRDB. Details of the CSP resource data and technology representation can be found in Appendix B of Murphy et al. (2019). By default, recirculating and dry cooling systems are allowed for future CSP plants getting built in ReEDS. CSP cost and performance estimates are a based on an assumed plant size of 100 MW.

Table 5. Characteristics of CSP Technology Storage Options

System	Configuration[19]	Dispatchability	Capacity Credit	Curtailments
no storage	solar multiple: 1.4	insolation-dependent	variable/ statistical	variable/ statistical
with storage	solar multiple: 2.4 or 2.7 storage duration: 10 or 14 hours	dispatchable	Calculated based on storage duration	none

The CSP resource classes are defined by power density of DNI, developable land area having been filtered based on land cover type, slope, and protected status. CSP resource in each resource region is therefore represented as a supply curve of megawatts of solar collector potential, assuming a power density of 14.9 MW/km.[2] Performance for each CSP resource class is developed using 2012 hourly resource data (Sengupta et al. 2018) from representative sites of each resource region. The 2012 weather files are processed through the CSP modules of the System Advisor Model (SAM) to develop performance characteristics for each CSP resource class and representative CSP system considered in ReEDS. As with wind and PV technologies, CSP resources are further distinguished by grid accessibility in each resource region (Section 6.3).

Table 6. Resource Classes for CSP Plants Using a Solar Multiple (SM) of 2.4

Resources are then scaled in ReEDS by the ratio of the model-determined SM and 2.4.

Resource Class	DNI (kWh/m²/day)	Weighted Average Field CF for SM=1 system (%)[a]	Available Resource (GW)
Class 1	5–5.25	17	2,641
Class 2	5.25–5.5	18	1,925
Class 3	5.5–5.75	19	1,495
Class 4	5.75–6	20	1,725
Class 5	6–6.25	21	1,850
Class 6	6.25–6.5	22	1,282
Class 7	6.5–6.75	23	1,252
Class 8	6.75–7	24	1,098
Class 9	7–7.25	26	1,381
Class 10	7.25–7.5	27	1,251
Class 11	7.5–7.75	28	677
Class 12	>7.75	29	114

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[19] The solar multiple (SM) is defined as the ratio of the design solar field aperture area to the aperture area required to produce the power cycle design thermal input (and power output) under reference environmental conditions.

^a The field capacity factors (CF) shown here are from SAM (version 2017.09.05, SDK version 181) simulation assuming an SM=1 system. This field capacity factor is meant to represent the upper limit of corresponding turbine capacity factor for all systems with SM>1.

The representative CSP system without storage used to define system performance in ReEDS is a 100-MW trough system with a SM of 1.4. As CSP systems without storage are non-dispatchable, output capacity factors are defined directly from SAM results. The average annual capacity factors for the solar fields of these systems range from 20% (Class 1 resource) to 29% (Class 12 resource).
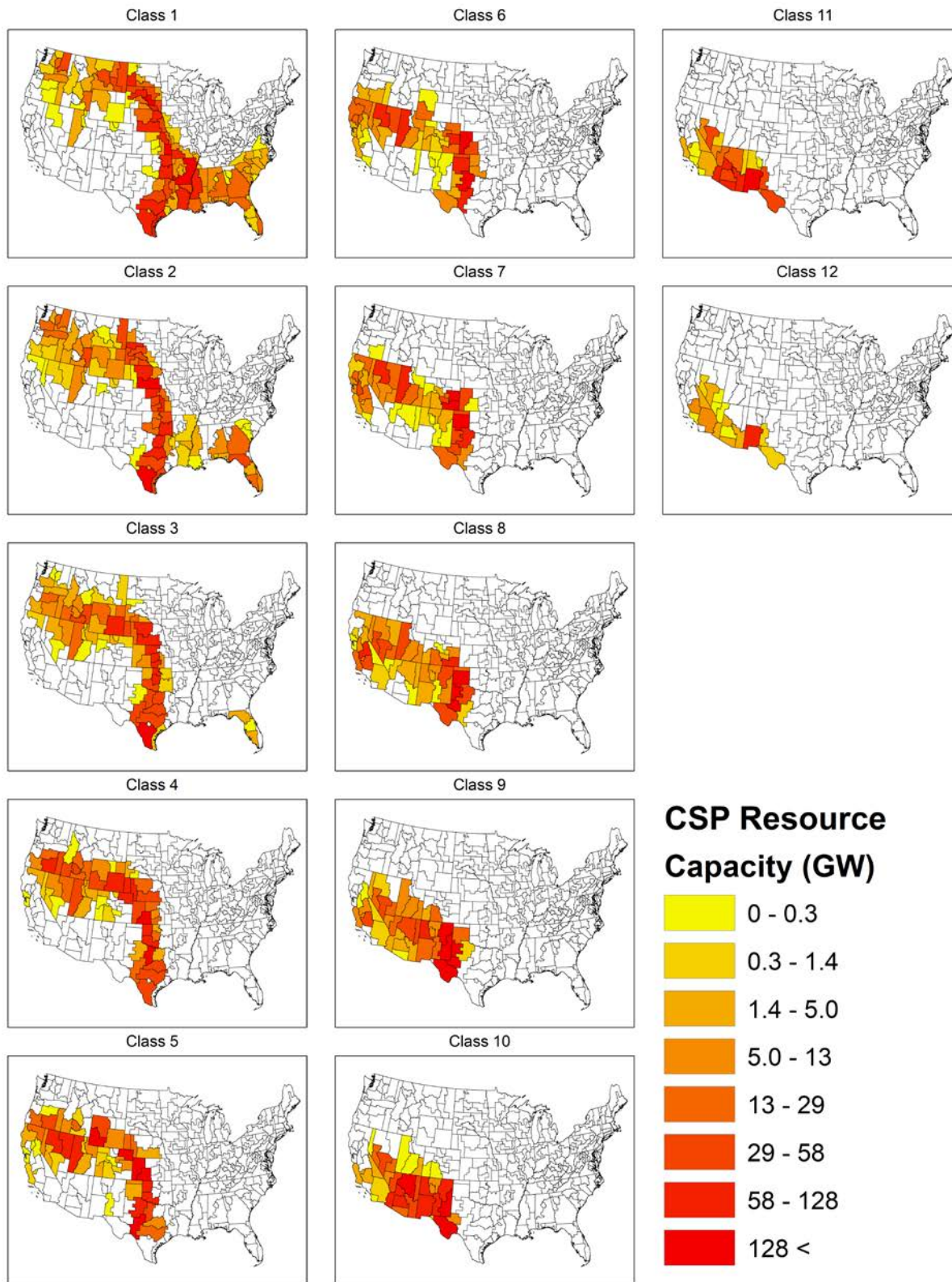
Figure 10. CSP resource availability in each ReEDS resource region by 12 resource class

The representative system for any new CSP with thermal energy storage is a tower-based configuration with a molten-salt heat-transfer fluid and a thermal storage tank between the heliostat array and the steam turbine.[20] Two CSP with storage configurations are available as shown in Table 5.

For CSP with storage, plant turbine capacity factors by time-slice are an output of the model, not an input, as ReEDS can dispatch collected CSP energy independent of irradiation. Instead, the profile of power input from the collectors (solar field) of the CSP plants are model inputs, based on SAM simulations from 2012 weather files.

The capacity credit of CSP with storage is calculated using the same method as the calculation of the capacity credit of other storage technologies, except that rather than using net load to show opportunities to charge, DNI resource is used to show opportunities to charge the storage. See Section 7.2.2 for details.

3.1.5 Geothermal

The geothermal resource has several subcategories in ReEDS:

- The hydrothermal resource represents potential sites with appropriate geological characteristics for the extraction of heat energy. The hydrothermal potential included in the base supply curve consists of only identified sites, with a separate supply curve representing the undiscovered hydrothermal resource.

- EGS sites are geothermal resources that have sufficient temperature but lack the natural permeability, in-situ fluids, or both to be hydrothermal systems. Developing these sites with water injection wells could create engineered geothermal reservoirs appropriate for harvesting heat.

- Near-field EGS is a subset of EGS that implies proximity to existing or known hydrothermal sites.

Table 7 lists the technical resource potential for the different geothermal categories.

Table 7. Technical Resource Potential (GW)

	Hydrothermal	Undiscovered Hydrothermal	Near-Field EGS	Deep EGS
Binary	1.7	6.8	0.6	2,263.4
Flash	3.4	12.0	0.8	1,111.9
Total	5.1	18.8	1.4	3,375.3

The default geothermal resource assumptions allow for new construction at identified hydrothermal sites and undiscovered geothermal sites. The development of undiscovered geothermal resources is limited by a discovery rate defined as part of the GeoVision Study (DOE 2019). Though near-field EGS and additional deep EGS resources are not allowed under default assumptions because of uncertain feasibility, these geothermal resource categories can be

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[20] Historical and announced trough-based systems are characterized with technology-appropriate characteristics.

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included as additional resource in ReEDS. The geothermal supply curves are based on the analysis described by Augustine et al. (2019) and are shown in Figure 11. The hydrothermal and near-field EGS resource potential is derived from the U.S. Geological Survey's 2008 geothermal resource assessment (Williams, Reed, and Mariner 2008), while the deep EGS resource potential is based on an update of the EGS potential from the Massachusetts Institute of Technology (Tester et al. 2006). As with other technologies, geothermal cost and performance projections are from the ATB (NREL 2019).
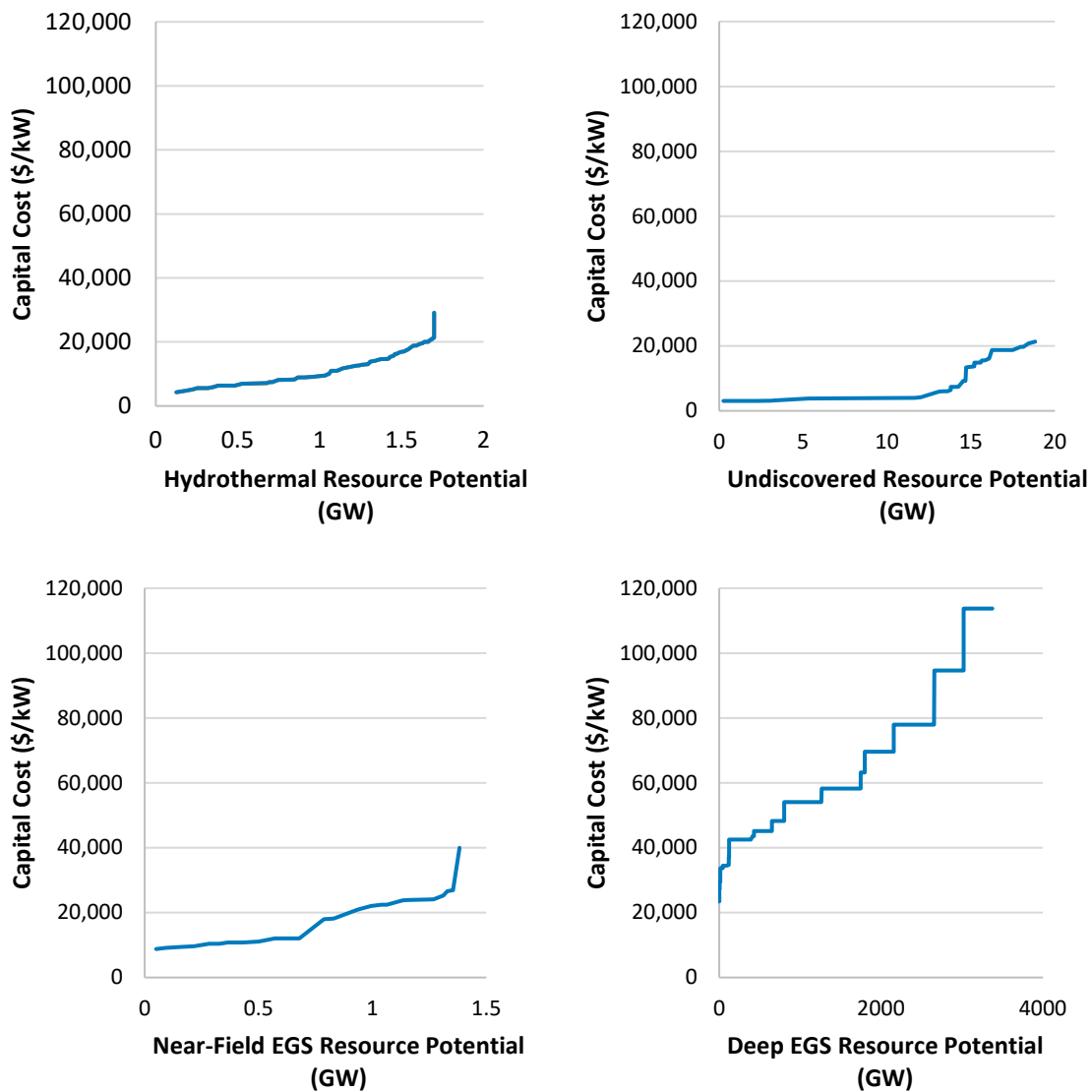
Figure 11. National capital cost supply curves for geothermal capacity used in the base model assumptions

3.1.6 Hydropower

The existing hydropower fleet representation is informed by historical performance data. From the nominal hydropower capacity in each BA, seasonal capacity adjustments are used for Western Electricity Coordinating Council (WECC) regions based on data from the Transmission

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Expansion Planning Policy Committee (TEPPC) 2024 Common Case (WECC 2013, 2015). Seasonal capacity adjustments allow more realistic seasonal variations in maximum capacity due to changes in water availability and operating constraints. These data are not available for non-WECC regions. Energy availability for the existing fleet for 2016 and beyond is defined seasonally using region-specific seasonal hydropower capacity factors averaged for 2006–2015 as reported by the National Hydropower Asset Assessment Program (NHAAP),[21] totaling 270 terawatt hours per year (TWh/yr). Capacity factors for 2010–2014 model years are calibrated so that modeled generation matches historical generation. PSH, both existing and new, is discussed in Section 3.3 on storage technologies.

Three categories of new hydropower resource potential are represented in the model:

1. Upgrade and expansion potential for existing hydropower
2. Potential for powering non-powered dams (NPD)
3. New stream-reach development potential (NSD).

The supply curves for each are discussed in detail in the Hydropower Vision report (DOE 2016b), particularly Chapter 3 and Appendix B.

ReEDS does not currently distinguish between different types of hydropower upgrades, so upgrade potential is represented generically as a potential for capacity growth that is assumed to have the same energy production potential per capacity (i.e., capacity factor) as the corresponding existing hydropower capacity in the region. The quantity of available upgrades is derived from a combination of limited resource assessments and case studies by the U.S. Bureau of Reclamation Hydropower Modernization Initiative (HMI), U.S. Army Corps of Engineers (Corps), and NHAAP Hydropower Advancement Project (Montgomery, Watson, and Harza 2009; Bureau of Reclamation 2011). Upgrade availability at federal facilities not included in the HMI is assumed to be the HMI average of 8% of the rated capacity, and upgrade availability at non-federal facilities is assumed to be the NHAAP average of 10% of the rated capacity. Rather than making all upgrade potential available immediately, upgrade potential is made available over time at the earlier of either (1) the Federal Energy Regulatory Commission (FERC) license expiration (if applicable) or (2) the turbine age reaching 50 years. This feature better reflects institutional barriers and industry practices surrounding hydropower facility upgrades. The total upgrade potential from this methodology is 6.9 GW (27 TWh/yr).

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[21] http://nhaap.ornl.gov/content/nhaap-data-sources
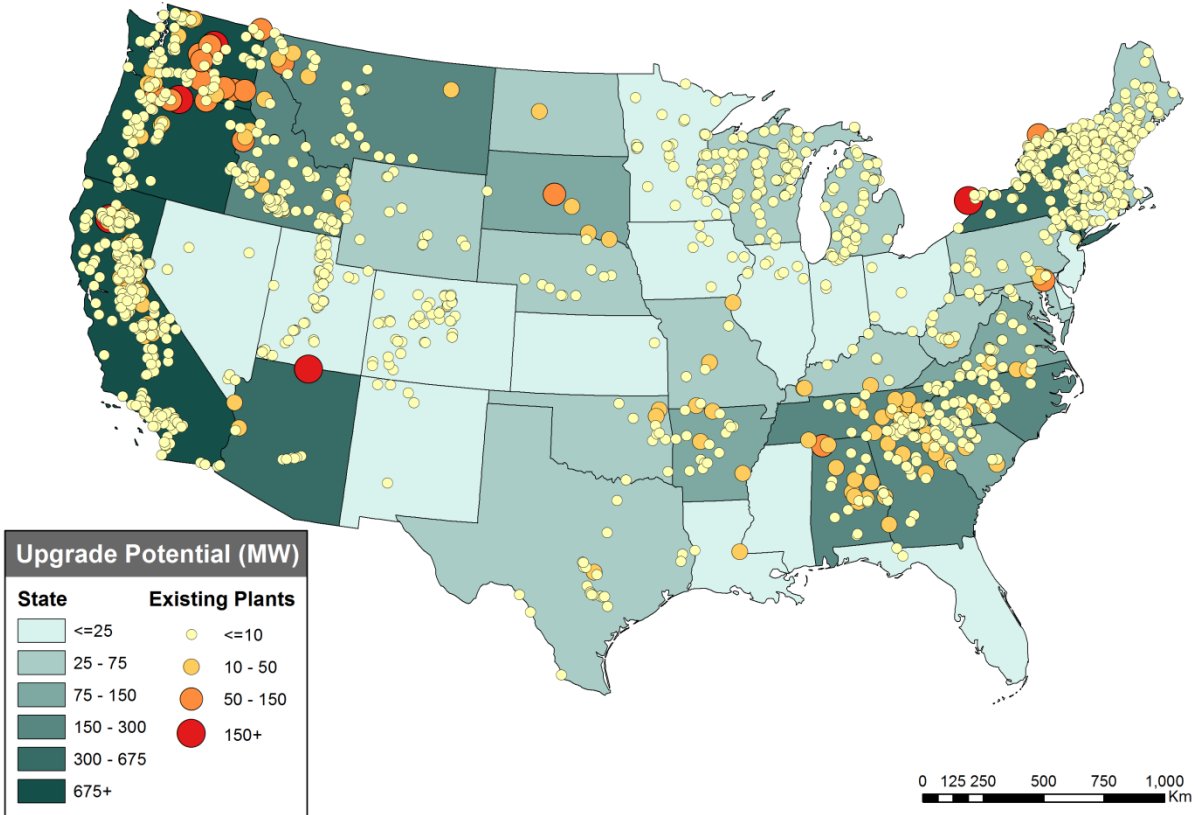
Figure 12. Modeled hydropower upgrade resource potential (DOE 2016b)

NPD resource is derived from the 2012 NHAAP NPD resource assessment (Hadjerioua, Wei, and Kao 2012; Hadjerioua et al. 2013), where the modeled resource of 5.0 GW (27 TWh/yr) reflects an updated site sizing methodology, data corrections, and an exclusion of sites under 500 kW to allow better model resolution for more economic sites.

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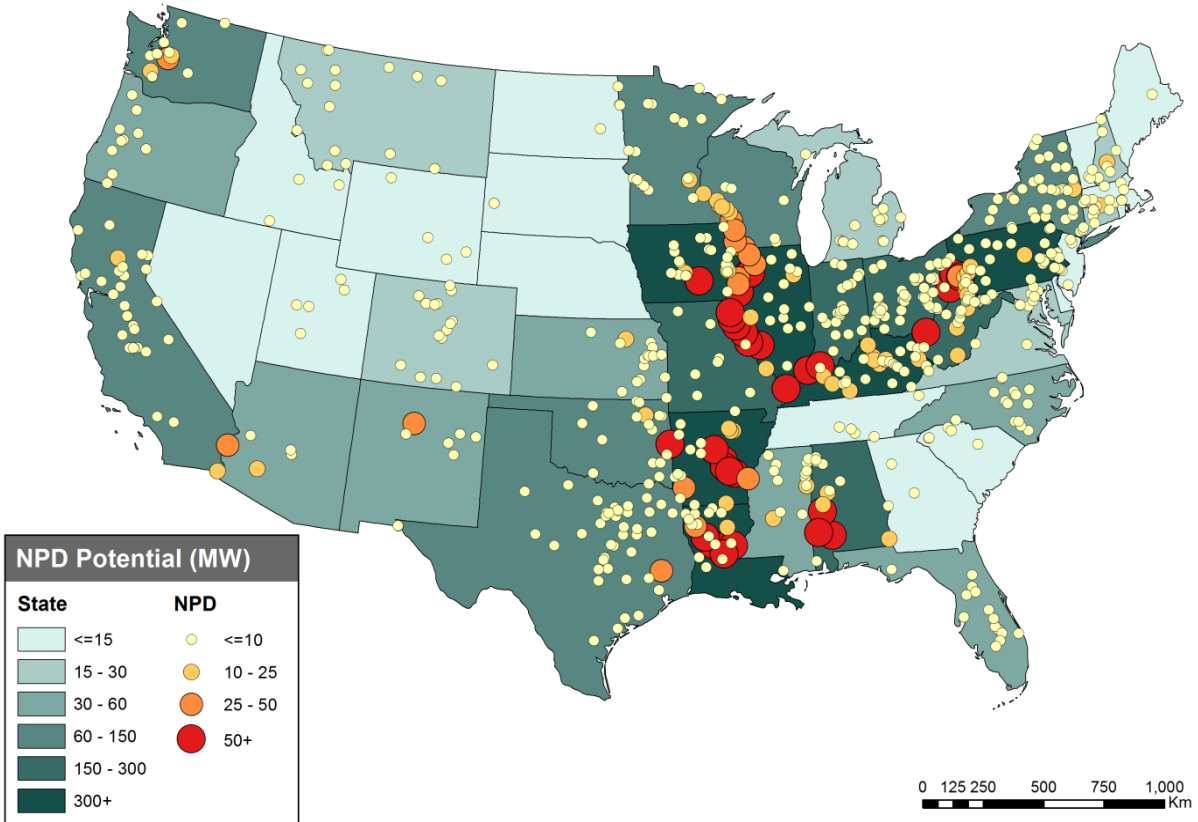
Figure 13. Modeled non-powered dam resource potential (DOE 2016b)

NSD resource is based on the 2014 NHAAP NSD resource assessment (Kao et al. 2014), where the modeled resource of 30.7 GW (176 TWh/yr) reflects the same sizing methodology as NPD and a sub-1 MW site exclusion, again to improve model resolution for lower-cost resource. The NSD resource assumes "low head" sites inundating no more than the 100-year flood plain and excludes sites within areas statutorily barred from development—national parks, wild and scenic rivers, and wilderness areas.
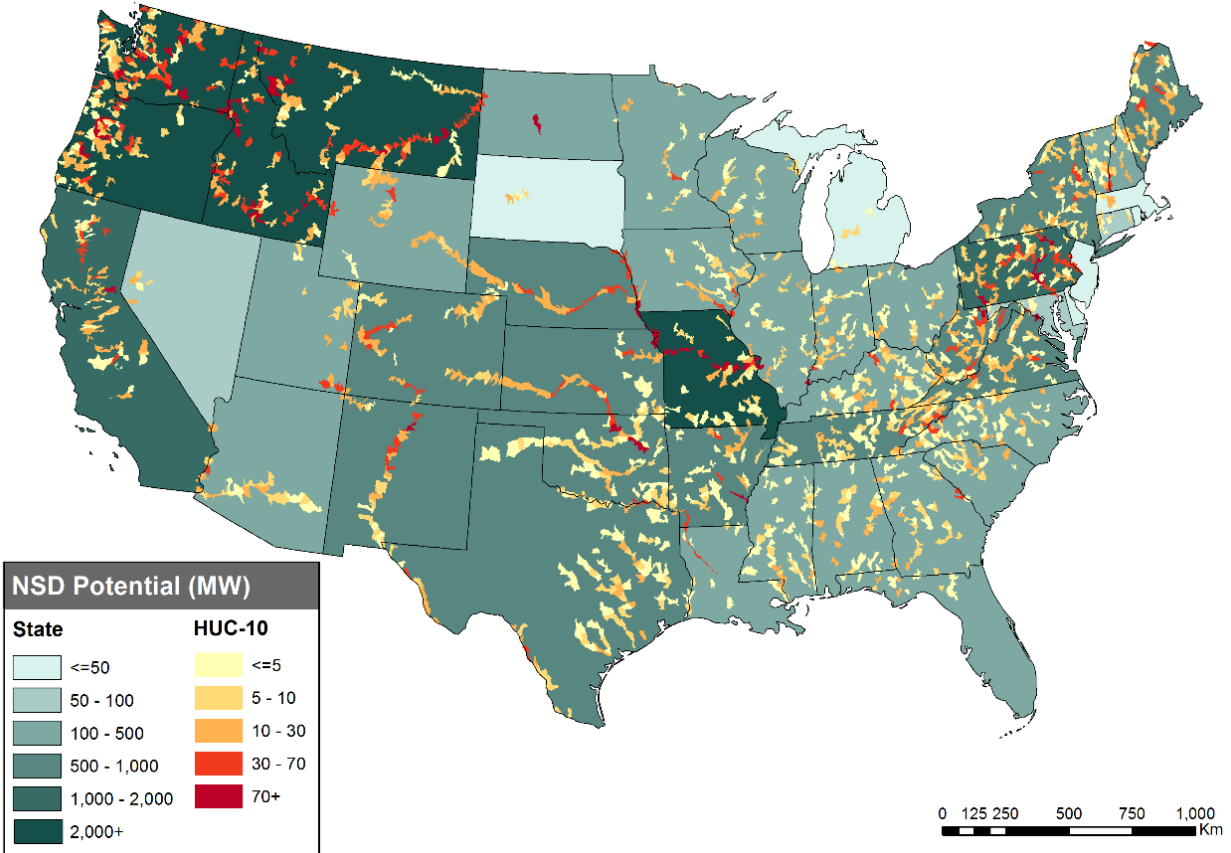
Figure 14. Modeled new stream-reach development resource potential (DOE 2016b)

The combined hydropower capacity coupled with the costs from the ATB (NREL 2019) results in the supply curve shown in Figure 15.
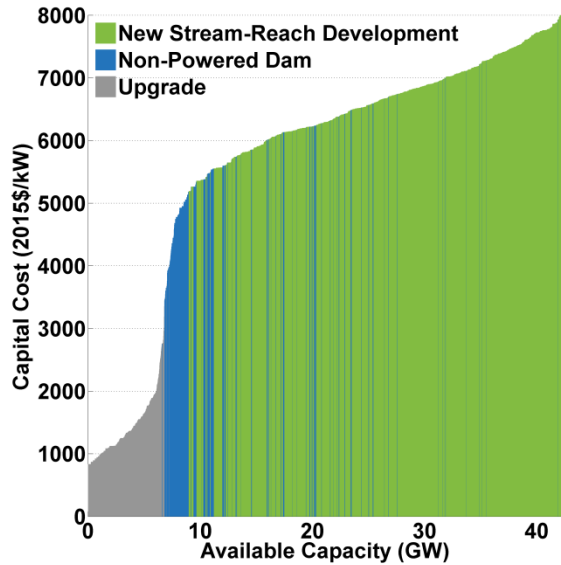
Figure 15. National hydropower supply curve of capital cost versus cumulative capacity potential

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The hydropower operating parameters and constraints included in ReEDS do not fully reflect the complex set of operating constraints on hydropower in the real world. Detailed site-specific considerations involving a full set of water management challenges are not easily represented in a model with the scale and scope of ReEDS, but several available parameters allow a stylized representation of actual hydropower operating constraints (Stoll et al. 2017).

Each hydropower category can be differentiated into "dispatchable" or "non-dispatchable" capacity, with "dispatchable" defined in ReEDS as the ability to provide the following services:

1. Diurnal load following within the capacity and average daily energy limits for each season

2. Planning (adequacy) reserves with full rated capacity

3. Operating reserves up to a specified fraction of rated capacity if the capacity is not currently being utilized for energy production.

"Non-dispatchable" capacity, on the other hand, provides:

1. Constant energy output in each season such that all available energy is utilized

2. Planning reserves equal to the output power for each season

3. No operating reserves.

Dispatchable capacity is also parameterized by a fractional minimum load, with the maximum fractional capacity available for operating reserves as one minus the fractional minimum load. The existing fleet and its corresponding upgrade potential are differentiated by dispatchability using data from the TEPPC 2024 Common Case for WECC and the NHAAP Hydropower Market Report for other regions (WECC 2013, 2015; Uria-Martinez, O'Connor, and Johnson 2015). All WECC facilities that do not follow load are assumed non-dispatchable, and all non-WECC facilities in the following NHAAP categories are non-dispatchable: run-of-river, run-of-river/peaking (downstream), and regulating. This methodology chooses only the most obvious facilities as non-dispatchable while leaving all other existing and upgrade capacity as dispatchable. In total, 43% of existing capacity and 49% of upgrade potential is assumed non-dispatchable.

The same TEPPC database is used to define region-specific fractional minimum capacity for dispatchable existing and upgrade hydropower in WECC. Lacking minimum capacity data for non-WECC regions, 0.5 is chosen as a reasonable fractional minimum capacity.

Both the NPD and NSD resource assessments implicitly assume inflexible, run-of-river hydropower, so all NPD and NSD resource potential is assumed non-dispatchable. Additional site-specific analysis could allow re-categorizing portions of these resources as dispatchable, but 100% non-dispatchable remains the default assumption.

3.1.7 Biopower

ReEDS can generate electricity from biomass either in dedicated biomass integrated gasification combined cycle (IGCC) plants or cofired with coal in facilities that have been retrofitted with an auxiliary fuel feed. These cofire-ready coal plants can use biomass in place of coal to supply the

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fuel for up to 15% of the plant's electricity generation. A cofire retrofit costs 305 $2017/kW based on EIA's Electricity Market Module assumptions (EIA 2017b, 101).

Dedicated and cofired plants source feedstock from the same biomass supply curves, which are derived from the *U.S. Billion-Ton Update* report (DOE 2011). The biomass types from this study included in ReEDS supply curves are crop and forest residues (including forest residues from federal lands) and energy crops. Figure 16 shows the national supply curve for biomass feedstock through the 2012 solve year, after which both supply and prices are adjusted each year through 2030 to follow projections in the *U.S. Billion-Ton Update* report (DOE 2011).
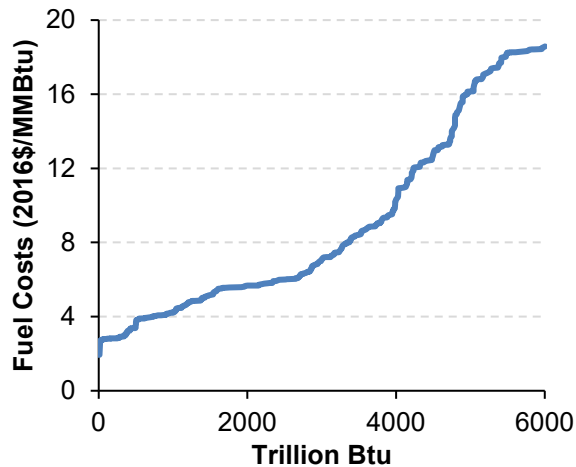
Figure 16. National supply curve for biomass feedstock through the 2012 solve year

3.1.8 Marine Hydrokinetic Wave

ReEDS does have a representation of marine hydrokinetic wave technologies, but this capability is not utilized in any of the recent or current ReEDS modeling work.

3.2 Conventional Energy Technologies

ReEDS includes all major categories of conventional generation technologies within its operating fleet or its investment choices. In the context of ReEDS, "conventional" is defined as thermal generating technologies driven by coal, gas, oil, or nuclear fuel. Coal technologies are subdivided into pulverized and gasified (IGCC) categories, with the pulverized plants further distinguished by 1) whether SO_2 scrubbers are installed and 2) their vintage[22] as pre- or post-1995. Pulverized coal plants have the option of adding a second fuel feed for biomass. New IGCC plants can be added with or without CCS technology.[23] Existing coal units built after 1995 with SO_2 scrubbers installed also have the option of retrofitting CCS capability.

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[22] While differentiating pre- and post-1995 is somewhat arbitrary, it allows the model to better represent performance differences between relatively old and new coal technologies.

[23] New coal plants without CCS plants are not allowed by default due the U.S. Environmental Protection Agency's proposed New Source Performance Standard. There is currently no option for partial CO_2 capture technologies in ReEDS, so CCS plants in ReEDS are assumed to be 90% capture plants, meaning that they capture 90% of the CO_2 emissions in the flue gas. Thus, the technology representation is more conservative than allowed under proposed EPA regulations. Transportation and sequestration of the CO_2 is not modeled, but an $11/tonne (2011$) costs is assumed based on (Timothy Fout 2015). No revenue from the potential use of CO_2 is currently captured in ReEDS.

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Natural gas generators are categorized as combustion turbine (CT), combined cycle (CC), or gas-CC with CCS.[24] There are also nuclear (steam) generators, landfill gas generators,[25] and oil/gas steam generators, though the latter two are not offered as options for new construction besides those that are already under construction. The model distinguishes each conventional-generating technology by costs, efficiency, and operational constraints.

Where renewable energy technologies have many unique characteristics, ReEDS conventional technologies are characterized more generally by the following parameters:

- Capital cost ($/MW)

- Fixed and variable operating costs (dollars per megawatt-hour [$/MWh])

- Fuel costs (dollars per million British thermal units [$/MMBtu])

- Heat rate (MMBtu/MWh)

- Construction period (years) and expenses

- Equipment lifetime (years)

- Financing costs (such as interest rate, loan period, debt fraction, and debt-service-coverage ratio)

- Tax credits (investment or production)

- Minimum turndown ratio (%)

- Ramp rate (fraction per minute)

- Planned and unplanned outage rates (%).

Cost and performance assumptions for all new conventional technologies are taken from the ATB (NREL 2019), which are based on the projections from the AEO2019 Reference scenario.[26] The NEMS Electricity Market Module, which is used for AEO analyses, represents technological learning endogenously, with costs falling as more capacity of that type is built. Because ReEDS does not include endogenous learning, the technology cost projections used in ReEDS reflect technology growth in the AEO Reference scenario. The AEO assumptions include a projected materials price index (MPI) that also influences capital costs over time; we remove the MPI from our projections for better consistency of ReEDS technology representations across both renewable and conventional energy sources. Regional variations and adjustments are included and described in Section 3.4.

In addition to the performance parameters listed above, technologies are differentiated by their ability to provide operating reserves. In general, natural gas plants, especially combustion

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[24] Retrofits from Gas-CC to Gas-CC-CCS are not currently an option in the model.
[25] Landfill gas generators are classified as conventional generators but can count toward renewable portfolio standard requirements.
[26] Where AEO includes two separate projections (advanced and conventional) for any single ReEDS technology, ReEDS uses an average of those figures to represent a medium level of technological advancement.

turbines, are better suited for ramping and reserve provision, while coal and nuclear plants are typically designed for steady operation.

The existing fleet of generators in ReEDS is taken from the NEMS unit database from AEO2019 (EIA 2019b). In particular, ReEDS uses the net summer capacity, location, heat rate, variable O&M, and fixed O&M to characterize the existing fleet. ReEDS uses a modified "average" heat rate for existing stock: a small, technology-specific increase on the full-load heat rate is applied to accommodate for units not always operating at their design point. The modifiers, shown in Table 8, are based on the relationship between full-load and average heat rates for generators in the ABB Velocity Suite database (ABB 2018). Coal adjustment factors also take into account the historical observed fleet-wide heat-rates, which are calculated using EIA form 923.

Table 8. Multipliers Applied to Full-Load Heat Rates to Approximate Heat Rates for Part-Load Operation

Technology	Adjustment Factor
Coal (all)	1.0674
Gas-CC	1.0545
Gas-CT	1.1502
OGS	1.1704

Emissions rates from conventional plants are a function of the fuel emission rate and the plant heat rate. Burner-tip emissions rates are shown in Table 9. Because ReEDS does not differentiate coal fuel types, the coal CO_2 emissions rate in the model is the average of the bituminous and subbituminous emissions rate.[27]

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[27] See https://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11, accessed November 11, 2016.

Table 9. Emissions Rate by Generator Type in Pounds per MMBtu (EPA 2008)[a]

Generator	SO_2 Emissions Rate	NO_x Emissions Rate	CO_2 Emissions Rate
Hydropower	0.0	0.0	0.0
Gas-CT	0.0098	0.15	117.00
Gas-CC	0.0033	0.02	117.00
Gas-CC-CCS	0.0033	0.02	11.70
Pulverized Coal with Scrubbers (pre-1995)	0.2	0.19	210.55
Pulverized Coal with Scrubbers (post-1995)	0.1	0.08	210.55
Pulverized Coal without Scrubbers	1.11	0.19	210.55
IGCC Coal	0.0555	0.085	210.55
Coal-CCS	0.0555	0.085	21.06
Oil/Gas Steam	0.299	0.1723	137.00
Nuclear	0.0	0.0	0.0
Geothermal	0.0	0.0	0.0
Biopower	0.08	0.0	0.0

[a] The assumed CO_2 pollutant rate for land-fill gas is zero, so ReEDS does not see the emissions benefits of land-fill gas. However, ReEDS can track land-fill gas emissions and the associated benefits as a post-processing calculation. Land-fill gas is assumed to have negative effective carbon emissions because the methane gas would be flared otherwise, thereby it produces the less potent greenhouse gas.

Not all parameter data are given in this document. For those values not included here, see the NREL ATB (NREL 2019), or see the values in the ReEDS repository.[28] Financing parameters and calculations are discussed in Section 10.1.

3.3 Storage Technologies

ReEDS includes three utility-scale energy storage options: PSH, batteries, and CAES. All three storage options are capable of load shifting (arbitrage), providing planning and operating reserves, and reducing curtailment of VRE. Load shifting can be done only within a season's representative day, and it is accomplished by charging the reservoir during inexpensive low-demand time-slices and discharging at peak times. The nameplate capacity of storage can contribute toward planning reserves (though at a potentially reduced rate, see Section 6.2.2), and capacity not being used for charge or discharging can be utilized to provide any of the operating reserves products represented in ReEDS (see Section 7 on how reserves are differentiated in ReEDS).

The ReEDS framework also allows for standalone thermal energy storage, though this technology is inactive by default because its site-specific nature makes it difficult to include in a nationwide optimization framework. This technology is representative of chilled water and ice storage units in buildings where, during the summer, cold water or ice is produced during cooler

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[28] See https://www.nrel.gov/analysis/reeds/request-access.html to get access to the repository.

hours when loads are lower and used to replace or supplement the air conditioning during the warmer hours. Only units for commercial buildings are considered. A supply curve for thermal energy storage units was developed at the NERC subregions level. The model restricts the use of thermal energy storage devices by the regional cooling load profile, with power delivered from thermal energy storage available only during times of high cooling load (e.g., summer afternoons). Thermal energy storage technologies can contribute to operating and planning reserves and reduce curtailment.

Although storage is neither directly linked nor assumed colocated with renewable energy technologies in ReEDS, it can play an important role in reducing curtailed electricity from variable generation resources by charging during time-slices with excess renewable generation. The ability of storage to reduce curtailment is calibrated using the REFlex and PLEXOS models (Denholm et al. 2010; Energy Exemplar 2019). For batteries, the curtailment calculation in ReEDS takes into account a finite storage duration[29], while CAES and PSH are assumed to have sufficient storage to operate as needed within the diurnal variations represented in the model (i.e., 12-hour duration).

Existing PSH totals 22 GW, and ReEDS includes the existing CAES facility in Alabama. New PSH and CAES are location-restricted due to hydrology and topography (for PSH) and geology (for CAES). In contrast, utility-scale batteries are not restricted to any subset of regions. New PSH potential is derived from FERC license applications since 1980[30] with an additional 750 MW of high-cost "artificial" resource placed in each region to prevent over-constraining PSH expansion in regions without FERC applications while remaining consistent across all regions. In total, there is 108.7 GW FERC-based PSH resource and 100.5 GW artificial PSH resource in ReEDS. FERC-based PSH capital costs are based on O'Connor et al. (2015), and artificial capacity is assumed to be $3,500/kW,[31] which is near the upper bound of greenfield PSH resource sized at 750 MW (Figure 18). PSH fixed O&M costs are also based on O'Connor et al. 2015, and round-trip efficiency is assumed to be 80% for all existing and new capacity. CAES site development costs are estimated based on the underground geology, where domal salt is the least costly resource at $1170/kW (22.6 GW available), bedded salt is the next most costly resource at $1,420/kW (37.0 GW), and aquifers (porous rock) are the most costly resource at $1,680/kW (61.6 GW) (Black & Veatch 2012; Lazard 2016). [32] CAES requires a natural gas fuel input when supplying power output, and its heat rate is assumed to be 4.91 MMBtu/MWh. This additional fuel input (to the electrical power input during compression) results in a round-trip efficiency of 125%.

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[29] The default storage duration is 4 hours but can be specified by the user.
[30] See "Preliminary Permits," FERC, updated October 11, 2016, http://www.ferc.gov/industries/hydropower/gen-info/licensing/pre-permits.asp.
[31] In 2015$
[32] Values in 2016$

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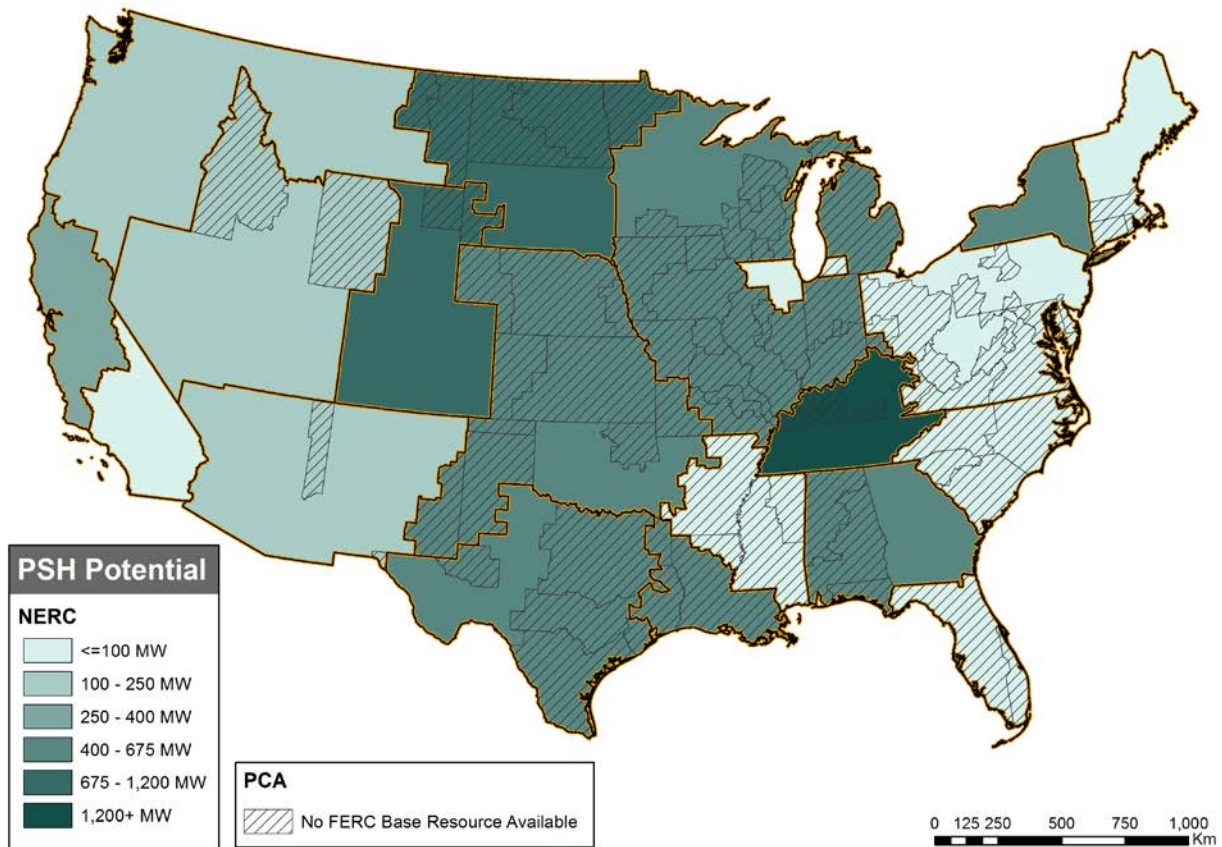
Figure 17. Modeled new PSH resource potential (DOE 2016b)
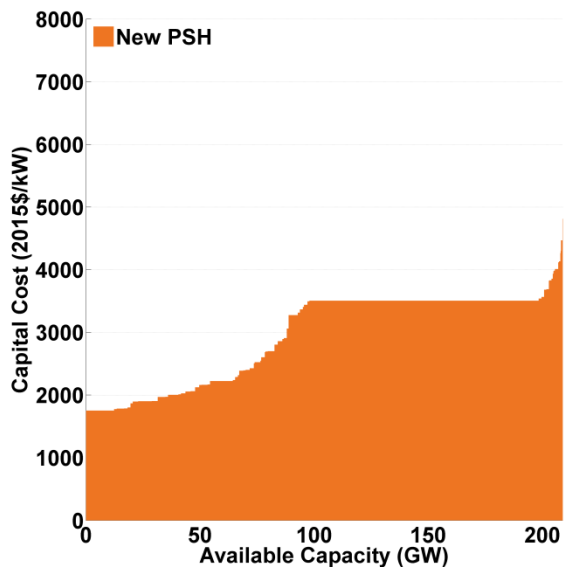
Figure 18. National PSH supply curve of capital cost versus cumulative capacity potential

Battery cost and performance assumptions are based on lithium-ion battery systems, with costs taken from Cole and Frazier (2019). Low, mid, and high cost projections are available and will

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scale with the user-defined battery duration. In contrast to all other generator technologies in ReEDS, which outlast the 20-year evaluation window of the model, the battery is assumed to last 15 years. As a result, its capital cost is uprated by 1.21 to account for the equipment lifetime shortfall. This uprate is the ratio of the 15-year CRF and the 20-year CRF. The batteries are assumed to have a round-trip efficiency of 85%. The contribution of storage toward the reserve margin requirement is discussed in Section 7.2. Battery storage has a representative size of 60 MW.

3.4 Capital Stock

3.4.1 Initial Capital Stock, Prescribed Builds, and Restrictions

Existing electricity generation capacity is taken from the EIA NEMS unit database (EIA 2019b). Units are mapped to ReEDS technologies based on a combination of fuel source and prime mover of the generation technology. Units of the same technology type within a region can be aggregated or represented individually.[33] If they are aggregated, the aggregation is done by clustering the units based on heat rates.

The binning structure is designed flexibly such that users can choose the appropriate levels of model fidelity and computational speed for each application. Historical units are binned using a k-means clustering algorithm for each BA and technology category (e.g., coal with or without SO2 scrubbers, and natural gas combined cycle) combination. The user specifies a maximum number of bins and a minimum deviation across unit heat rates. Any two plants are eligible to form separate bins if the difference between their heat rates is greater than the minimum deviation parameter. The number of bins formed is then equal to the smaller of the maximum bin number parameter and the number of units after applying the minimum deviation criteria. For each bin, the assigned heat rate is equal to the capacity-weighted average of the heat rates for the units inside the bin. An illustrative example of the results is depicted for two BAs in Figure 19, assuming a maximum of seven bins and minimum deviation of 50 BTU per kWh. The horizontal axis corresponds to the heat rate for a given power plant unit from the NEMS database, while the vertical axis corresponds to the heat rate each bin is assigned in ReEDS. Points on the 45-degree line illustrate units for which the ReEDS heat rate is the same as the NEMS heat rate. The more tightly clustered the points are around this line, the less the model will suffer from aggregation bias. The figure illustrates that, in general, the fewer the number of units in a given technology category (in this example, nuclear and scrubbed coal), the closer the binned heat rates are to the actual heat rates.

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[33] The level of plant aggregation is a scenario input option. Plants can be aggregated to one plant type per region or left at their native unit-level resolution.
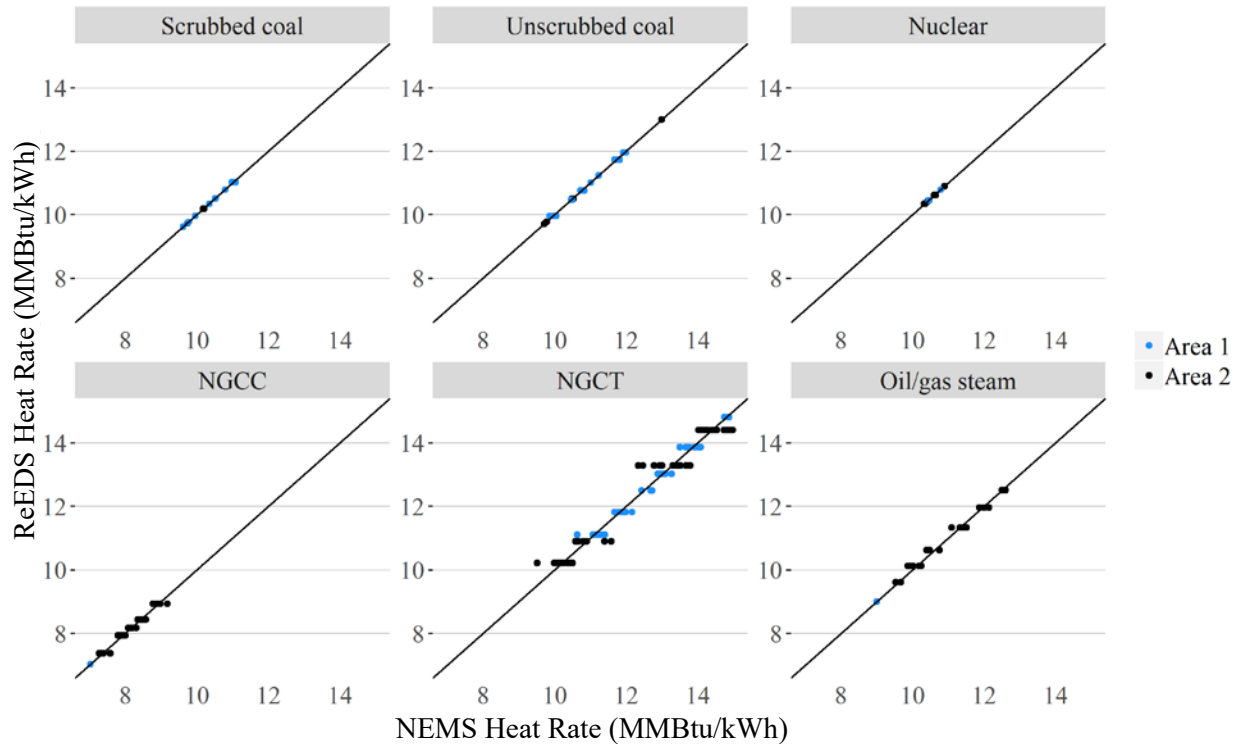
Figure 19. Example of capacity binning results for two BAs

Hydropower has additional subcategories to differentiate dispatchability as discussed in Section 3.1.6. In addition, any plants that are listed as under construction become prescribed builds. In other words, ReEDS builds any under-construction units, with the units coming online in the anticipated online year listed in the database.

For wind technologies, near-term regional growth restrictions reflect the difficulty of immediately scaling the wind industry. Specifically, wind plant construction through the 2020 solve year is limited to plants that are planned to be installed before the end of 2020. After 2020, no wind capacity limits are implemented.

3.4.2 Retirements

Renewable energy generator and battery retirements are (by default)[34] based on assumed lifetimes. Once a generator has reached its lifetime, it is retired. Renewable energy and battery lifetime assumptions are shown in

Table 10. When renewable energy capacity is retired, the resource associated with that capacity is made available, and ReEDS can choose to rebuild a renewable energy generator using the newly available resource, without the need to rebuild the grid interconnection infrastructure. A consequence of this assumption is that retired renewable capacity can be replaced without incurring interconnection costs and, with all other considerations being equal, re-powered or re-

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[34] When running with endogenous retirements, any technology type can be eligible to be retired endogenously by the model. However, some technologies are not represented properly to be appropriately considered for endogenous retirements.

built renewable capacity has lower cost than new "green-field" capacity of the same type.[35] One exception to this procedure is hydropower, which due to assumed non-power requirements is never retired unless there is an announced hydropower capacity retirement listed in the NEMS unit database (EIA 2019b).

Table 10. Lifetimes of Renewable Energy Generators and Batteries

Technology	Lifetime (Years)	Source
Land-based Wind	30	LBNL Survey (Wiser and Bolinger 2019)
Offshore Wind	30	LBNL Survey (Wiser and Bolinger 2019)
Solar Photovoltaic	30	SunShot Vision (DOE 2012)
Concentrating Solar Power	30	SunShot Vision (DOE 2012)
Geothermal	30	Renewable Electricity Futures Study, Vol. 1 (Mai et al. 2012)
Hydropower	100	Hydropower Vision (DOE 2016b)
Biopower	50	ABB (2010)
Marine Hydrokinetic	20	Previsic et al. (2012)
Battery	15	(Cole, Wesley and Frazier, A. Will 2019)

Retirements of existing conventional energy generators in ReEDS are primarily a function of announced retirement dates and technology-specific estimated lifetimes, taken from the ABB Velocity Suite database (ABB 2018). Estimated retirement dates depend on the size of the unit, and the most common lifetimes are shown in Table 11 for plants that are smaller or larger than 100 MW. Nuclear plants are assumed to have a mix of 60- and 80-year lifetimes as explained below. All conventional generators that are economically built in ReEDS are given the lifetime of plants greater than 100 MW, and these lifetimes are used as necessary when the solution period extends beyond 2050.

Table 11. Lifetimes of Conventional Energy Generators (ABB 2018)

Technology	Lifetime less than 100 MW (Years)	Lifetime greater or equal to 100 MW (Years)
Gas Combustion Turbine	50	50
Gas Combined Cycle and CCS	60	60
Coal, all techs, including cofired	65	75
Oil-Gas-Steam	50	75
Compressed-Air Energy Storage	100	100

In addition to age-based retirements, ReEDS includes the option to endogenously retire technologies. When doing endogenous retirements, ReEDS is effectively trading off the value

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[35] ReEDS does not account for any decommissioning costs for renewable or any other capacity type.

provided to the system by the plant versus the costs incurred by keeping the plant online. If the value is not sufficient to recover the costs, ReEDS will choose to retire the plant.

ReEDS includes four exogenous nuclear retirement scenario settings. The four settings are defined by first dividing the currently operating reactors into two bins. Any plants participating in a restructured market and all single-reactor plants are assigned to Bin 1. The remaining plants, which are all multi-reactor plants in a traditional regulated environment, are assigned to Bin 2. The only exception to these categorizations is that plants that have announced their intent to seek a second operating license renewal from the Nuclear Regulatory Commission (NRC) are included in Bin 2. Table 12 breaks down the bins and shows total capacity in each case. These bins are categorizations that reflect the current discussion pointing to more economic pressure on restructured and single-reactor units (Haratyk 2017; Steckler 2017).

Table 12. Amount of Nuclear Power Plant Capacity (in GW) in Each Bin

Plant Category	Bin 1	Bin 2
Restructured, Single Reactor	8.7	—
Restructured, Multi Reactor	27.5	2.0[a]
Regulated, Single Reactor	15.7	—
Regulated, Multi Reactor	—	42.1
Total	**51.9**	**44.1**

[a] The Peach Bottom plant (2.0 GW) has announced its intent to seek a second license renewal. Therefore, it is moved from Bin 1 to Bin 2 even though it is in a restructured market.

The four nuclear retirement scenarios are: (1) Early Retirement, (2) 60-Year Lifetime, (3) Mid-Case (mix of 60 and 80-year lifetimes), and (4) 80-Year Lifetime (see Table 13). The Early Retirement scenario retires nuclear capacity in Bin 1 when its lifetime reaches 50 years, and capacity in Bin 2 at 60 years. The 50-year lifetime emulates the retirements of recent plants that did have a renewed operating license but retired before they reached the end of their license. The 60-Year Lifetime scenario retires all plants at 60 years, which would be at the end of their first operating license renewal. The 80-Year Lifetime scenario retires all plants at 80 years, simulating a successful completion of a second operating license renewal from the NRC. The Mid-Case scenario serves as the default setting in ReEDS and retires capacity in Bin 1 at 60 years and capacity in Bin 2 at 80 years.

Table 13. Nuclear Power Plant Lifetime for Each Scenario by Bin (years)

Scenario Name	Bin 1	Bin 2
Early Retirement	50	60
60-Year Lifetime	60	60
Mid-Case	60	80
80-Year Lifetime	80	80

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3.4.3 Growth Constraints

As of the 2019 version of ReEDS, there are no longer growth penalties as had existed in the previous versions of ReEDS. Instead, there are optional growth constraints that are disabled by default. The model can represent either absolute growth constraints (e.g., wind builds cannot exceed 100 GW per year) or relative growth constraints (e.g., wind capacity cannot grow by more than 50% per year). The growth constraints are designed to target a broader technology group as opposed to the individual classes of wind, PV, and CSP; as an example, the growth constraint would restrict the builds of all wind technologies and classes and not just a specific a specific TRG. The default values for the absolute growth constraints are the highest year-over-year changes of each technology type's capacity from 2010 to 2019 (computed by appending the necessary EIA AEOs). For CSP, the default absolute growth limit is assigned the same as PV, as it has not seen the capacity buildout as PV or wind have as of 2020. The relative growth limits are user-defined. For both the relative and absolute growth constraints, the user should exercise caution when defining the limits of technology buildouts.

3.5 Regional Parameter Variations and Adjustments

For most generation technologies, regional cost multipliers are applied to reflect variations in installation costs across the United States (see Figure 20). These regional multipliers are applied to the base overnight capital cost presented in earlier sections. The regional multipliers are technology-specific and are derived primarily from the EIA/Leidos Engineering report (EIA 2016b) that is the source of capital cost assumptions for the NEMS model. While the regional costs presented in the EIA/Leidos Engineering report are based on particular cities, the regional multipliers for ReEDS are calculated by interpolating between these cities and using the average value over the ReEDS regions for each technology. For technologies such as CSP that are not included in the newer report, we rely on the older EIA/Science Applications International Corporation report (EIA 2013).

Batteries · **Biomass** · **Coal (no CCS)** · **Coal (with CCS)** · **Natural Gas Combined Cycle** · **Advanced Gas Combustion Turbine** · **Nuclear** · **Photovoltaic**

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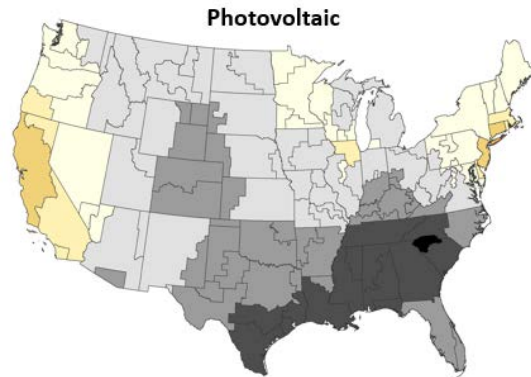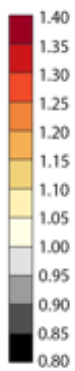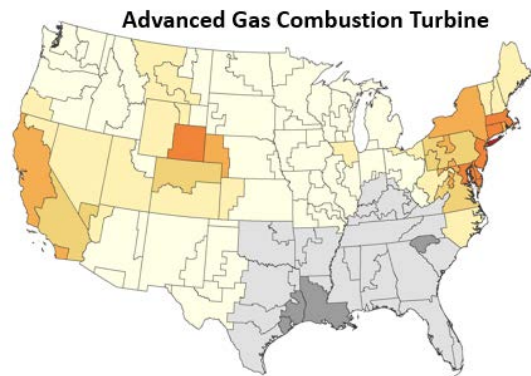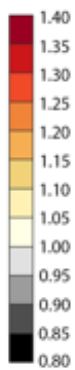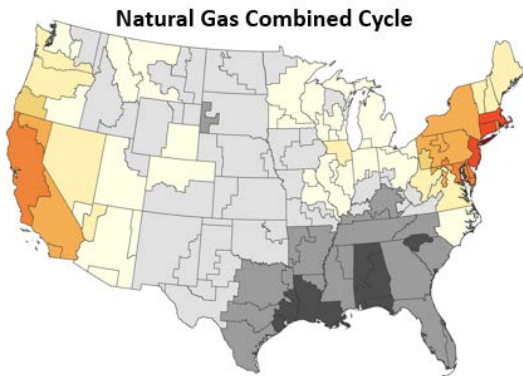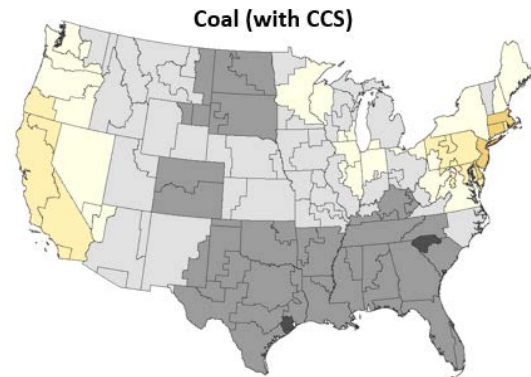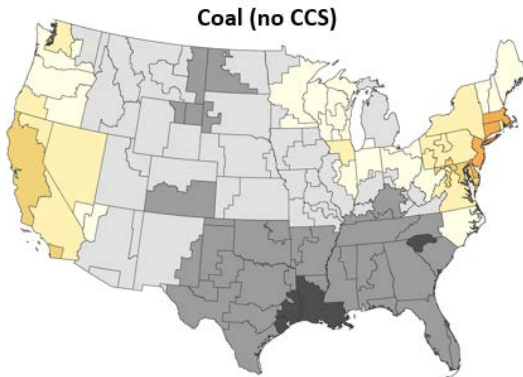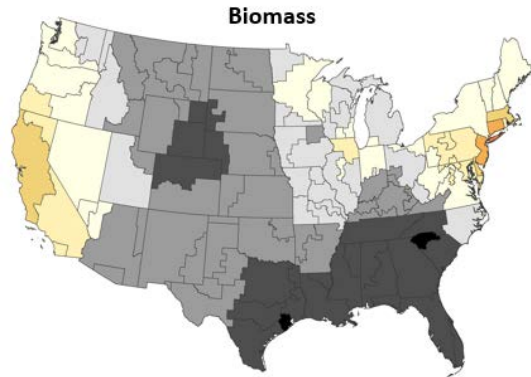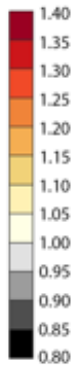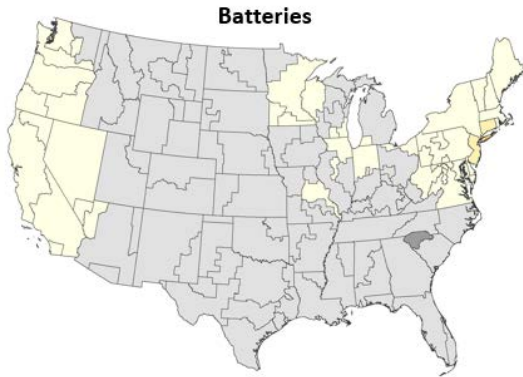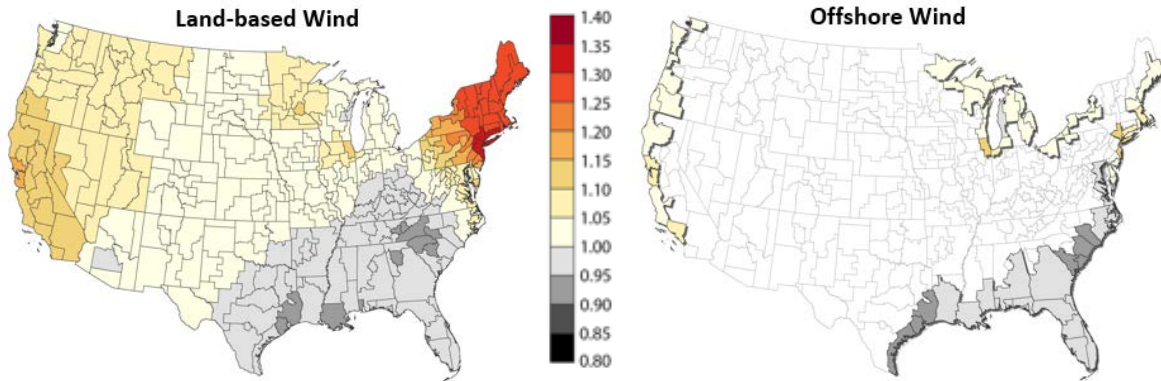
Figure 20. Maps of regional capital cost multipliers for the various technology types

Regions shown in white for offshore wind indicate that there is not offshore wind resource in that region.

4 Fuel Prices

Natural gas, coal, and uranium prices in ReEDS are based on the most recent AEO. Coal prices are provided for each of the nine EIA census divisions. Low and high natural gas price alternatives are taken from the Low and High Oil and Gas Resource and Technology scenarios. ReEDS includes only a single national uranium price trajectory. Base fuel price trajectories are shown in Figure 21 for the AEO2019 (EIA 2019b). Biomass fuel prices are represented using supply curves with five bins in each region. The costs and resource availability are based on the *U.S. Billion-Ton Update* study (DOE 2011). Biomass costs range from $2.02/MMBtu to $19.43/MMBtu (in 2018$).
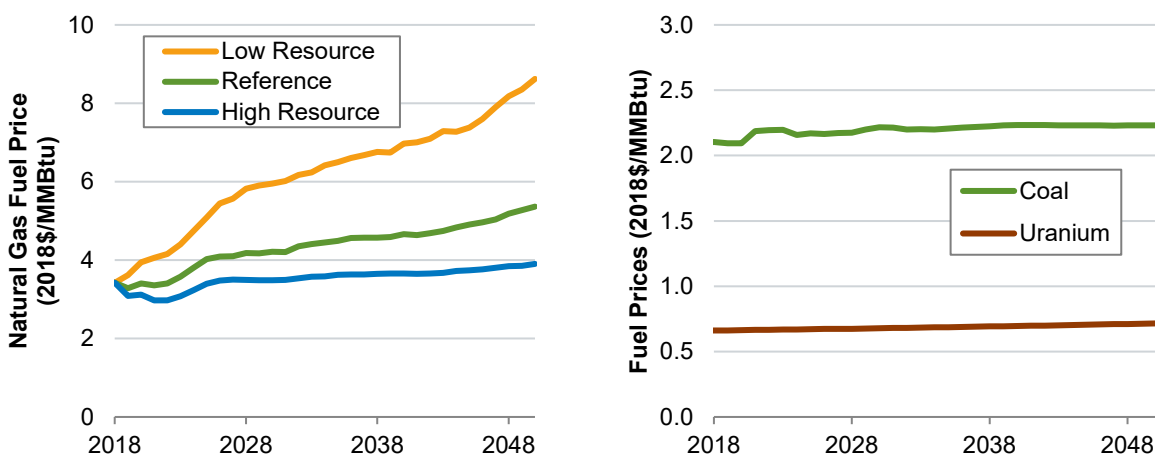
Figure 21. Fuel price assumptions

Coal and uranium are assumed to be perfectly inelastic; the price is predetermined and insensitive to the ReEDS demand for the fuel. With natural gas, however, the price and demand are linked. Actual natural gas prices in ReEDS are based on the AEO scenario prices but are not exactly the same; instead, they are price-responsive to ReEDS natural gas demand. In each year, each census division is characterized by a price-demand "set point" taken from the AEO Reference scenario but also by two elasticity coefficients: regional (β_r) and national (β_n) elasticity coefficients for the rate of regional price change with respect to (1) the change in the regional gas demand from its set-point and (2) the overall change in the national gas demand from the national price-demand set point respectively. The set of regional and national elasticity coefficients are developed through a linear regression analysis across an ensemble of AEO scenarios[36,37] to estimate changes in fuel prices driven solely by electric sector natural gas demand (as described in Logan et al. (2013) and Cole, Medlock III, and Jani (2016), though the coefficients have since been updated for the latest AEO data). Though there is no explicit representation of natural gas demand beyond the electricity sector, the regional supply curves reflect natural gas resource, infrastructure, and nonelectric sector demand assumptions embedded

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[36] Supply curves are nonlinear in practice, but a linear regression approximation has been observed to be satisfactory under most conditions.

[37] The elasticity coefficients are derived from all scenarios of AEO2018, but the price-demand set points are taken from any one single scenario of the AEO.

within the AEO modeling. For details, see the Natural Gas Supply Curves section of the appendix.

ReEDS includes options for other types of fuel supply curve representations. Supply curves can be national-only, census-region-only, or static. With the national-only supply curve, there are census division multipliers to adjust prices across the census divisions. In the static case, fuel prices are not responsive to demand.

The natural gas fuel prices also include a seasonal price adjustor, making winter prices higher than the natural gas prices seen during the other seasons of the year. For details, see the Seasonal Natural Gas Price Adjustments section of the appendix.

5 Thermal Cooling Water

Previous versions of ReEDS, including the 2018 version (Cohen et al. 2019), included a representation of thermal cooling water supply and demand constraints. Those constraints were not included in the 2019 version of ReEDS, but they are anticipated to be reimplemented into the 2020 version of ReEDS. For more information on how the thermal cooling water constraints worked, see Section 4 of the 2018 version documentation (Cohen et al. 2019).

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6 Transmission

6.1 Transmission System

ReEDS uses a synthetic network with 134 nodes defined by roughly 300 corridors for the contiguous 48 states. Each corridor has a nominal carrying capacity limit (Figure 22) that is determined for the start-year (2010) based on power-flow analysis using ABB's GridView model and NERC-reported line limits (NERC 2010). The carrying capacity of DC transmission connections are taken from project websites. A few notable DC transmission connections that are modeled in ReEDS are listed in Table 14.

In later years, ReEDS can expand these carrying capacities, though the model cannot build new node-to-node pathways. Transmission expansion is limited before 2020 based on new construction that is already planned (ABB 2013). After 2020, that limitation is dropped. ReEDS constrains transmission flows in each of the 17 time-slices when dispatching generation and contracting operating reserves, and available transmission capacity can also be used for firm power contracts to meet system adequacy needs.
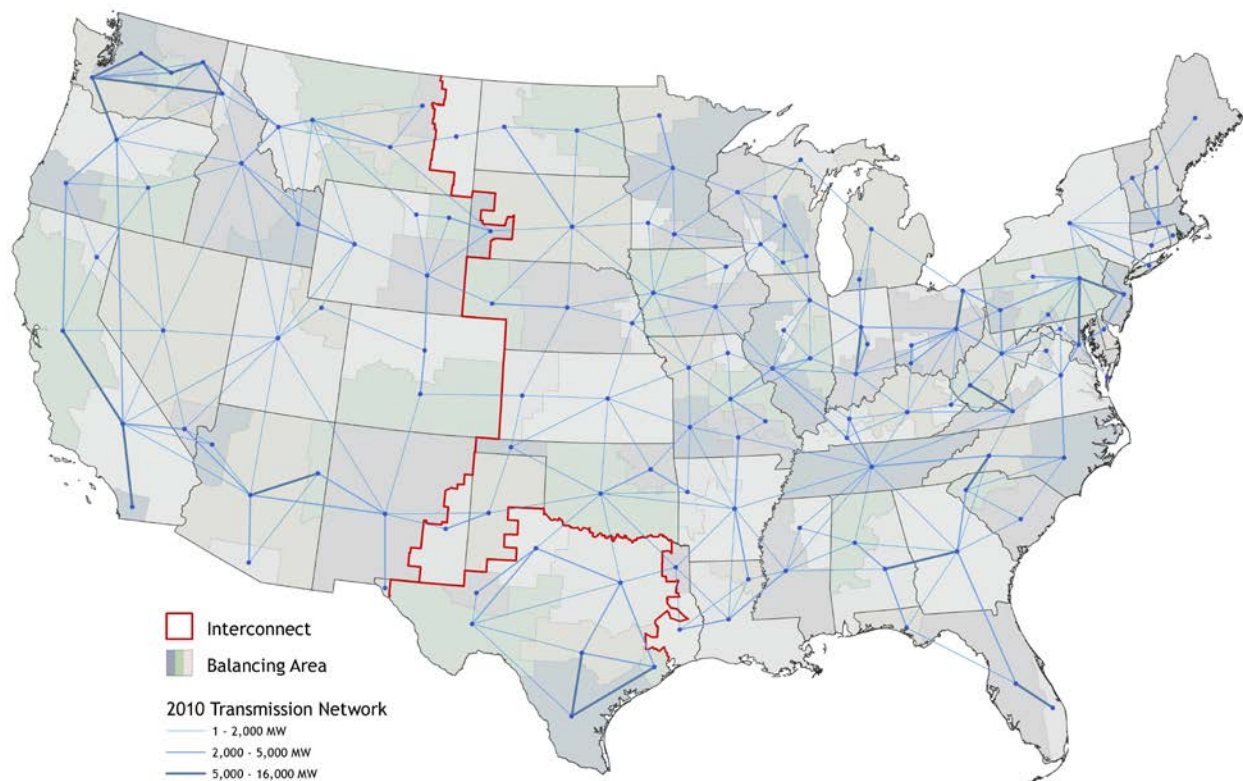
Figure 22. Existing long-distance transmission infrastructure as represented in ReEDS

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Table 14. List of Notable DC Transmission Connections Modeled in ReEDS

Project	Capacity (MW)
Pacific DC Intertie	2,780
Intermountain Power Project	1,920
Miles City Intertie (West-East)	200
Virginia Smith Intertie (West-East)	200
Segall Intertie (West-East)	110
Artesia Intertie (West-ERCOT)	200
Blackwater Intertie (West-East)	200
Rapid City Intertie (West-East)	200
Lamar Intertie (West-East)	210
CU HVDC	1,500
Square Butte	
Oklaunion Intertie (ERCOT-East)	220
Welsh Intertie (ERCOT-East)	600

In general, the modeled nodes are located at the largest population center of each BA, although some manual adjustments are made.[38] Distances between BA nodes are estimated by tracing the "shortest path" distance along existing transmission lines, giving preference for the trace follow higher voltage lines. Voltages for each transmission line were defined using the Homeland Security Infrastructure Project (HSIP) transmission database and converted into 1-km grid. The maximum voltage in each grid cell was identified and assigned a weight based on the voltage classification per Table 15 to create a tension grid. Using this tension grip, a least "cost" (lowest weight) path was traced between every BA-to-BA corridor was determined using the tension grid. Finally, the great circle formula is used to calculate the distance of the traced paths. Figure 26 shows the resulting transmission paths between the modeled nodes. The lengths of DC corridors are taken from values reported on project websites.

Table 15. Weights for Each Voltage Class

Voltage Class (kV)	Weight
No line	1,000
100–161	10
230–300	5
345	3
500	2
735 and above	1

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[38] For example, Vancouver and Portland are the largest populations centers in the southern Washington and northern Oregon regions respectively. However, these centers are only about 10 miles apart. Modeling such a short distance between these nodes would potentially create a bias for transmission investments between Washington and Oregon. So Yakima was used in lieu of Vancouver as the node location for southern Washington.

Figure 23. Modeled BA nodes and transmission paths

Transmission network flows in ReEDS are limited based on the nominal carrying capacity of the corridors (Figure 22). ReEDS can choose to build additional transmission capacity on the existing network to reduce congestion, but expansion of AC-DC-AC interconnection ties are not allowed.[39] ReEDS does not represent reactive power and does not address AC-power-flow issues of voltage, frequency, or limiting phase angle differences. Intra-BA T&D networks are similarly ignored, effectively ignoring the effects of transmission congestion within each region.

Transmission and distribution losses are considered in the model. There are bulk transmission losses of 1% per 100 miles for power that flows between BAs. In addition, distribution losses of 5.3% are assumed and thus added to the end-use demand (Section 7.1) to scale end-use demand to busbar load. Distribution losses do not apply to rooftop PV, as they are assumed to be downstream within distribution networks, but they do apply at a lower rate to DUPV systems, which are assumed to connect directly to low-voltage distribution substations (Section 7.1).

Wind, CSP, and PV technologies are highly sensitive to location and often require spur lines to connect remote locations to the bulk transmission system. The GIS supply curve algorithm described in Section 6.3 estimates spur line distances and costs for potential development sites for these technologies, which are then grouped into supply curve bins. These spur lines, which are distinct from the inter-BA bulk transmission system for ReEDS, are assumed to link remote sites to the larger transmission system and to load centers. All other technologies are assumed to be built close to existing transmission infrastructure, and they therefore need only a nominal-distance spur line. Because the plant envelope used to determine technology capital cost

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[39] The Renewable Electricity Futures Study includes sample ReEDS transmission flows. (NREL 2012)

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assumptions includes the onsite switchyard, a short spur line, and relevant upgrades at the substation (EIA 2013), those technologies incur no additional grid interconnection cost.

6.2 Transmission Cost

The long-distance and spur-line transmission costs in ReEDS are based on regional line voltage and cost premium assumptions. For long-distance interregional transmission lines, an assumed voltage (345 kV, 500 kV, or 765 kV) is applied for each region. The voltage assumption in each BA for long-distance transmission is taken from the highest voltage line currently operating in the BA from the Homeland Security Infrastructure Project (HSIP 2012). For BAs where the highest voltage of currently operating transmission lines is less than 500 kV, the voltage in the future is assumed to be 765 kV, and the associated costs for 765-kV lines are used for all years. For BAs where the highest voltage of currently operating transmission lines is 500 kV, the costs for 500-kV lines are used. The only exception to these rules for voltages in the Eastern Interconnection are for BAs in New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont), which are assumed to use 345-kV transmission lines for all years.

Each voltage class is associated with a base capital cost sourced from the Phase II Eastern Interconnection Planning Collaborative (EIPC) report: $2,333/MW-mile, $1,347/MW-mile, and $1,400/MW-mile for 345-kV, 500-kV, and 765-kV transmission lines respectively (EIPC 2012).[40] All wind and solar spur line costs are based on 230-kV line costs, assumed to be $3,667/MW-mile (ibid).[41] For DC transmission lines, an additional cost of $253,000/MW (in 2015$) is applied to account for the cost of the converter stations.

In addition to the base transmission costs, regional multipliers are also applied and are largely based on assumptions from EIPC (2012). Regional transmission cost multipliers are the average of the EIPC report's high and low multipliers in each North American Electricity and Environmental Model region, and they are associated with the assumed voltage within the region. BAs in ERCOT and the Western Interconnection (excluding Canada and California) are assumed to have a regional transmission multiplier of one (1). Long-distance transmission costs in BAs in the California Independent System Operator are 2.25 times the cost of the other baseline costs for the rest of the Western Interconnection. For long-distance transmission between BAs with different transmission costs, the average cost is used. The same process is applied to wind and solar spur line costs.

Figure 24 and Figure 25 show the regional long-distance and spur-line transmission costs, respectively, that result from the previously described steps and assumptions.

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[40] The base transmission costs for ReEDS are converted to $/MW-mile according to new transmission line cost and capacity assumptions for single circuit conductors for each voltage in EIPC (2012). The costs reported are in 2010$ as used by the EIPC.

[41] Wind and solar spur line costs are applied within the development of the resource supply curves.
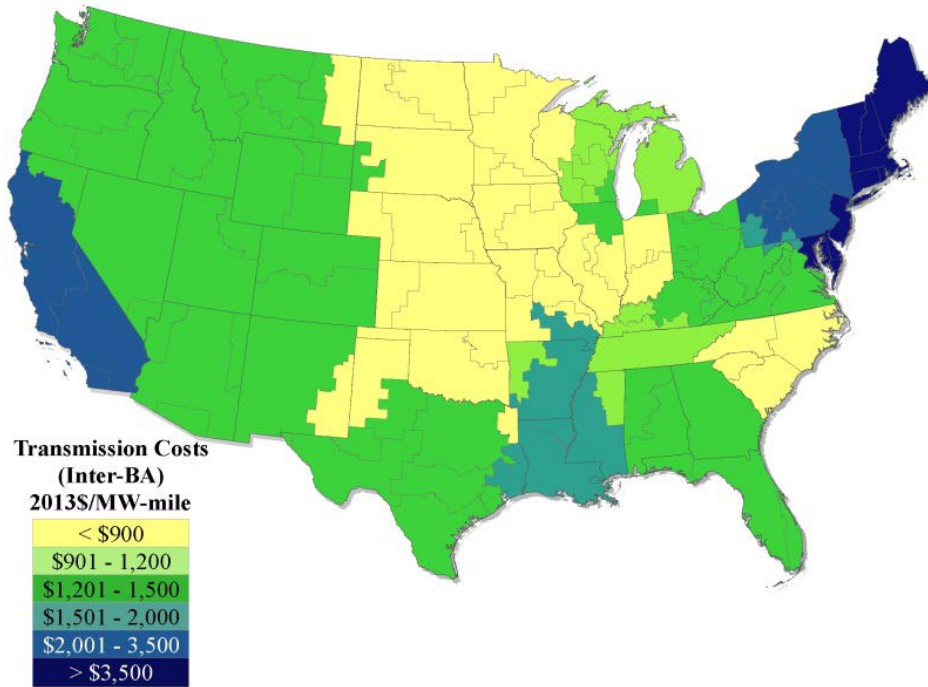
Figure 24. Map of long-distance transmission costs
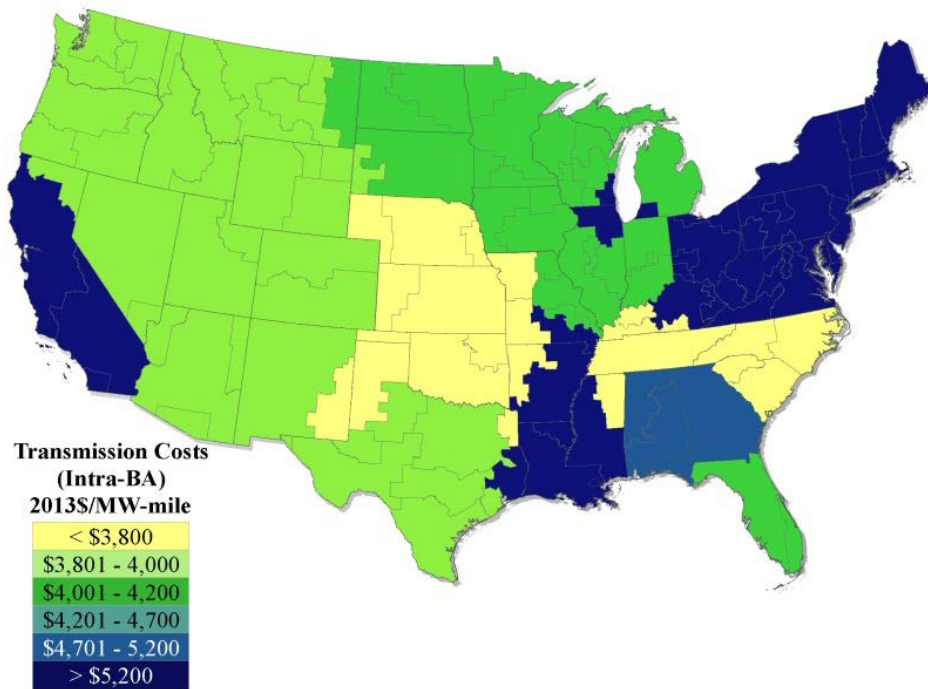
Figure 25. Map of spur-line transmission costs

6.3 Spur Lines

To supplement the resource assessments that seed ReEDS with renewable potential, GIS analysis adds an accessibility dimension to the supply curves for wind, PV, and CSP technologies based on the expected cost of linking renewable resource sites to the transmission network. Coupled

with supply curves for the renewable resource itself, the resulting two-dimensional supply curves allow ReEDS to make internal decisions about tradeoffs between resource quality and interconnection cost.

The geospatial site-connection algorithm evaluates each potential link from a wind or solar resource site to an electricity infrastructure feature, and the model assigns to the link a cost of development. For the algorithm, wind resource assessed at 2-km resolution are downscaled to 90 m resolution for the purpose of identifying developable and non-developable locations based on numerous land cover, land use, and protected areas GIS data sets. The 90 m resolution pixels are then aggregated to a grid of roughly 5.7 km resolution to reduce the number of points to be used in additional analyses downstream. CSP sites are similarly grouped into 1.35 km x 1.35 km cells, and PV sites are grouped into 3.15 km x 3.15 km cells. Each resource site is characterized by a LCOE that includes the expected cost of interconnection.

The resource supply curves are the result of successively selecting the least-cost site-to-infrastructure link and allocating that site to the infrastructure component until the transmission lines are saturated. At the start, each transmission line is assumed to have 10% of its nominal carrying capacity available for renewable connections, and each time a link is added, the remaining headroom is decremented by the capacity of the site being tied in. As the available capacity at transmission infrastructure features decreases, resource sites look farther afield for available linkages.

The resource supply curves are described in detail by Maclaurin et al. (2019), and Murphy et al. (2019).

6.4 International Electricity Trade

ReEDS is capable of endogenously representing Canada and Mexico (Section 11), but our default model configuration only covers the contiguous United States and represents electricity trade with Canada exogenously. In the default configuration, imports and exports are specified by Canadian province based on the National Energy Board's (NEB) Canadian Electricity Futures Reference Scenario (NEB 2018), with net exports across all regions shown in Figure 26 (values beyond NEB projections to 2040 are held constant at the 2040 value). Each province is required to send electricity to or receive electricity from any of the ReEDS BAs that have connecting transmission lines to that province, with the split among BAs approximated based on the transmission connecting the BAs to the provinces. Seasonal and time slice estimates for imports and exports are based on the historical monthly flows between the countries.[42] Canadian imports are assumed to be from hydropower and are counted toward RPS requirements where allowed by state RPS regulations. Canadian imports also count toward reserve margin requirements.

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[42] See https://www.neb-one.gc.ca/nrg/sttstc/lctrct/stt/lctrctysmmr/lctrctysmmr-eng.html.
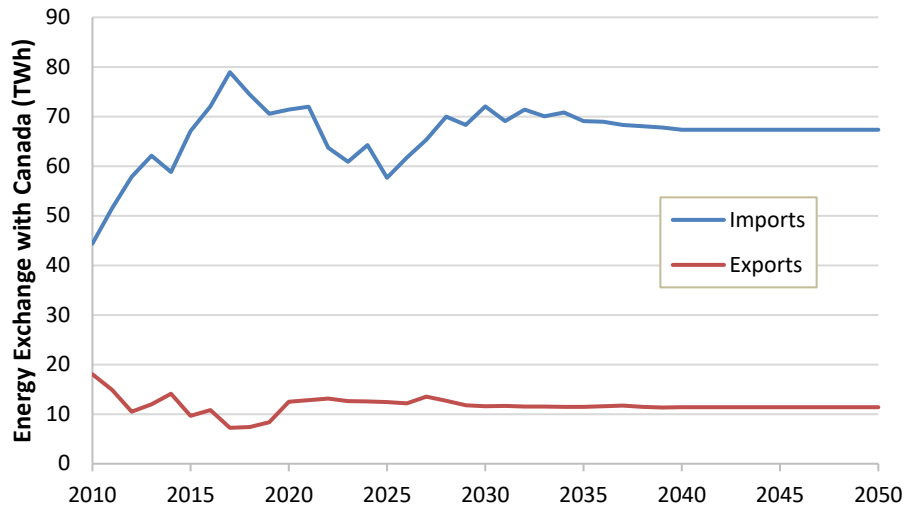
Figure 26. Imports from Canada to the United States and exports from the United States to Canada

7 Electricity System Operation and Reliability

ReEDS finds the least-cost way of building and operating the electricity system while meeting certain requirements that are dominated by the need to meet electricity load while maintaining system adequacy and operational reliability.

7.1 Electricity Load

The primary constraint in ReEDS is to serve electricity load in each BA and time-slice. The end-use electricity load projection used in ReEDS is exogenously defined,[43] based on scenarios from AEO2019 (EIA 2019b). Hourly load profiles are sourced directly from regional transmission organization (RTO) and independent system operator (ISO) websites for the applicable regions, with load data being requested at the most granular resolution available. For regions served by utilities, FERC Form 714 hourly load data are used. Hourly profiles for transmission zones are summarized and averaged to the 17 time-slice load profiles for the model BAs. These 2012 profiles are then scaled to ensure a match with the state-level annual retail energy load data from EIA's Electricity Data Browser (EIA 2015). Within a state in ReEDS, further adjustments to load profiles use county level load participation factors from Ventyx (2014). The regional growth factors for years after 2010 are calculated from the AEO scenario electricity consumption by census division. For each model year in ReEDS, the regional load profiles are scaled by regional growth factors, but the shape of the load profile is assumed to be constant throughout the study period.[44]

The end-use load, described in the previous paragraph, is defined at the meter level. ReEDS includes inter-BA transmission system losses in the optimization but does not represent distribution losses, so the end-use load must be scaled up to busbar load to account for distribution losses. The 5.3% distribution loss factor used for this conversion is estimated based on a combination of EIA and ReEDS numbers. ReEDS is required to generate sufficient power in each time-slice and BA (allowing for transmission of power but accounting for losses) to meet this busbar load. [45]

7.1.1 Demand Response

Demand response is not typically active in ReEDS due to the difficulty defining cost and availability for demand response at the resolution available in ReEDS. When active, however, demand response in ReEDS allows shifting of electricity use during hours with high electricity prices or peak load. Demand response is limited by a fraction of electricity load that grows from grows from 2% in 2018 to 10% in 2050. In addition to load shifting, demand response can also provide operating reserves.

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[43] An endogenous demand module is also available within ReEDS, though this module has not been used in any ReEDS analysis to date. More details on the module is available in the appendix under the section "Demand Module."

[44] Demand profiles and annual consumption can be altered with different plug-in hybrid electric vehicle and rooftop PV scenarios; however, absent these demand-side technologies, the profiles are assumed to be the same as those from 2010.

[45] Load balancing is implemented with equality constraints, so there is no physical representation of lost load and an associated cost.

7.1.2 Plug-In Electric Vehicles

Because ReEDS does not include vehicle choice or transportation sector modeling, the deployment of plug-in electric vehicles or plug-in hybrid electric vehicles (and their associated charging infrastructure) is input into ReEDS.[46] The number of plug-in vehicles is simply translated in the model into additional annual demand for electricity. This annual demand can be met through either a fixed charging profile over the 17 time-slices within a year in ReEDS, an endogenously determined dynamic profile, or some combination of the two. The endogenous profile allows for time-of-day flexibility within seasons but does not allow for load shifting across seasons. Ultimately, this profile is driven by the net load and is determined simultaneously with investment and operation of dispatchable and non-dispatchable resources within each time-slice of ReEDS.

In addition to not modeling vehicle deployment, the ReEDS model does not consider vehicle-to-grid or reserve services from vehicles. Plug-in vehicles cannot be used to meet the planning reserve requirements. Likewise, these vehicles cannot contribute to meeting operating reserve requirements. However, dynamically charged plug-in vehicles are allowed one operational benefit in ReEDS—adjusting load to better match generation profiles.

7.1.3 Energy Efficiency

Energy efficiency investment decisions are not modeled endogenously, although, past efforts have used exogenously specified trajectories (Bird et al. 2011).

7.2 Resource Adequacy

Resource adequacy is "the ability of supply- and demand-side resources to meet the aggregate electrical demand" (NERC 2016). Planning reserve requirements in ReEDS ensure adequate resource is available at all times, within an acceptable probability of failing to do so. In practice, this constraint is enforced by requiring the system to have sufficient firm capacity to meet the forecasted peak demand plus a reserve margin. This constraint is enforced for each season to accommodate the potential for peak net load to shift seasons as renewable penetration increases.

Each technology is assigned a capacity credit[47] reflecting its expected availability when power is needed, typically during the highest-risk hours, which are ideally identified as the hours with highest loss of load probability (LOLP)[48]. For conventional non-variable generators in ReEDS, the CC is one.

7.2.1 VRE Capacity Credit

For VRE technologies (i.e., wind and solar), ReEDS estimates a seasonal capacity credit for each region/class combination via an hourly LDC approximation of expected load carrying capability

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[46] For details and an example of how transportation electrification can be represented in ReEDS, see NREL (2012, Appendix K) and Melaina et al. (2016).

[47] In ReEDS, capacity credit is defined as the fraction of nameplate capacity that contributes to the planning reserve requirement.

[48] LOLP is defined as the probability of a loss-of-load event in which the system load is greater than available generating capacity during a given period.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

(ELCC)[49] performed between solve years.[50] ELCC can be described as the amount of additional load that can be accommodated by adding those generators while maintaining a constant reliability level. The "8760-based" methodology can capture the highest load and net load hours, which typically represent the highest risk hours, and can thereby support a reasonable representation of capacity credit. Details of this LDC approach, as well as a comparison against a former statistical method, can be found in Frew et al. (2017).

The LDC approach for calculating capacity credit is based on explicit hourly (8,760 hours) tracking of time-synchronous load and VRE resources. The capacity method uses a capacity factor proxy that is applied to top 10 hours in load and net load-duration curves (LDCs and NLDCs) in each season to estimate ELCC by season. Figure 27 graphically represents the ReEDS capacity credit methodology. The LDC reflects the total load in a given modeling region, which is sorted from the hours of highest load to lowest load and is shown by the blue line. The NLDC represents the total load minus the time-synchronous contribution of VRE, where the resulting net load is then sorted from highest to lowest, as shown by the solid red line.[51] The NLDC(δ), which represents further addition of VRE resources, can be created by subtracting the time-synchronous generation of an incremental capacity addition from the NLDC, where the resulting time series is again sorted from highest to lowest; this is shown by the dashed red line.
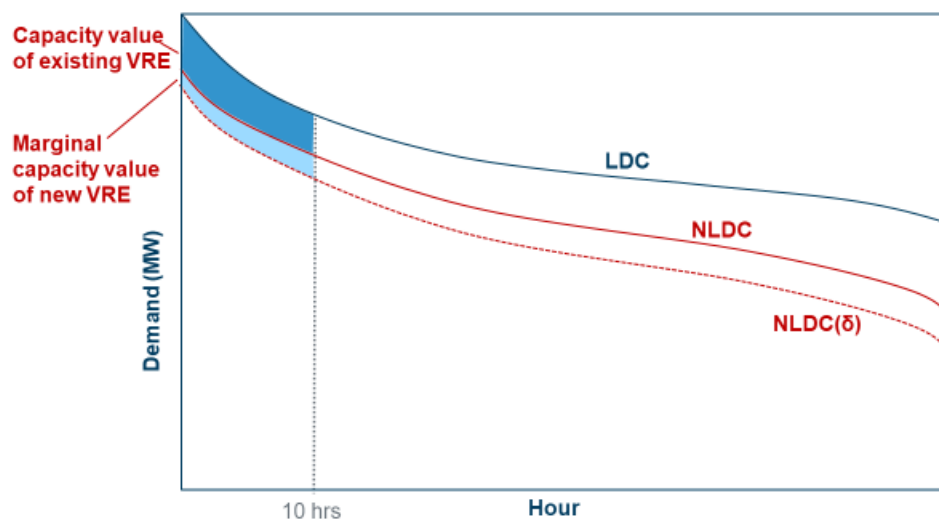
Figure 27. LDC-based approach to calculating CV

ReEDS calculates the ELCC as the difference in the areas between the LDC and NLDC during the top 10 hours of the duration curves in each season, as represented by the dark blue shaded area in Figure 27. These 10 hours are a proxy for the hours with the highest risk for loss of load (i.e., the LOLP).[52] Similarly, the contribution of an additional unit of capacity to meeting peak

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[49] ELCC is the contribution (units of MW that can then be reported as a fraction of the installed capacity to represent CV) that an additional resource provides toward meeting the system's load while maintaining a fixed system-wide reliability level.

[50] When running intertemporally, these values are calculated after each intertemporal solve. The model solves, recomputes these values, then solves again, and continues until convergence is reached.

[51] Residual LDC, or RLDC, is an equivalent term to NLDC and is used in the literature.

[52] We currently use only a single year of wind, solar, and load data to calculate capacity. Expansion of this method to use multiple years of data would increase the robustness of this calculation, and it is currently under development.

load is the difference in the areas between the NLDC and the NLDC(δ), as shown by the light blue shaded area in Figure 27. To ensure resource adequacy, ReEDS calculates capacity credit based on a 1,000-MW incremental capacity size of new solar and wind builds. These areas are then divided by the corresponding installed capacity and number of top hours (10 hours per season in this case, although the number of hours can be adjusted by the user) to obtain a fractional seasonal-based capacity credit.

The resulting existing and marginal capacity credit[53] values then feed into ReEDS to quantify each VRE resource's capacity contribution to the planning reserve requirement. Existing VRE capacity credit calculations are performed by region and technology. For all candidate VRE resources that might be built in the coming year, the *marginal* capacity credit is calculated by region, technology, and resource class. In all cases, the VRE profile is compared against the RTO-level load profile for determining the capacity credit (Figure 28). We use the RTO-level load profile to simplify the challenge of representing the ability of transmission to wheel VRE capacity from one BA to another. Essentially, we assume a copper plate within each RTO for the purpose of sharing VRE capacity. We use RTO regions rather than NERC regions for this assumption because transmission and trading tend to be more closely related to RTO regions than NERC regions.
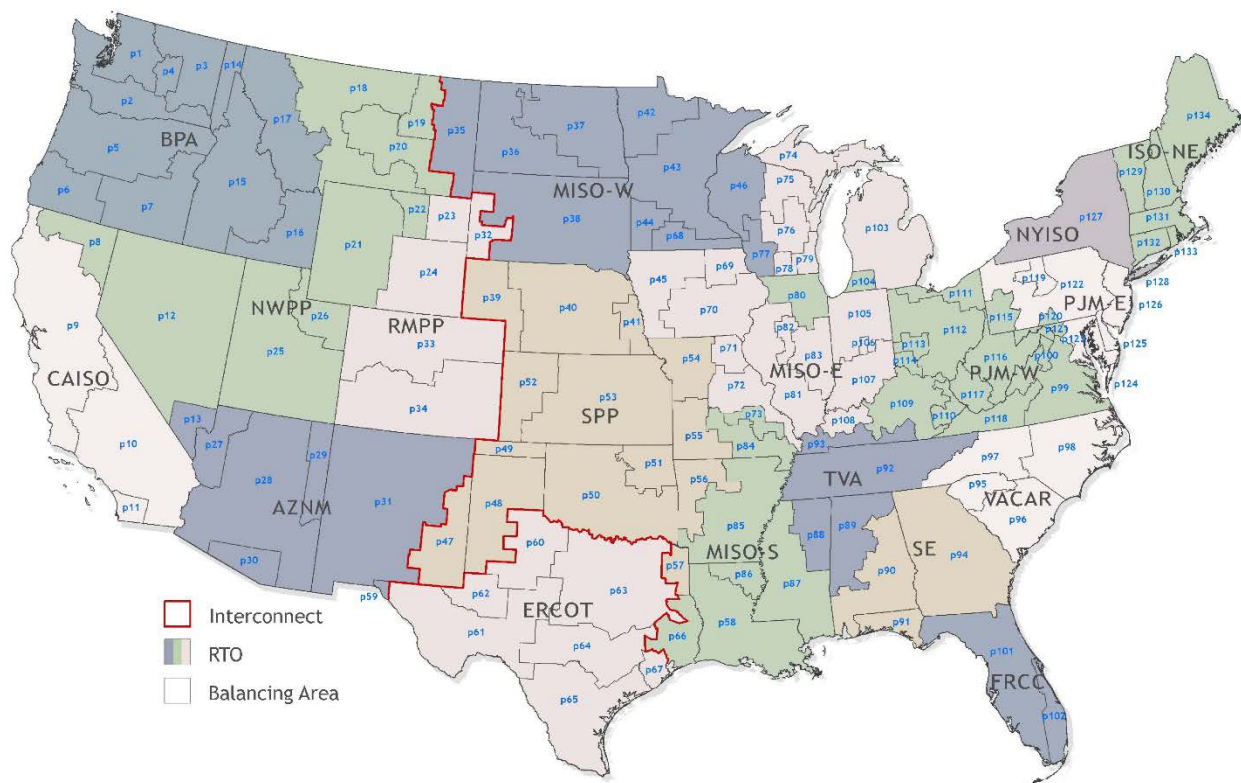
Figure 28. Map of ReEDS 134 BA regions and 18 RTO subregions

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[53] We refer to "existing" CV as the reliable capacity contribution from resources that have already been deployed in the model before the buildout of additional "marginal" resources.

7.2.2 Storage Capacity Credit

The storage capacity credit method in ReEDS characterizes the increase in storage duration that is needed to serve peak demand as a function of storage penetration. The potential of storage to serve peak demand is considered by performing several simulated dispatches against the load profiles within each of the RTO regions shown in Figure 28. Load profiles net of wind and PV generation are used to capture the effects of VRE resources on the overall net load profile shape in a region.

The method begins by selecting a target peaking capacity contribution for storage. This target peaking capacity contribution represents the power capacity of a test storage system. Subtracting this peak contribution from the peak load yields a max load target. For example, if the peak load for the given load profile is 50,000 MW and the chosen target peaking storage contribution is 10,000 MW, the max load target would be 40,000 MW. This static max load target is used to identify the storage discharge requirements that would keep the load profile at or below 40,000 MW, as well as the storage charging potential that could be used to charge energy storage to prepare for a peak event.

Figure 29 shows, for an example of a peak net load day, storage discharging requirements and charging potential to keep the load profile at or below the max load target. Because the target peaking capacity contribution is 10,000 MW in this example, storage charging is limited to be no more than 10,000 MW for consistency. Also, charging potential is limited in any hour that has a demand greater than 30,000 MW but less than 40,000 MW to ensure demand never exceeds the max load target.
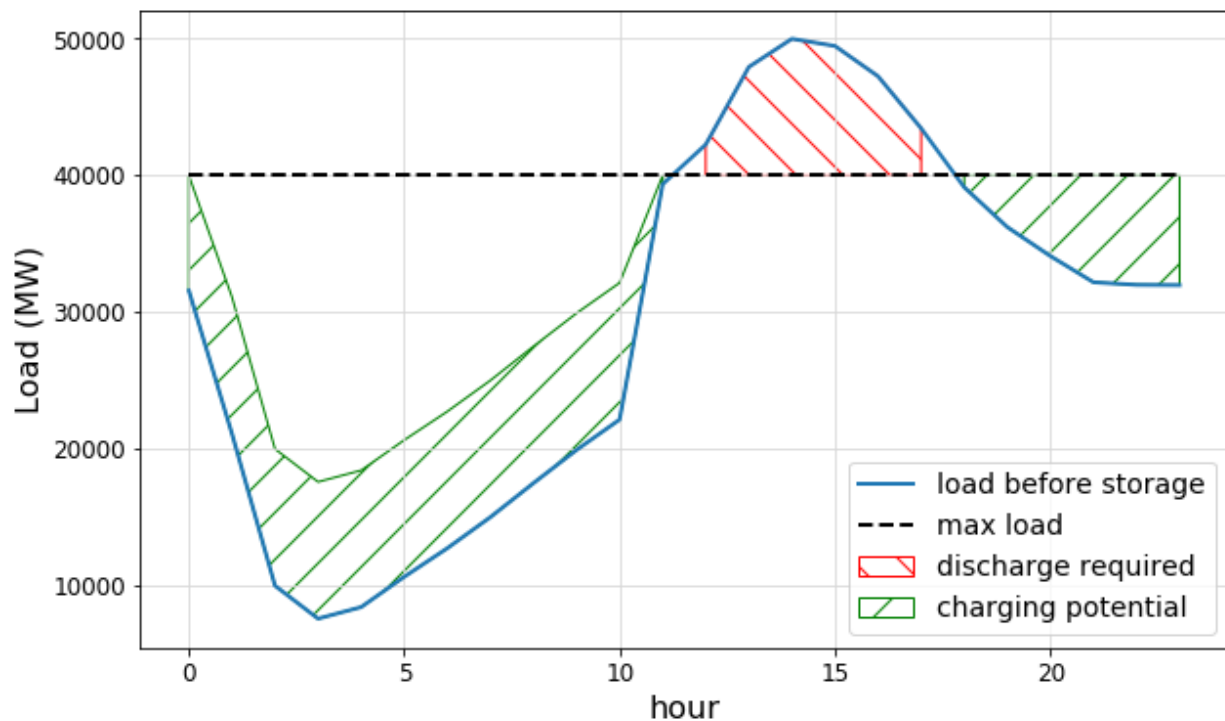
Figure 29. Charging potential and discharging requirements shown for a single day

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All round-trip efficiency losses are included in storage charging. For example, a storage resource with a round-trip efficiency of 85% and a power capacity of 10,000 MW can dispatch 10,000 MW to the grid for 1 hour using 10,000 MWh of energy capacity. However, when the same resource draws 10,000 MW from the grid for 1 hour, its state-of-charge increases by only 8,500 MWh.

The test storage system is dispatched over the course of the time-series. Storage is discharged whenever the load profile exceeds the max load target required, and it is charged whenever its state-of-charge is less than full and there is charging potential available (see Figure 30 top). The cumulative state-of-charge of the storage system is tracked over the course of the dispatch (see Figure 30 bottom).

The state-of-charge is assumed to be full at the beginning of the time-series, meaning it cannot charge beyond that point. Its depth, however, is unconstrained throughout the process. Once the dispatch of the entire time-series is complete, the minimum of the state-of-charge variable (assuming discharging is negative) represents the minimum energy capacity needed to keep peak demand at or below the max energy target. Dividing this minimum energy capacity result by the storage peaking power capacity target yields the minimum storage duration needed to serve peak demand with a capacity credit of 1.
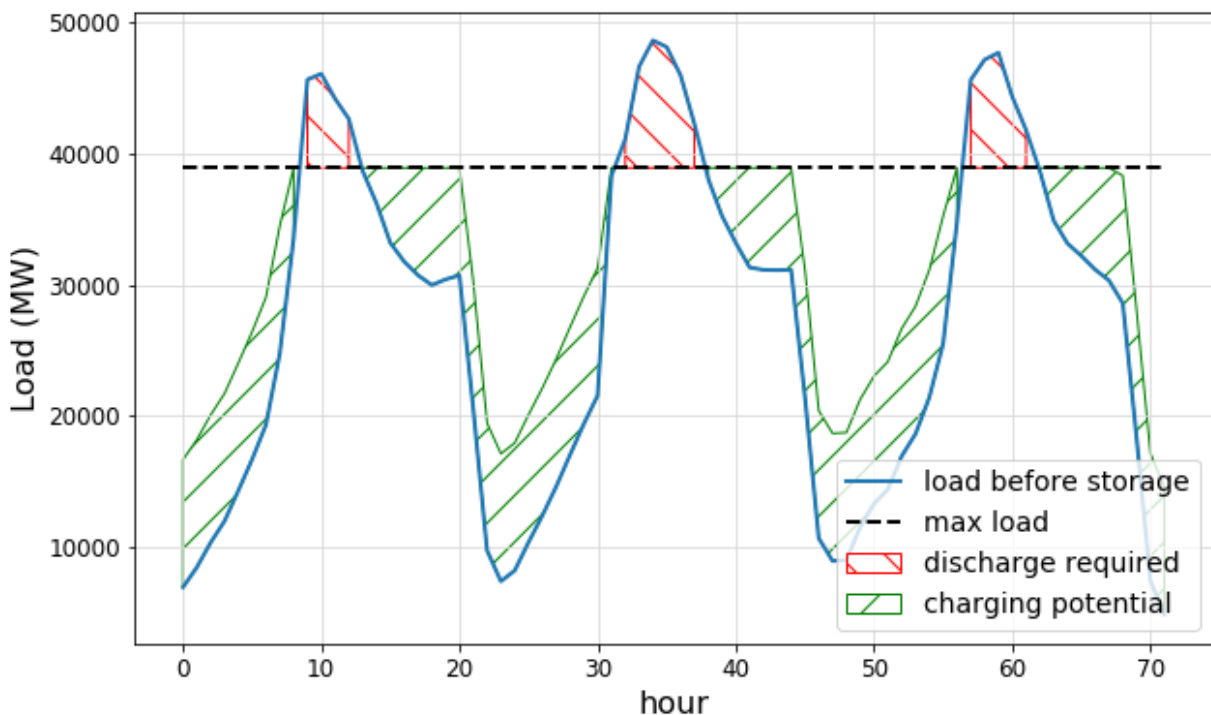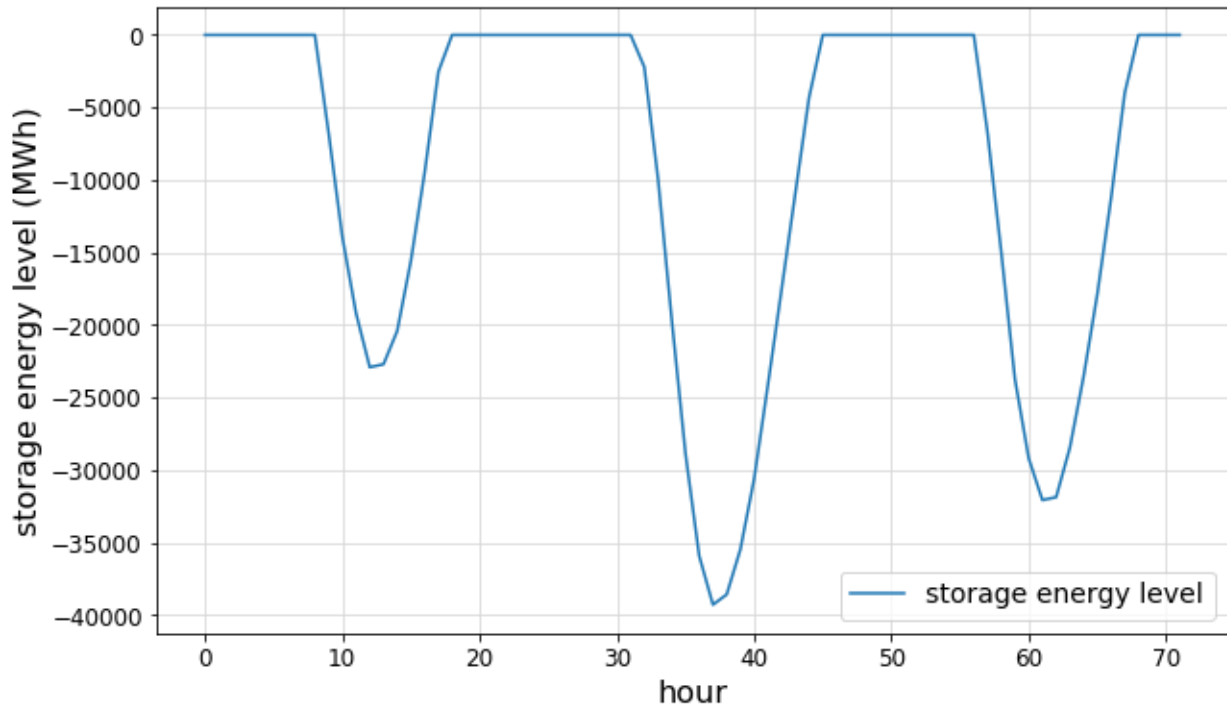
Figure 30. Storage dispatch for a three-day period, with the peak day in the middle (top) and storage energy level (state-of-charge) over that same period (bottom)

This process is repeated 100 times with different power capacities, from 0 MW up to the amount of installed power capacity in each RTO, with an additional data point of 1,000 additional MW of energy storage for determining marginal capacity credit of additional storage. Each point on the curve in represents a single instance of the calculation described previously. Examples of storage systems for each power capacity level shown are dispatched over the course of a time-series load profile net of wind and PV generation. The minimum value of the state-of-charge is obtained in each instance, and the pair is plotted together here. Interpolating these values generates a curve that shows the optimal power and energy capacity sizing for energy storage in that region to serve as a peaking capacity resource with a capacity credit of 1.

We use this curve to approximate the capacity credit of energy storage. Consider the example of a curve generated from the 2012 load profile in the New York Independent System Operator in Figure 31. If we consider the peaking potential of energy storage in that region, which totals 3,500 MW and 16,000 MWh, we see that when the actual storage fleet is plotted in the figure (yellow diamond), it is above the storage duration curve. This area corresponds to a storage capacity credit less of than 1 (Figure 31). In this case, 16,000 MWh of energy storage capacity can only serve up to 3,000 MW of peak demand. Therefore, the capacity credit of storage in this example would be about 0.86 (i.e., 3,000/3,500).
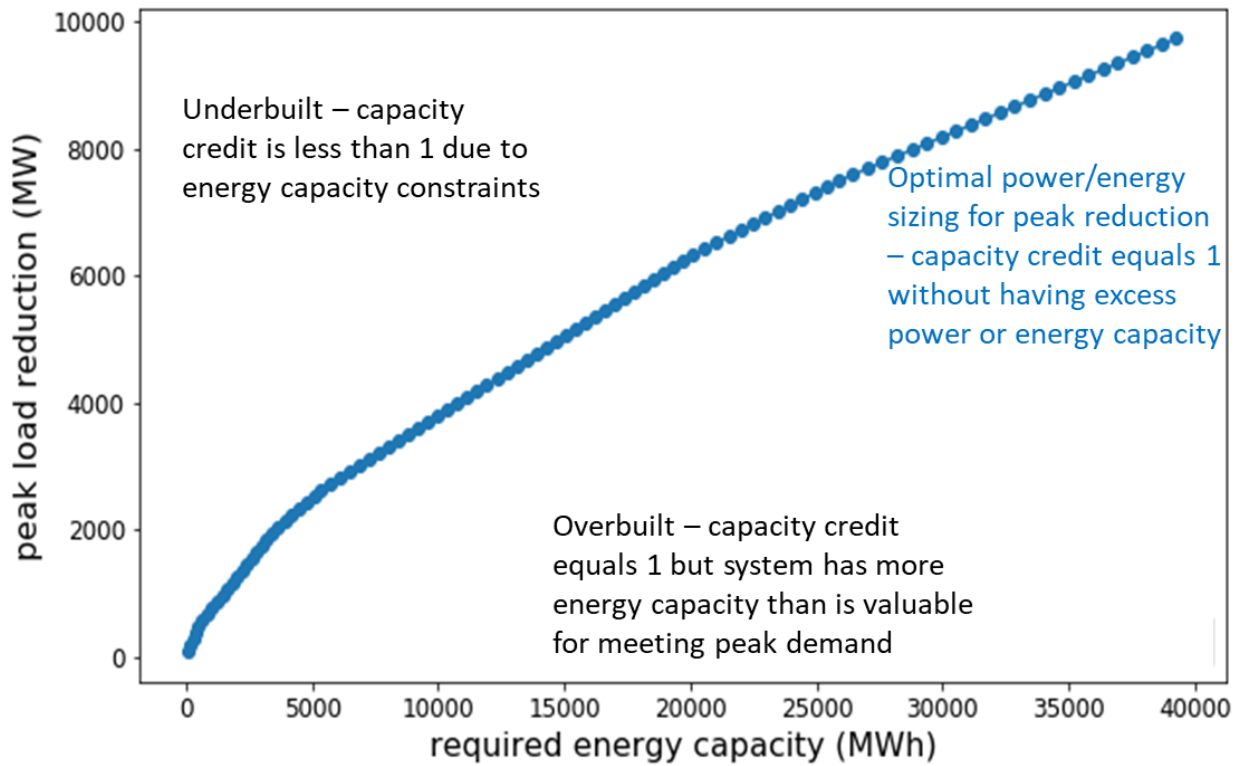
Figure 31. The relationship between peaking storage power capacity and the minimum energy capacity needed for that amount of storage power capacity to receive a capacity credit of 1

Plotted in Figure 32 are estimates of the capacity credit of energy storage additions. Plotted in blue is where the storage fleet would lie if another 1,000 MW of four-hour storage were added to the system (blue diamond). The green diamond shows the peaking storage potential for a system with 20,000 MWh. Simple algebra can be used to relate the capacity credit of storage before and after this addition, allowing an easy approximation of the marginal capacity credit for 1,000 additional MW of four-hour storage in this case. Also shown (in purple and orange) is the same situation but with the addition of eight hours of storage.
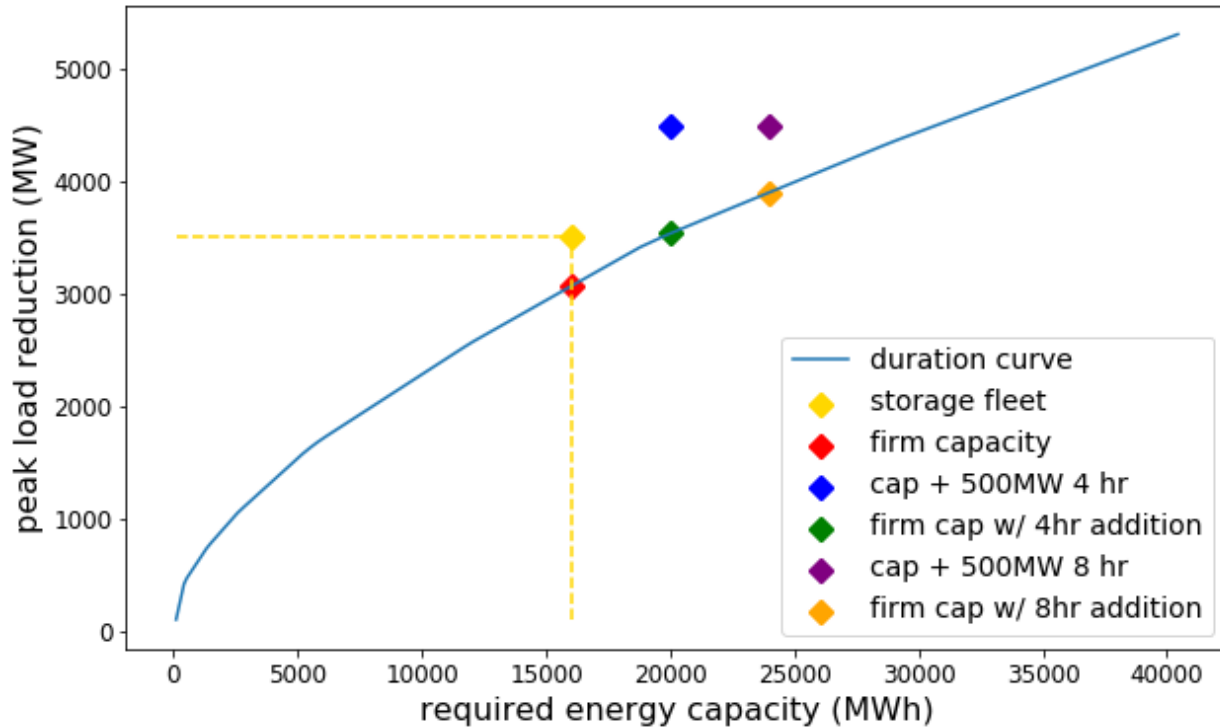
Figure 32. Storage duration curve for the 2012 load profile for the New York Independent System Operator compared with an example of a storage fleet totaling 3,500 MW and 16,000 MWh of capacity

Denholm et al. (2019) demonstrated how the storage peaking potential of storage interacts with VRE penetration.

7.2.3 *Planning Reserve Margins*

The planning reserve margin fractions applied in ReEDS are based on reserve margin requirements for NERC reliability subregions (NERC 2010) (see Figure 33). Each ReEDS BA must meet the requirement, but regions can engage in bilateral contracts for firm capacity subject to transmission limits on AC or DC corridors. The planning reserve margin is enforced seasonally such that each BA much meet the reserve margin requirement in each of the four seasons.

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Figure 33. Map of ReEDS 134 BA regions and 18 NERC reliability subregions as applied to the ReEDS BA regions

The planning reserve margin is constant over time for all regions except ERCOT. Because ERCOT was below its NERC-recommended level in 2018, the ERCOT reserve margin is set to the actual level of 10.9%, and the 2019 value is set at the 2019 projected level of 8.5%. The 2020 value is set as the average of 8.5% and the NERC-reference level of 13.75%, and years from 2021 and onward are set at 13.75%.

7.3 Operational Reliability

In addition to ensuring adequate capacity to satisfy long-term planning reserve requirements, ReEDS requires operational reliability—that is, the ability to continue operating the bulk-power system in the event of a sudden disturbance (NERC 2016). In practice, ancillary reserve requirements ensure there is sufficient flexibility from supply-side and demand-side technologies to rebalance fluctuations in generation and demand.

ReEDS represents three type of operating reserve products, including, spinning, regulation, and flexibility reserves (Cole, Eurek, et al. 2018). The requirement specified for each product in each time-slice is a function of load, wind generation, and photovoltaic capacity (during daytime

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

hours).[54] Technologies providing these reserve products must be able to ramp their output within a certain amount of time (Table 16).

Table 16. Summary of Operating Reserve Requirements

Reserve Product	Load Requirement (% of load)[a]	Wind Requirement (% of generation)[b]	PV Requirement (% of capacity)[b]	Time Requirement to Ramp (minutes)
Spinning	3%	—	—	10
Regulation	1%	0.5%[c]	0.3%[c]	5
Flexibility	—	10%	4%	60

[a] See Lew et al. (2013, Section 5.3.4).
[b] Reserve requirements for wind and PV are derived from the outcomes from Lew et al. (2013). The flexibility requirement for wind is estimated as the ratio of the change in the reserve requirement to the change in wind generation from the Lew et al. High Wind scenario; the requirement was estimated similarly for PV using the Lew et al. High Solar scenario.
[c] The estimated regulation requirements (0.5% wind generation and 0.3% PV capacity) are based on incremental increases in regulation reserves across all scenarios in Lew et al. (2013).

All ancillary reserve requirements must be satisfied in each BA for each time-slice; however, reserve provision can be traded between BAs using AC transmission corridors. Trades are only allowed within an RTO and not across RTO boundaries. The amount of reserves that can be traded is limited by the amount of carrying capacity of an AC transmission corridor that is not already being used for trading energy.

The ability of technologies to contribute to reserves is limited by the ramping requirement for a given reserve product, the plant ramp rate, and online capacity (Table 17). Online capacity is approximated in ReEDS as the maximum generation from all time-slices within a modeled day. Reserves can be provided by generation and storage technologies that are turned on but not fully dispatched in a time-slice. In addition, demand-side interruptible load can also contribute to reserve requirements, if enabled in a scenario. Nuclear, PV, and wind are not allowed to contribute toward the supply of reserves.

The cost for providing regulation reserves is represented in ReEDS using data from (Hummon et al. 2013); see Table 18. Because ReEDS does not clearly distinguish between coal fuel types, $12.5/MWh is the assumed regulation cost for all coal technologies. The cost of providing regulation reserves from Gas-CT, geothermal, biopower, land-fill gas, and CAES is assumed to be the same as oil/gas steam.

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[54] The PV reserve requirement is only valid during daytime hours when the PV systems are operating. In addition, the requirement is a function of capacity rather than generation because reserves are especially important around sunrise and sunset when PV generation is low.

Table 17. Flexibility Parameters of the ReEDS Generation Technologies

	Assumed Ramp Rate (%/min)	Upper Bound (% of online capacity) = Ramp Rate (%/min) × Ramp Requirement (min)		
		Spinning	Regulation	Flexibility
Gas-CT[a]	8	8×10=80	8×5=40	8×60=480, so 100
Gas-CC[a]	5	5×10=50	5×5=-25	5×60=300, so 100[a]
Coal[a]	4	4×10=40	4×5=20	4×60=240, so 100
Geothermal[b]	4	4×10=40	4×5=20	4×60=240, so 100
CSP with Storage[c]	10	10×10=100	10×5=50	10×60=600, so 100
Biopower[b]	4	4×10=40	4×5=20	4×60=240, so 100
Oil/Gas Steam[a]	4	4×10=40	4×5=20	4×60=240, so 100
Hydro	100	No Upper Bound		
Storage	100			

[a] See (Bloom et al. 2016b).
[b] Geothermal and biopower values are assumed to be the same as oil/gas steam units. In practice, geothermal plants typically do not ramp given their zero or near-zero variable costs, and therefore only provide energy and not operating reserves.
[c.] See (Jorgenson et al. 2013).

Table 18. Cost of Regulation Reserves

Generator Type	Cost of Regulation Reserves (2013$/MWh)
Supercritical Coal	15
Subcritical Coal	10
Combined Cycle	6
Gas/Oil Steam	4
Hydro	2
Pumped Storage Hydropower	2

7.4 Curtailment

Curtailment is a reduction in the output of a generator from what it could otherwise produce given available resources. Most renewable generators, being resource dependent and lacking fuel costs, are subject to curtailment that reduces plant revenue, in particular, when there is ample generating capacity committed, insufficient load to absorb it locally, and limited options to export surplus power via the transmission network. The economics of investment in renewable generators can be impacted by the amount of curtailment to which a plant will be subjected, so ReEDS estimates curtailment fractions for both existing renewable generators and candidate sites.

The ReEDS curtailment calculation is a statistical estimate of expected surplus generation in each BA and time-slice given the expected load level, expected VRE output, expected minimum

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turndown level for committed thermal units (see Table 17), and the variances and correlations of the preceding factors. Recommitting thermal capacity from one year to the next can change curtailment patterns by changing the minimum stable output level of the thermal fleet. Similarly, adding new storage capacity can reduce curtailment levels by effectively increasing the available load.

Short et al. (2011) describe the calculation details for curtailment in ReEDS. The only difference in the current version of ReEDS is that storage is no longer explicitly included in the statistical calculations for the existing and marginal VRE curtailments. Instead, the contribution of all storage toward reducing curtailment via charging by region and time-slice is captured within a storage effectiveness parameter. This parameter is nominally set to 1, which assumes full reduction in curtailment for energy placed into storage, for all load and renewable energy generation levels. Details about this parameter can be found in Cole, Marcy, et al. (2016).

8 Climate Impacts

Previous versions of ReEDS, including the 2018 version (Cohen et al. 2019), included a representation of climate impacts. That representation was not included in the 2019 version of ReEDS, but it is anticipated to be reimplemented into the 2020 version of ReEDS. For more information on how the climate impacts worked, see Section 7 of the 2018 version documentation (Cohen et al. 2019).

9 Policy Descriptions

Policies modeled in ReEDS include federal and state-level emission regulations, tax incentives, and portfolio standards. This section primarily focuses on existing policies, but Section 8.4 does discuss additional frameworks that exist in the model.

9.1 Federal and State Emission Standards

9.1.1 Cross-State Air Pollution Rule

ReEDS applies the Cross-State Air Pollution Rule (CSAPR) using caps on power plant emissions to the states in the eastern half of the United States over which the rules are imposed. From 2017 onward, CSAPR annual emission allowance budgets for NO_x are applied at the state level using the Phase 2 caps (EPA 2016). The caps are applied only during the ozone season. ReEDS applies a seasonal estimate of these ozone season caps that adjusts for the overlap of ReEDS season definitions and ozone season definitions. States can trade allowance credits within the eligible trading groups, but must keep emissions below the required assurance levels.

Sulphur Dioxide (SO_2) emission limits are not represented in the model because the caps would not be binding in the model except in historical years.

9.1.2 Mercury and Air Toxic Standards

Because compliance with the Mercury and Air Toxic Standards (MATS) has already been largely achieved, we do not represent MATS in the ReEDS model.

9.1.3 California Carbon Cap

California's Global Warming Solution Act of 2016 (referred to as Assembly Bill 398 or AB 398) established a program to reduce economy-wide greenhouse gas emissions to 1990 levels by 2020. In 2016, legislation was passed that codified the 2030 greenhouse gas target to 40% below 1990 levels. In ReEDS, these state carbon caps are modeled as a cap on electricity-system CO_2 emissions from generators either located in California or serving load in the state. Direct CO_2 emissions from generators located in California count toward the cap. Imported electricity is assumed to have a emissions rate of 0.26 ton CO_2/MWh (CARB 2019).

Because California's greenhouse gas reduction targets are legislated for all economic sectors while ReEDS only models the electricity sector, we rely on published economy-wide modeling results to estimate electric sector-specific caps that are used in ReEDS. In particular, we apply power sector caps based on the annual CA electric sector emissions (from in-state and imported electricity) from California Public Utilities Commission (CPUC 2018), which provides guidance for a 42 million tCO_2 cap by 2030. We enforce that cap from 2030 to 2050. The pre-2030 cap ramps linearly from 60 million tCO_2 in 2020 to the 42 million tCO_2 in 2030. Note that we also model California's RPS policy.

9.1.4 Regional Greenhouse Gas Initiative

The Regional Greenhouse Gas Initiative (RGGI) cap-and-trade program limits the CO_2 emissions for fossil fuel-fired power plants in ten states: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont.

We enforce allowance budgets from the updated model rule adopted in 2017.[55] Beginning in 2020, we also enforce an additional budget of 18 million short tons for the addition of New Jersey to the set of states included in the RGGI[56]. The budget for New Jersey is set to decline by 30% through 2030[57]. We ignore the provision for privately banked allowances and therefore use the unadjusted budgets: 165 million short tons in 2012 declining to 91 million by 2014, then declining 2.5% per year from 2015 to 2020. According to the 2017 Model Rule, the 2021 cap is set at 75 million short tons and decreases by 2.275 million tons per year until 2030. With the additional cap set by New Jersey, we wet the total 2021 cap to 92.6 million short tons with a deduction of 2.82 million tons per year until 2030. We assume the budget remains constant beyond 2030. We do not model banking of allowances, emissions offsets, or recycling of initiative allowance revenues.

9.2 Federal and State Tax Incentives

9.2.1 Renewable Production and Investment Tax Credits

Existing federal tax incentives for renewable energy are included in ReEDS. These include the PTC and the ITC—and the Modified Accelerated Cost Recovery System (MACRS) depreciation schedules. [58] The most recent renewable tax credit extensions were passed in December 2015 as part of the Consolidated Appropriations Act, 2016. Our representations of the PTC and ITC are based on this act, including tax credit values, schedules, expirations, and technology eligibility (Mai et al. 2016). Current technology-specific depreciation schedules are modeled for all years, because we assume they are permanent parts of the tax code.

Model representations of the latest tax credit extensions are complicated by the "commenced-construction" provision in these policies, the annual ramp-down in tax credit value, and the two-year modeling intervals used in ReEDS. Because ReEDS accounts for when plants come online rather than when they begin construction, we represent the commenced-construction provision by assuming the tax credit received by facilities corresponds to the value of the tax credits at the time the plant would typically start construction. For most purposes, we assume construction starts two years prior to the commercial operation date for utility-scale solar and wind and one year prior for commercial rooftop PV. However, guidance from the Internal Revenue Service (IRS)[59] allows for a longer construction period and equipment warehousing for wind projects to qualify for the PTC. It is unclear how the wind industry and wind deployment will react to this unprecedented IRS guidance. As a result, we conservatively represent a three-year period for

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[55] "2017 Model Rule," accessed April 26, 2018, https://www.rggi.org/program-overview-and-design/program-review. For more information, see:
- "About the Regional Greenhouse Gas Initiative (RGGI)," fact sheet updated August 2016, https://www.rggi.org/docs/Documents/RGGI_Fact_Sheet.pdf
- "The RGGI CO_2 Cap," https://www.rggi.org/design/overview/cap
- "Regional Greenhouse Gas Initiative," December 2013, http://www.c2es.org/docUploads/rggi-brief-12-18-13-updated.pdf.

[56] RGGI press release officially adding New Jersey to the set of RGGI states, https://www.rggi.org/sites/default/files/Uploads/Press-Releases/2019_06_17_NJ_Announcement_Release.pdf

[57] New Jersey State press release, specifying New Jersey's RGGI budget, https://nj.gov/governor/news/news/562019/approved/20190617a.shtml

[58] Note that the eligible cost basis for MACRS is reduced by one-half the value of the tax credit.

[59] "Beginning of Construction for Sections 45 and 48: Notice 2016-31," IRS 2016, https://www.irs.gov/pub/irs-drop/n-16-31.pdf.

wind in our PTC representation, meaning a project with a commercial online date of 2019 would qualify for the PTC value in 2016, for example.

For utility solar, facilities must be placed in service before the end of 2023 to qualify for a tax credit greater than 10%. To simplify representation in the model, we assume a two-year construction period.[60] For residential PV, the ITC is a placed-in-service tax credit, meaning the commenced-construction provision does not apply. Furthermore, the effective value of the tax credit during each two-year model period is based on the average value of the tax credit available after accounting for these under construction periods. For example, an effective 28% ITC is modeled for utility-scale solar during the 2022 ReEDS model year (representing 2021–2022) based on the average of the 30% ITC available in 2019 and the 26% ITC available in 2020.[61] Table 19 presents the effective wind PTC and solar ITC schedules modeled in ReEDS compared with the nominal schedule listed by the policy.

Though they are not shown in Table 19, we also include tax credits for other renewable energy technologies in the modeled scenarios. The model representation of the tax credit extensions includes effective PTCs for biopower, geothermal, and hydropower lasting through the 2017–2018 model period to account for the commenced-construction deadline at the end of 2016. A PTC value of 2.3 ¢/kWh is applied to geothermal, and a PTC of 1.2 ¢/kWh[62] is applied to new hydropower during this period. No tax credits are assumed for hydropower after 2018. A geothermal ITC of 10% is modeled for all years after 2018. Another nuance not shown on Table 19 is the ITC option in lieu of the PTC for certain qualifying facilities, including offshore wind. For offshore wind, we include an effective ITC through the 2020 model year.[63]

Due to these complexities and the required simplifications, we also limit near-term wind capacity deployment as discussed in Section 3.4.1.

Although nuclear technologies can qualify for a PTC, we do not model this PTC because no new construction is expected to occur because of the PTC (i.e., only already-under-construction plants are anticipated to be eligible for the PTC).

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[60] This is justified by the typically shorter construction periods for utility PV. Also, these assumptions are largely consistent with IRS guidance for commenced-construction provisions in earlier tax credit policies; see "Beginning of Construction for Sections 45 and 48: Notice 2015-25," Internal Revenue Service, U.S. Dept. of the Treasury, accessed January 28, 2016, https://www.irs.gov/pub/irs-drop/n-15-25.pdf.

[61] This representation may underestimate the impact of the tax credit on near-term deployment, as more projects may be moved forward to gain the higher tax credit value in earlier years. However, we conducted test scenarios and found little impact in renewable energy capacity deployment results when shifting the effective tax credit schedule slightly to account for this behavior.

[62] These values in implemented in ReEDS in 2015$.

[63] The current legislation specifies a ramp-down schedule for the ITC that is available to offshore wind wherein a 30% ITC is available in 2016 and reduces by six percentage points annually through 2019. However, we have not implemented the ability to model ITC ramp-downs for offshore wind. We include a full 30% offshore wind ITC for all model years from 2016 to 2020, but in most scenarios, no new offshore wind capacity is endogenously added during this period by the model. For this reason, we conclude that a more accurate representation of the ramp-down schedule would yield the same result.

Table 19. Actual and Modeled Schedule of Wind and Solar Tax Credits from the Consolidated Appropriations Act, 2016

Consolidated Appropriations Act, 2016		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Wind PTC		Full	Full	80%	60%	40%	0%	0%	0%	0%	0%	0%	0%
Solar ITC	Utility	30%	30%	30%	30%	30%	26%	22%	10%	10%	10%	10%	10%
	Commercial/Third-Party-Owned	30%	30%	30%	30%	30%	26%	22%	10%	10%	10%	10%	10%
	Residential Host-Owned	30%	30%	30%	30%	30%	26%	22%	0%	0%	0%	0%	0%

Model Representation		2015–16		2017–18		2019–20		2021–22		2023–24		Future	
Wind PTC		Full		Full		90%		50%		0%		0%	
Solar ITC	Utility	30%		30%		30%		28%		16%		10%	
	Commercial/Third-Party-Owned	30%		30%		30%		24%		10%		10%	
	Residential Host-Owned	30%		30%		28%		11%		0%		0%	

Table is adapted from Mai et al. (2016) but is updated to reflect the longer construction periods allowed for qualifying wind facilities.

9.2.2 *Penalty for Monetizing Tax Credit Incentives*

Many developers do not have the tax appetite to monetize the full value of non-refundable tax credit incentives (such as the ITC, PTC, and 45Q) as the credits accrue. They typically must be monetized either by applying the credits to the developer's tax burden in later years (which reduces the credit's effective value due to the time-value of money) or by finding equity partners with greater tax appetite (which reduces the credit's effective value, as the tax equity partners generally receive higher rates of return than a typical source of equity). ReEDS directly reduces the value of these tax credit incentives to reflect these monetization costs. The default penalty for all tax credit incentives is a one-third reduction in the value of the credit, although the penalty can vary by technology, year, and region.[64] For a more thorough discussion of tax credit monetization, including a summary of studies that sought to estimate the costs of monetization, see Bolinger (2014).

9.3 State Renewable Portfolio Standards

ReEDS models state RPSs, including technology set-asides and renewable energy certificates (RECs) that can count toward RPS compliance. RPS rules are complex and can vary significantly between states. The RPS representation in ReEDS attempts to model the primary impacts of these RPS rules but includes many simplifying assumptions. In addition, in recent years there have been numerous changes to RPS legislation. We periodically update our representation to capture the recent changes to the legislation; however, the numerous and frequent changes to state laws create challenges to having a current representation of all RPS legislation.

Table 20 shows the respective RPS targets and technology set-asides for years 2020, 2025 and 2030 as a percentage of state electricity sales as modeled within ReEDS. These values—along with many other data that we use to represent nuanced RPS rules—are based on data compiled by Lawrence Berkeley National Laboratory, which takes into account the in-state REC multiplier incentives and load adjustments (e.g., sales-weighted RPS targets considering different load-serving entities subject to compliance, such as investor-owned utilities, municipal utilities, and cooperatives).[65] Solar includes UPV and rooftop PV, wind includes both land-based and offshore technologies, and distributed generation (DG) includes rooftop PV and ground-mounted PV systems located within the distribution network.[66] ReEDS also models alternative compliance payments for unmet RPS requirement for both main RPS targets and solar set-asides as is consistent with the available data.[66]

Technology eligibility for state RPS requirements is appropriately modeled for each state.[66] For instance, California's RPS does not allow in-state rooftop solar technologies to contribute toward

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[64] When stating the value of tax credit incentives, note that we state the pre-penalty value. For example, we would say that the ITC value is 30%, even if the monetization penalty would make it so that the incentive would ultimately only be worth 20% of the qualified capital costs.

[65] See Barbose (2017) and https://emp.lbl.gov/projects/renewables-portfolio. Spreadsheet accessed January, 2017.

[66] See Database of State Incentives for Renewables & Efficiency (DSIRE) website at dsireusa.org . If data are unavailable, ReEDS forces RPS target to be met by using a default alternative compliance payment and solar alternative compliance payments of $200/MWh and $400/MWh respectively.

its RPS.[67] Additionally, every state has specific rules regarding hydropower generation's eligibility toward contributing RECs, which are usually based on each unit's vintage and size (e.g., small hydro with specific capacity cut-offs are eligible in some states). ReEDS models these as allowable capacity fractions (estimated from ABB Velocity Suite database (ABB 2018)), which is imposed on each state's total hydropower generation thereby limiting the amount of hydropower RECs that each state could generate. Additionally, ReEDS also imposes an upper limit on the total hydropower RECs that a state can use toward its RPS based on historical data as compiled and estimated by Lawrence Berkeley National Laboratory.

Table 20 also lists the allowable states from which each state may import RECs; interstate REC transactions that are required to be bundled with energy are marked with an asterisk. Except for California, ReEDS enforces an upper limit on the total RECs (both bundled and unbundled) that can be imported for that state's RPS compliance. For California alone, due to its unique out-of-state rules, ReEDS enforces two upper limits, one on the total unbundled REC imports and the other on the total bundled REC imports. There is a myriad of possibilities of interstate REC transactions, in terms of both which two states can transact and the quantity of those transactions. To constrain the solution space of ReEDS to credible values, the interstate REC trading modeling is based on historical observations (Holt 2016), as shown in the final two columns of Table 20. The out-of-state total REC import percentages for each state in are limited to those observed in 2012–2013 (Heeter 2015).

Several states have implemented policies directed at offshore wind. To represent these actions in ReEDS, we prescribe a floor to offshore wind capacity based on known projects and policy mandates. Specifically, we include offshore wind capacity that meets at least one of three criteria: (1) currently operating capacity; (2) projects in active solicitation processes; and (3) to meet statutory policy requirements. The projects are based on tracking conducted for the NREL Offshore Wind Technologies Market Report. The 2019 version of ReEDS relies on projects and policies as of July 2019 and includes estimated offshore wind capacity in six states (CT, MA, MD, NJ, NY, and RI) totaling 14,698 MW by the end of 2030 and 19,698 MW by the end of 2040 (see Table **21**). The model allows for economic deployment of offshore wind capacity beyond these levels. All prescribed projects are assumed to be rebuilt once they are retired.

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[67] This version of ReEDS does not include CA Senate Bill 100 requiring 100% carbon-free electricity by 2045, as this bill was passed too recently to be included in this model version. The CA Senate Bill 100 policy will be included in future ReEDS versions.

Table 20. Effective State RPS Requirements in ReEDS

State	RPS Target/Solar/Wind Set-Asides (%)			Allowable States for REC Import, includes Canadian Provinces (*bundling requirement)	REC Import Limit (% of RPS target)
	2020	2030	2050		
AZ	5.8/-/-	8.7/-/-	8.7/-/-	CA*, CO*, NM*	100
CA	30.4/-/-	55.4/-/-	55.4/-/-	AZ*, ID, MT, NM, NV*, OR*, UT*, WA, WY*, MEX*	25<2013 15<2016 10>2017 (only unbundled, 100% for bundled)
CO[a]	19.2/-/-	19.8/-/-	20.1/-/-	WY	8
CT	24.9/-/-	43.8/-/-	43.8/-/-	MA, ME, NH, NY*, RI, VT, NB*, NL*, NS*, QC*, NFI*, PEI*	59
DE[b]	13/1.7/-	18.7/3/-	18.7/2.9/-	IL*, IN*, MD, PA*, VA*, WV*	94
IL[b,c]	14.4/1.4/1.4	24.4/2.9/2.9	25.6/2.9/2.9	IA, IN, MD, MN, MO, ND, NY, OH, PA, SD, VA, WI, WV	60
MA[b]	16.6/7.2/-	33/10/-	50.3/9.6/-	CT, ME, NH, NY*, RI, VT, NB*, NL*, NS*, QC*, NFI*, PEI*	62
MD[b,d]	26.1/5.3/-	54.6/12.7/-	56.7/13.4/-	DE, IA, IL, IN*, NC*, NY*, OH*, PA*, TN*, VA*, WI*, WV*	70
ME	36/-/-	72.4/-/-	72.4/-/-	CT, MA, NH, RI, VT, NB*, NL*, NS*, QC*, NFI*, PEI*	18
MI	10.8/-/-	12.5/-/-	11.9/-/-	IA, IN, MN, WI	0
MN	25.2/0.8/11.1	28/0.8/11.1	28/0.8/11.1	IA, MI, ND, SD, WI, MB, ON, SK	24
MO[b]	6.7/0.1/-	10/0.2/-	10/0.2/-	IA, KS,	94
MT	10.8/-/-	10.8/-/-	10.8/-/-	ND*, OR*, WA*, BC*	6
NC	5/0.2/-	4.7/0.2/-	4.3/0.2/-	AL*, FL*, GA*, LA*, MS*, OH*, PA*, SC*, TN*, VA*, WV*	43
NH[b]	17.4/0.7/-	20.6/0.7/-	20.6/0.7/-	CT, MA, ME, NY*, RI, VT, NB*, NL*, NS*, QC*, NFI*, PEI*	35

State	RPS Target/Solar/Wind Set-Asides (%)			Allowable States for REC Import, includes Canadian Provinces (*bundling requirement)	REC Import Limit (% of RPS target)
	2020	2030	2050		
NJ[b]	27.5/4.7/-	53.5/2.2/-	51.2/-/-	DE, IL*, IN*, MD, OH*, PA*VA*, WV*	76
NM	15.8/-/-	44.8/-/-	65.3/-/-	-	0
NV	16.6/-/-	44.2/-/-	44.3/-/-	-	100
NY	32.4/-/-	74.5/-/-	74.5/-/-	RI*, ON*, QC*	4
OH[b]	4.8/-/-	-/-/-	-/-/-	IN*, KY*, MI*, PA*, WV*	57
OR[b]	13.7/-/-	25.1/-/-	34.8/-/-	CA*, ID*, MT*, UT*, WA*, WY*, BC*	42
PA[b]	7.2/0.4/-	7.8/0.5/-	7.8/0.5/-	DE, IL, IN, MD, NC, NJ, OH, VA, WV	47
RI	15.9/-/-	30.8/-/-	38.2/-/-	CT, MA, ME, NH, NY*, VT, NB*, NL*, NS*, QC*, NFI*, PEI*	77
TX	4.2/-/-	3.8/-/-	3.5/-/-	-	0
VT	59/-/-	71/-/-	75/-/-	CT, MA, ME*, NH, RI	100
WA	12.1/-/-	12.4/-/-	12.3/-/-	ID, MT, OR, BC*	43
WI	9.9/-/-	9.9/-/-	9.9/-/-	IA*, MI*, MN*, ND*, SD*, MB*, SK*	41

[*] Interstate REC transactions that are required to be bundled with energy are marked with an asterisk.

[a] Based on historical observation, only 50% of the actual DG carve out for Colorado is assumed to be met using distributed solar technologies (DUPV and distributed PV).

[b] Based on historical observation, the solar carve out in these states are seen to be met primarily using distribution side solar technologies.

[c] Illinois allows for 50% of its RPS target to be met using alternative compliance payments, and hence ReEDS targets are adjusted to reflect this.

[d] Washington, D.C. RPS targets are rolled into Maryland (Washington D.C. load also rolled into Maryland).

Table 21**. Cumulative Offshore Wind Capacity (MW) Mandated in ReEDS**

State	2020	2030	2040	2050
CT	—	2,000	2,000	2,000
MA	—	3,200	3,200	3,200
MD	—	1,568	1,568	1,568
NJ	—	3,500	3,500	3,500
NY	—	4,000	9,000	2,530
RI	30	430	430	430

For example, there has been a total of 2,000 MW of offshore wind capacity mandated through 2050. This mandate represents a lower bound on offshore wind capacity.

9.4 Clean Energy Standards

As of July 2019, six states had clean energy standards (CESs) (see Table 22). These CESs are in effect generalized versions of RPSs; their model representations are very similar with technology eligibility being the only difference. For all but one of the CES policies (Massachusetts), we assume all zero-carbon-emitting sources (on a direct emissions basis) can contribute to the CES requirement. This includes all renewable energy technologies (including hydropower and distributed PV), nuclear power, and imports from Canada.[68] The modeled CES policies set a floor on electricity generated from clean energy technologies but does not cap generation from nonclean sources. As a result, in the model representation, a state can continue to generate from existing fossil plants if the amount of clean energy generation exceeds the requirement (even if the requirement approaches 100% of sales). Most of the CES policies are assumed to start in 2030 and ramp to their final targets by 2040 or 2050.[69] For other aspects of the CES model representation, we use the same assumptions as the corresponding state RPS. These include assumptions about credit trading and variations in load-serving entity requirements.

Table 22. Clean Energy Requirement as a Percentage of In-State Sales

State	2020	2030	2040	2050
CA	0%	55%	85%	100%
CO	19%	44%	50%	55%
MA	20%	37%	54%	71%
NM	0%	45%	75%	100%
NY	0%	75%	100%	100%
WA	0%	80%	93%	100%

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[68] For Massachusetts, we assume CCS technologies are also eligible, but we disallow hydropower because of the post-2010 commercial operation date requirement in the state policy (DOER 2018).

[69] The modeled CES for CO_2 is assumed to start in 2020 and includes the clean energy commitments from the largest electric utility in the state (Xcel Energy), which were codified into law in 2019. The modeled CES for Massachusetts begins at 16% in 2018 and increases to 80% by 2050.

9.5 Storage Mandates

Five state storage mandates are represented in ReEDS.[70] These include a 1,503 MW storage requirement in California by 2024, a 50 MW storage requirement in Massachusetts by 2020, a 2.5 MW storage requirement in Oregon by 2020, a 2,000 MW requirement in New Jersey by 2030, and a 3,000 MW requirement in New York by 2030. These are enforced through prescribed builds of four-hour battery storage in each of the states, and the mandates are required to be maintained throughout the model horizon (i.e., once a battery is retired it must be rebuilt if the retirement causes the capacity to fall below the mandate).

9.6 Other Policy Capabilities

In addition to the existing policies described above, ReEDS also includes several optional policy implementations that are useful for exploring alternative futures or the impact of existing policies. These additional policy frameworks include

- **National Clean Energy Standard:** This framework allows the user to specify which technologies count as "clean energy" and enforce a minimum limit for the penetration of these clean energy technologies.

- **National Renewable Portfolio Standard:** This standard enforces a national RPS, with the RPS trajectory defined by the user.

- **Carbon Cap-and-Trade:** This feature allows the user to specify national-or subnational carbon cap-and-trade policies, including options to represent trading limitations and banking and borrowing of allowances.

- **Carbon Tax:** This feature implements a user-specified carbon tax on burner-tip emissions from the power sector.

- **National Emissions Limit:** This framework limits the total national emissions according to user-specified values. The limit is often referred to as a carbon cap or CO2 cap.

- **Alternative ITC and PTC Schedules:** In addition to the ITC and PTC schedules described in Section 8.2, the ITC and PTC can be modified to apply for any number of years and to any technology.

- **Alternative Financing Measures:** Policy-related financing impacts such as MACRS or the under-construction provisions for the ITC and PTC can be modified as specified by the user.

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[70] Additional storage policies will be evaluated for inclusion in future model versions.

10 Capital Financing, System Costs, and Economic Metrics

10.1 Financing of Capital Stock

The financing assumptions used in ReEDS are taken directly from the 2019 ATB spreadsheet (NREL 2019), using the "Market Factor Financials" and the 20-year capital recovery period options. The ATB has technology-specific and time-varying financing parameters, including interest rate, rate of return on equity, debt fraction, and tax rate. Other elements of the ATB included in ReEDS include construction schedules, MACRS depreciation schedules, and inflation rates. These values are further defined and explained in the ATB, with additional explanation of our financing implementation detailed in the Capital Cost Financial Multipliers appendix of this document. The only deviation in ReEDS from the ATB is associated with the MACRS implementation. Because of the bonus depreciation opportunities in the most recent tax law, the MACRS schedules for all technologies use the 5-year MACRS schedule through 2023, then those schedules ramp back up to the schedules specified in the ATB by 2026.

In previous versions of ReEDS, technology-specific costs of capital were reflected through technology-specific discount rates. Due to the different model structure of the intertemporal mode, and the desire to keep the financial representations the same between modes, since the 2019 version the model has had only a single technology-agnostic discount rate. Instead of varying the discount rate, the impact of any difference between a technology's weighted average cost of capital (WACC) and the system average WACC is captured in a lump-sum adjustment that represents the present-value of the higher (or lower) return to capital. This representation implicitly assumes that differences in financing terms primarily come from diversifiable risk, as opposed to non-diversifiable risk.

10.2 Electric Sector Costs

Two system-wide cost metrics are calculated from each ReEDS run: a present value of direct electric sector system costs and electricity price. These cost calculations are not part of the ReEDS optimization process; they are calculated after the ReEDS optimizations have been conducted. The cost metrics provided directly from ReEDS do not include any environmental or health externalities (e.g., social cost of carbon emissions).

10.2.1 Present Value of Direct Electric Sector Cost

The present value system cost metric accounts for capital and operating expenditures incurred over the entire study horizon for all technology types considered, including generation, transmission, and storage. The cost in each future year is discounted by a user-defined social discount rate, and by default it is set to 7% (Office of Management and Budget 2018). Not to be confused with the discount rate used in the optimization for investment decisions, the *investment* discount rate is selected to represent private-sector investment decisions for electric system infrastructure, and it approximates the expected market rate of return of investors. All costs incurred before the start of the specified economic horizon are assumed to be sunk and are therefore not included in the system cost metric. Details about how the system costs are calculated in ReEDS can be found in the Present Value of Direct Electric Sector Cost section of the appendix.

10.2.2 Electricity Price

ReEDS calculates "competitive" electricity prices at different regional aggregation levels (F. H. Murphy and Smeers 2005; Ventosa et al. 2005; EIA 2017b). This calculation takes advantage of the linear programming formulation of the model. Specifically, the marginal price on a model constraint represents how much the objective function would change given a change in the right side of the constraint. Each constraint can be viewed as a market with a marginal price and quantity. At optimality, the total revenue (i.e., the product of price and quantity) across all constraints equals the objective function value. The constraints within ReEDS are written such that the marginal values from the load constraints can be used as a proxy for the competitive electricity price. The load constraints are linked to the supply-demand balance constraints, capacity constraints, operating reserve constraints, and others through load variables. Taking the marginal value from the load balance constraint, we can find the marginal value of an additional unit of load (e.g., MWh) to the system, accounting for other requirements. Specifically, the reported competitive prices in ReEDS capture five categories of requirements, including energy, capacity, operating reserves, and state-level and national-level RPS requirements (see Table 23). The competitive prices can be reported at different regional aggregation level, scaled by requirement quantities. Details about how these prices are calculated in ReEDS can be found in the Marginal Electricity Prices section of the appendix.

Table 23. Relationships of Constraints to Grid Services Used to Calculate the Competitive Electricity Price

Constraint Category	Grid Service (s)	Region (r)	Time (h)	Units	
				Price (p_{srht})	Quantity (q_{srht})
Operation	Energy	BA	Time-slice	$/MWh	MWh
	Flexibility Reserve	BA	Time-slice	$/MW-h	MW-h
	Regulation Reserve	BA	Time-slice	$/MW-h	MW-h
	Spinning Reserve	BA	Time-slice	$/MW-h	MW-h
Resource Adequacy	Capacity	BA	Season	$/kW-yr	kW
Policy	State RPS	State	Annual	$/MWh	MWh
	National RPS	National	Annual	$/MWh	MWh
	CO2 Cap	National	Annual	$/metric ton	metric ton
	RGGI CO2 Cap	Regional	Annual	$/metric ton	metric ton
	SB32 CO2 Cap	Regional	Annual	$/metric ton	metric ton

10.3 Modeled Economic Metrics

ReEDS calculates multiple economic metrics for analyzing investment decisions in the model, including:

- Levelized cost of energy (LCOE)

- Technology value

- Net value of energy (NVOE)

- Net value of capacity (NVOC)

These metrics are described in detail below.

10.3.1 Levelized Cost of Energy

LCOE measures the unit cost of electricity of a specific technology, which is normally calculated as lifetime costs divided by energy production. Specifically, the LCOE is calculated as follows (NREL 2019):

$$LCOE = \frac{FCR \times CAPEX + FOM}{CF \times 8,760} + VOM + FUEL$$

where FCR is the fixed charge rate; CAPEX is the capital expenditures; FOM is the fixed operations and maintenance costs; CF is the capacity factor; 8,760 is the number of hours in a year; VOM is variable operations and maintenance costs; and FUEL is fuel costs (if applicable).

In each model year, ReEDS reports the LCOE for all technology options considering different variations in tax credit treatments and capacity factor assumptions. ReEDS also calculates the LCOE for technologies that are built in this model year using the generation from these technologies.

10.3.2 Technology Value

ReEDS reports the value that generators receive from providing grid services. Value is calculated as the product of service prices and service provision quantities. For example, the value of a generator that comes from providing energy service to meet planning reserve margin requirement is calculated as the price of capacity multiplied by the amount of firm capacity the generator can provide. The reported revenues capture energy, capacity, operating reserve, and state-level and national RPS requirements. Revenues can be normalized either by the amount of generation or by the amount of installed capacity.

Revenues are closely related to, but are different from the electricity price and service requirement quantity parameters. Revenues consider the *provision* of different services from a certain generator in a region, whereas service requirement quantities calculate the *demand* of different services in a region. The sum of revenues from all generating technologies in a specific region does not necessarily equal the sum of products of all service prices and corresponding service requirements.

10.3.3 Net Value

ReEDS reports different economic viability metrics that consider both *costs* and *values* of generating technologies to fully evaluate the economic competitiveness of a certain technology, and to provide intuitive explanations about investment decisions in the model. "Values" of a generator reflect the potential economic benefit from displacing or avoiding the cost of providing the services from other (marginal) assets, while "costs" aggregate all different sources of costs needed to build and operate a power plant to provide services. We define "net value" as the difference between values and costs. Net value is related to a concept in linear programming called "reduced cost." Mills and Wiser (2012) describe reduced cost in the context of electricity system modeling.

We report three types of such metrics to assess the economic viability of generators: net value of energy, net value of capacity, and system profitability metrics (Table 24). These metrics are reported both for new investments in certain model year and for existing generators that have been built.

Table 24. Summary of Net Value Metrics

Metric	Conceptual Expression [Typical Units]
Net value of energy (NVOE)	(Value – Cost)/Energy [$/MWh]
Net value of capacity (NVOC)	(Value – Cost)/Capacity [$/kW-yr]
System profitability	f(Value/Cost) [unitless]

Net value of energy (NVOE) measures the unit profit of a specific technology, calculated as the difference between generator revenue and costs, then normalized by the energy production. The typical unit is dollars per megawatt-hour ($/MWh). Similarly, net value of capacity (NVOC) measures the unit profit of a specific technology, calculated as the difference between generator revenue and costs, then normalized by the installed capacity. The typical unit is dollars per megawatt ($/MW).

Both of these two metrics are normalized metrics; because the denominators vary broadly for different generator types, they may not reflect the competitiveness of technologies consistently. Therefore, we report a third type of economic viability metric, namely system profitability metrics, which are essentially unitless functions of the ratio between values and costs. Examples include profitability index (value/cost) and return on investment (value/cost minus one). We report both metrics in ReEDS, acknowledging that there are other formats of system profitability metrics.

These economic viability metrics help explain investment decisions in the model. Specifically, for all types of new investment in a certain model year, the model considers all the costs to build and operate a certain technology as *costs*, and the contribution of the technology to all binding constraints as *values* (i.e., service provision). Typical value sources are discussed above in Section 10.3.2. In calculations of economic viability metrics, however, other types of "values" are included to fully reflect model decisions. For example, an increase of ancillary service requirements that are due to higher wind penetration is counted as a negative value stream for

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wind, and it is included in the metrics calculation here. Therefore, these metrics fully reflect all the model constraints related to the investment decision.

11 ReEDS North American Expansion

As discussed in Section 6.4, ReEDS includes an exogenous representation of Canada. However, the ReEDS model also includes the capability to model both Canada and Mexico endogenously. This continental version of the ReEDS model, which is referred to as ReEDS-North America, is described here. Country specific models can be run separate from the continental model as ReEDS-Canada and ReEDS-Mexico. The ReEDS-Canada model includes 20 additional BAs, regions as shown in Figure 34, and 47 new wind/CSP resource. The Canadian BAs only cover areas where the grid is directly connected to the U.S. system and therefore do not include the Yukon, Northwest Territories, and Nunavut. The ReEDS-Mexico model includes 49 additional BAs, which are also used for defining wind/CSP resource regions. This representation directly aligns with the transmission regions used by Secretaría de Energía for Mexico (SENER) in their annual report Programa de Desarrollo del Sistema Eléctrico Nacional (PRODESEN). The Mexican BAs cover all regions in Mexico but do not include exporting generators on the Mexico-California border, which are modeled endogenously when modeling the United States.
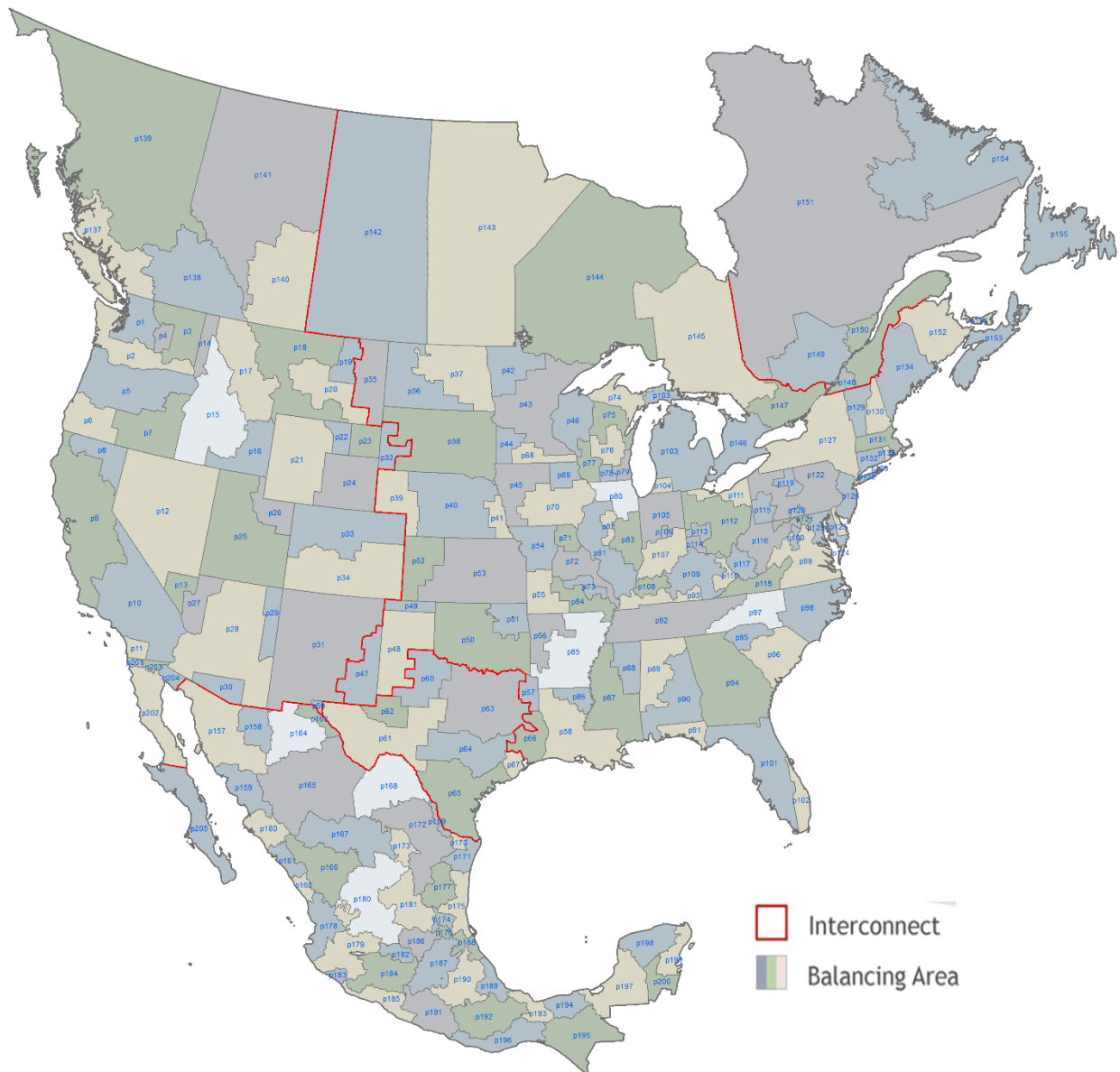
Figure 34. Regions defined in the North America version of the ReEDS model

11.1 Fuel Price and Availability

Natural gas supply and demand dynamics are represented in ReEDS through regional supply curves along EIA Census Division boundaries (see the Natural Gas Supply Curves section of the appendix). For Canadian provinces, the U.S.-only regional supply curves are modified based on consumption projections from the National Energy Board's *Canada's Energy Future 2016* (NEB 2016). Natural gas supply curves are modified to capture the additional supply and demand for natural gas in Canadian regions; adjacent Canadian provinces are assigned to EIA census divisions. A map of this allocation is shown in Figure 35.

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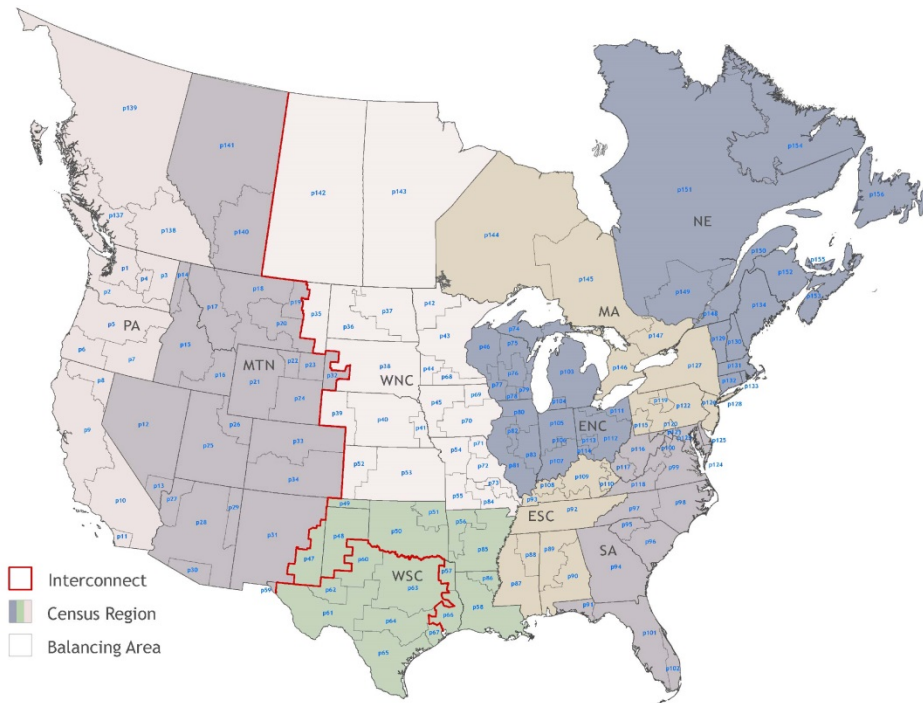
Figure 35. Map of EIA Census Division boundaries extended to Canadian provinces

A single Mexican natural gas curve is adapted from the WSC census division in the AEO. Mexico-specific natural gas consumption is taken from PRODESEN 2018 and incorporated in the new gas curve. Prices were inflated by 9% for Mexico relative to WSC to reflect the higher price of natural gas in Mexico, based on Henry Hub prices from 2010 to 2015.

Canadian coal prices are provincial and represented as inelastic to changes in consumption; they are consistent with Canadian provincial coal price projections from NEB (2016). The price of nuclear fuel for Canadian units is assumed to be same as those for nuclear units in the United States.

Mexican coal and uranium prices are matched with the WSC census division in the AEO and are inelastic.

11.2 Electricity Demand

Canadian annual electricity demand projections are based on the NEB (2016) reference scenario, and they reflect annual provincial load reduced by customer-sited electricity cogeneration. Provincial and zonal load shapes are described in Martinez et al. (2013). For provinces composed of multiple ReEDS BAs (Alberta, British Columbia, Ontario, and Quebec), the spatial distribution of annual provincial electricity demand among BAs is also described in Martinez et al. (2013).

Mexican load shapes and annual demand projections are based on 2016 PRODESEN. The PRODESEN load projection extends through 2030. For projections beyond 2030 load growth is projected based on the average load growth for the years 2020–2030. Load shape data in

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PRODESEN are available for nine regions that were mapped to the ReEDS BA representation through provided load participation factors.

11.3 Generation Fleet Representation

Consistent with the ReEDS representation of the generation fleet in the contiguous United States, the ABB Velocity Suite is used as a basis for Canadian and Mexican generation units (ABB 2018). This data set is then cross-referenced with NEB (2016) for Canada, PRODESEN for Mexico, and any Canadian provincial energy plans to represent the Canadian fleet. The existing fleet, prescribed new builds, and prescribed retirements are based on the ABB Velocity Suite database. Additionally, any new hydropower or geothermal capacity projected in NEB (2016) and PRODESEN is also included in ReEDS (ReEDS does not include hydropower or geothermal resource supply curves for Canada or Mexico, and thus cannot represent new builds of those technologies endogenously).

There are currently 18,215 MW of existing transmission capacity between the United States and Canada from a combination of AC and DC lines dispersed across the border. Potential new transmission lines between the United States and Canada are derived from a list of pending applications as of January 2016 (DOE 2016a). Lines that are not yet under construction can be built in the ReEDS-Canada model, but they are not prescribed.

There are currently 2,238 MW of existing transmission capacity between the United States and Mexico, which include DC lines connecting Texas and Mexico and the AC lines connecting southern California to Mexico. Potential new transmission lines between the United States and Mexico are limited to reinforcements of existing cross-border connections. New connections specified in PRODESEN, including the DC interconnection between the main Mexican system asynchronous Baja California system and the Baja California Sur system, are allowed but not forced to be built in the ReEDS-Mexico model.

Transmission lines in Canada and Mexico are assumed to have the same cost as their neighboring regions in the United States. Table 25 summarizes pending cross-border transmission lines as of January 2016.

Table 25. Pending Cross-Border Transmission Lines as of January 2016 (DOE 2016a)

Name	Sponsor	State-Province	Length (miles)	Voltage and Capacity	Purpose	In-service Date	Permit Status
Champlain Hudson Power Express	Transmission Developers Inc.	New York-Québec	333	1,000 MW, HVDC[a] (underwater, underground, merchant)	Deliver hydro and wind energy from QC to New York City area	Fall 2017 (expected)	Permit issued October 2014
Great Northern Transmission Line	Minnesota Power (MP)	Minnesota-Manitoba	220	500 kV, 750 MW, AC	Part of MP-MB Hydro PPA; supports building wind in North Dakota	June 2020 (expected)	Application filed April 2014
Lake Erie Connector	ITC	Pennsylvania-Ontario	72.4	1,000 MW, HVDC (underwater, merchant)	Deliver surplus ON renewable energy, enhance service reliability	Q4 2019	Application filed May 2015
New England Clean Power Link	TDI-New England	Vermont-Québec	154	1,000 MW, HVDC (underwater, underground, merchant)	Deliver renewable energy from QC into VT and New England	2019 (expected)	Application filed May 2014
Northern Pass	Northern Pass Transmission LLC	New Hampshire-Québec	187	1,200 MW, HVDC line with 345 kV AC spur	Deliver QC hydro into NH and New England	2017 (expected)	Application filed October 2010; re-filed with new route July 2013
Soule River Hydroelectric Project	Soule Hydro, LLC	Alaska-British Columbia	10	138 kV, HVAC (submarine)	Support 77 MW hydro project in AK (sales to BC or Pacific NW)	To be determined	Application filed March 2013

[a] high-voltage, direct current

11.4 Renewable Energy Representation

11.4.1 Hydropower Generation Capacity

ReEDS is not allowed to endogenously build new hydropower capacity in Canada or Mexico due to a lack of available hydropower supply curves that are compatible with those developed for the United States. Instead, we rely on a schedule of expected builds from NEB (2016) for new Canadian hydropower units. Though annual hydropower output can fluctuate significantly from year to year based on precipitation and other weather patterns, we assume there is no inter-annual variation in available hydropower generation in ReEDS; rather, average capacity factors are assumed that reflect long-run historical averages. Seasonal hydropower capacity factors are specified for each Canadian province and are derived from NEB (2013).

In Mexico, existing hydropower capacity is represented, but no new prescribed capacity is added to the system. Operating characteristics are determined from the historical fleetwide capacity factor from PRODESEN.

11.4.2 Wind Resource

For Canada and Mexico, the onshore-wind resource is represented using the same methodology described in Section 2.1.1. Using reV, the quality, capacity, and spur line costs are calculated and represented within the model at the wind resource region level. Wind turbine performance is modeled using results from the WIND Toolkit. Toolkit data include complete coverage of Mexico and Southern Canada. Meteorological data for northern Canada are supplemented using NASA's MEERA-2 data set. Resource calculations are preformed using 2012 data; however, the methodology flexibly supports alternate weather years.

Offshore-wind technology is not represented as an available resource for Canada or Mexico because a comprehensive resource assessment has not been completed.

11.4.3 Solar Resource

UPV and DUPV resources are calculated for Canada and Mexico using the same approach described in Section 2.1.3. The quality, capacity, and spur line costs are calculated using reV and represented within the model for BA regions. The performance of PV panels is based on insolation data from the NSRDB 2.0 using a 2012 metrological year.

The deployment of residential and commercial rooftop PV systems is exogenously defined in for the United States using output from NREL's dGen model (see Section 3.1.3). Because this model is not currently designed to capture consumer behavioral dynamics in Canada and Mexico, we assume no rooftop PV deployment outside the United States. Direct normal irradiance throughout Canada is below the threshold necessary to produce economic CSP generation, and thus is not represented in Canada. Though the direct normal irradiance is high in Mexico, comprehensive resource data for CSP in Mexico have not been developed due to its expected competitive disadvantage relative to PV. Thus, CSP is not represented as an available resource in Mexico.

11.4.4 Geothermal Resource

Geothermal technologies are not available for development outside the United States due to a lack of sufficient information on the location and potential of geothermal resources. Mexico does currently produce electricity from geothermal technology, and any existing capacity is included in ReEDS-Mexico.

11.4.5 Biomass Resource

The biomass feedstock supply curve for each Canadian BA is assumed to be the same as that of the contiguous BAs in the United States (scaling to account for differences in area). Biomass is not available as a resource or generation technology in Mexico because resource data are unavailable. Future resource assessments for biomass feedstocks are needed to improve these representations.

11.5 Policy and Regulation

ReEDS represents existing RPS requirements for:

- New Brunswick: 40% by 2020[71]

- Nova Scotia: 5% by 2011, 10% by 2013, 25% by 2015, and 40% by 2020 (Nova Scotia Department of Energy 2010)

- Prince Edward Island: 15% by 2010 (Department of Environment, Energy and Forestry, n.d.).

Canadian contributions to U.S. state RPS (and vice versa) are permitted in alignment with existing laws, regulations, and practices as of October 2014. We list the rules for U.S.-Canada REC trading in Table 26, focusing on U.S. states that are physically or electrically adjacent to a Canadian province, or where international REC trading activity has been observed in practice.

Table 26. International REC Trading Rules Implemented in ReEDS

State/Province	Canadian RECs Accepted?	Notes
California	Yes	Power must be delivered to state
Colorado	No	—
Massachusetts	Yes	Power must be delivered to ISO-New England[a]
Maine	No	—
Michigan	No	—
Minnesota	Yes	Power must be delivered to state from Manitoba
Montana	No	—
Nevada	No	—
New Hampshire	No	—
New York	No	—

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[71] "Provincial Government Strengthens its Commitment to Renewable Energy," news release dated August 7, 2014 http://www2.gnb.ca/content/gnb/en/news/news_release.2014.08.1007.html.

State/Province	Canadian RECs Accepted?	Notes
Nova Scotia	Yes	RECs accepted from New England Power Pool
Ohio	No	—
Oregon	Yes	Subject to same bundling rules as U.S. states
Pennsylvania	No	—
Rhode Island	Yes	Power must be delivered to ISO-New England
Washington	Yes	Power must be delivered to state
Wisconsin	Yes	Power must be delivered to state

a ISO = independent system operator

British Columbia has a carbon tax that is applied to in-province electricity generation (British Columbia Ministry of Finance 2015). This tax is also applied to imported electricity; in this case, the average carbon intensity of delivered electricity is endogenously calculated from the imported generation mix in the previous solve year[72] and taxed appropriately. We also implement the British Columbia 2016 requirement for electricity self-sufficiency[73] (*Clean Energy Act of 2010* 2010).

New Canadian coal units that do not have carbon capture and storage are not in allowed in the model beginning in the 2016 solve year. Any early retirements of existing coal units are reflected in the exogenous retirements of Canadian coal units.[74]

The Mexico clean energy standard of 35% of load by 2024 is also modeled. (Presidencia de la República 2016) Renewable energy and nuclear power are allowed to contribute to this policy, while CCS is excluded.

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[72] This calculation uses a proportional sharing construct adapted from Bialek (1996).

[73] The requirement is structured such that plants within British Columbia must generate as much energy as is required to serve load within the province.

[74] For details about the electricity regulations for coal units in Canada, see "Coal-Fired Electricity Generation Regulations: Overview," Government of Canada, modified December 16, 2013, https://ec.gc.ca/cc/default.asp?lang=En&n=C94FABDA-1.

12 Model Linkages

12.1 ReEDS-dGen

All ReEDS scenarios utilize dGen to project rooftop PV deployment, but the two models are also capable of operating in a more tightly coupled manner with two-way feedback in each solve year. Under this arrangement, ReEDS provides dGen with estimated curtailment of rooftop PV resources, which dGen uses to update its projected rooftop PV deployment for the following solve year. This coupled configuration improves rooftop PV projections by disincentivizing new capacity that would achieve low utilization within the interconnected bulk system modeled in ReEDS. Additional details on this linkage and its influence on results can be found in (Cole, Lewis, et al. 2016; Gagnon et al. 2017).

12.2 ReEDS-PLEXOS

The ReEDS reduced-form dispatch and variable renewable parameterization aims to represent enough operational detail for realistic capacity expansion decisions, but the model cannot explicitly represent detailed power system operations. To verify the feasibility of ReEDS solutions and better inform its representation of system operation, NREL has developed utilities to implement a ReEDS capacity expansion solution for any solve year in the PLEXOS production-cost model (PCM).

PLEXOS is a commercial PCM tool capable of representing individual generating units and transmission nodes for least-cost dispatch optimization at hourly or subhourly time resolution. It can incorporate unit-commitment decisions and detailed operating constraints (e.g., ramp rates, minimum runtime) to simulate realistic power system operations. NREL has previously used PLEXOS in several analyses such as the Western Wind and Solar Renewable Integration Study and the Eastern Renewable Grid Integration Study (Lew et al. 2013; Bloom et al. 2016a).

The ReEDS-PLEXOS linkage involves disaggregating the ReEDS solution and adding necessary parameters for to the resolution necessary for PLEXOS. To facilitate the translation, the existing linkage maintains the spatial resolution of ReEDS and operates PLEXOS as a zonal model matching ReEDS BAs to PLEXOS transmission zones. PLEXOS uses the ReEDS transmission line capacity, and reactance and resistance are calculated from ReEDS transmission properties to represent the aggregated transmission system. Generating capacity within each zone is, however, converted from aggregate ReEDS capacity to individual units in PLEXOS using a characteristic unit size for each technology. For consistency, ReEDS cost and performance parameters are used when possible and reasonable, but values are taken from the average across WECC data when parameters are not available from ReEDS or are available but used inconsistently in ReEDS due to structural differences between the models.[75]

Once the ReEDS solution is converted to a PLEXOS database, one can simulate hourly dispatch over a full year and compare results with ReEDS outcomes. A consistent solution builds confidence in the effectiveness of ReEDS capacity expansion decisions, while inconsistencies

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[75] Minimum load is an example of one such parameter. The aggregate representation of minimum load in ReEDS at the technology-BA level does not effectively reflect unit-level operating constraints used in PLEXOS, so PLEXOS uses native assumptions for minimum load.

and reliability concerns such as load shedding indicate the need for improving capacity expansion model structures.

Additional discussion of this capability is forthcoming in ongoing analyses where detailed mechanics and results will be discussed.

12.3 ReEDS-JEDI

A linkage between ReEDS outputs and the Jobs and Economic Development Impact Models (JEDI) allows the analysis of technology-specific economic results (jobs, earnings, value added, total output) to ReEDS scenarios. Currently, linkages have been built for the JEDI land-based wind, photovoltaics, natural gas, and coal models, so economic results are limited to these technologies alone. ReEDS outputs of capacity, generation, fuel use, capital cost, O&M cost, and fuel cost by BA are processed through the JEDI models to produce state-level economic results.

12.4 ReEDS-reV

The ReEDS supply curve for renewable technologies, including onshore wind, CSP, and utility scale PV are produced by reV. The ReEDS-reV linkage allows for regional ReEDS investment decisions to be mapped backed to individual reV supply curve sites. Site-specific supply curve data from reV is binned for the ReEDS supply curve into five spur line cost bins, from which investment decisions are made. By tracking the timing and investment decisions within each of these bins, the ReEDS-rev linkage maps regional capacity back to the individual sites from which the bins were derived.

The resulting siting data is used to further the understanding of the ReEDS capacity expansion decisions and identify areas for improvement for resource siting in reV. The ReEDS-reV linkage is a key component in the translation of ReEDS capacity expansion results to a nodal production cost modeling databases.

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Appendix

Natural Gas Supply Curves

The ReEDS model does not explicitly model the U.S. natural gas (NG) system, which involves multiple sectors of the economy and includes complex infrastructure and markets. Rather, a regional supply curve representation is a used to approximate the NG system as it interacts with the electric sector. For more information on the impact of natural gas representation in ReEDS, see Cole et al. (2016).

The premise of using regional supply curves is that the price in each region will be a function of both the regional and national NG demand. The supply curves are parameterized from AEO scenarios for each of the nine EIA census divisions (see Figure 36). Two methods exist to parameterize the natural gas supply curves and both are discussed here. The first method which involves estimating a linear regression of prices on regional and national quantities has been used in previous version in ReEDS and is discussed first. The second method is relatively new to ReEDS and involves parameterizing a constant elasticity of supply curve and is discussed second. Through multiple tests, we have found minimal differences in results between the two versions (1% or less of a change in national generation by technology).
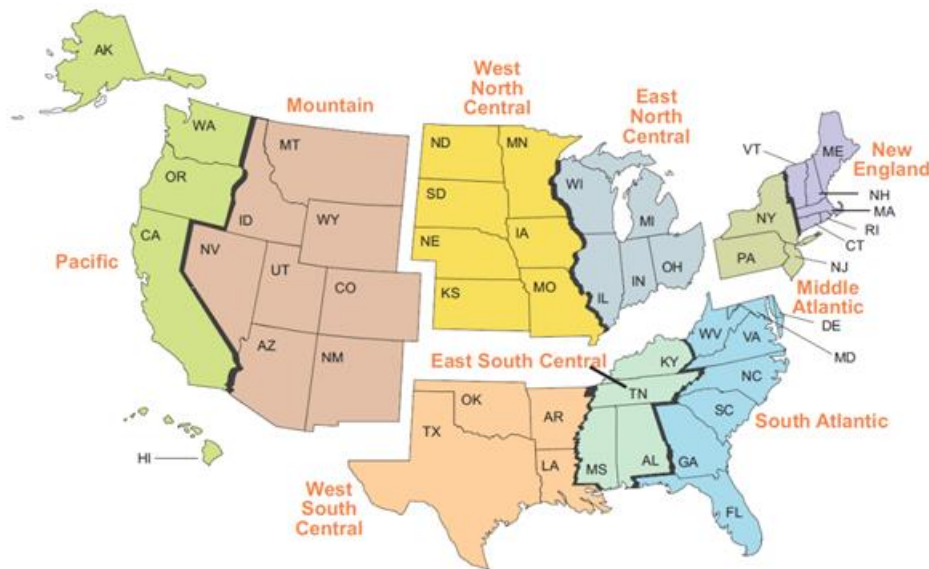
Figure 36. The nine census divisions defined by EIA (EIA 2014)

A regional supply curve was created in ReEDS for each of these census divisions.

Linear Regression Approach

The AEO scenarios were used to estimate parameters for the following NG price-consumption model:

$$P_{i,j} = \alpha + \alpha_i + \alpha_j + \alpha_{i,j} + \beta_{nat} Q_{nat_j} + \beta_i Q_{i,j} \qquad [1]$$

where $P_{i,j}$ is the price of natural gas (in \$/MMBtu) in region i and year j, the α parameters are the intercept terms of the supply curves with adjustments made based on region (α_i), year (α_j), and

the region-year interaction ($\alpha_{i,j}$), β_{nat} is the coefficient for the national NG demand (Q_{nat}, in quads), β_i is the coefficient for the regional NG demand ($Q_{i,j}$) in region i. Note that the four α parameters in [1] can in practice be represented using only $\alpha_{i,j}$.

The β terms are regressed from AEO2014 scenarios, with nine of the 31 AEO2014 scenarios removed as outliers (EIA 2014). These outlier scenarios typically include cases of very low or very high natural gas resource availability, which are useful for estimating NG price as a function of supply but not for estimating NG price as a function of demand—for given supply scenarios. The national and regional β terms are reported in Figure 37. We made a specific post-hoc adjustment to the regression model's outputs for one region; the βi term for the West North Central division was originally an order of magnitude higher than the other βi values because the West North Central usage in the electricity sector is so low (0.05 quad[76] in 2013, compared to ~0.5 quad or more in most regions). The overall natural gas usage (i.e., not just electricity sector usage) in West North Central is similar to the usage in East North Central, so intuitively it makes sense to have a βi for West North Central relatively close to that of East North Central. We therefore manually adjusted the West North Central βi term to be 0.6 (in 2004$/MMBtu/quad) and recalculated the alpha terms with the new beta to achieve the AEO2014 target prices. The situation in West North Central whereby such a small fraction of NG demand goes to electricity is unique; we do not believe that the other regions warrant similar treatment.
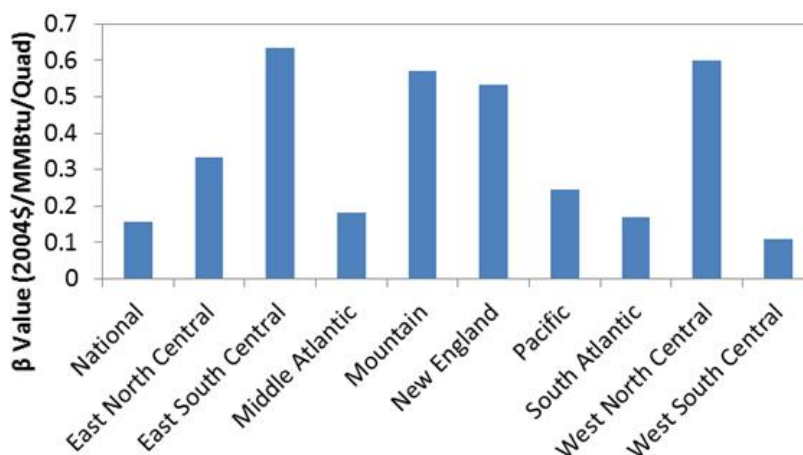
Figure 37. *β* values for the nine census divisions

The "National" value at the far left is *β*$_{nat}$. A *β* of 0.2 means that if demand increases by one quad, the price will increase by $0.20/MMBtu (see Equation [1]).

The α terms are then regressed for each individual scenario assuming the same β values for all scenarios. Although the β terms are derived from AEO2014 data, α terms are regressed using AEO2018 data for the scenario they are intended to represent (EIA 2019a). Thus, we assume natural gas price elasticity has remained constant while price projections shift over time as represented by the α values.

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[76] A quad is a quadrillion Btu, or 10^{15} Btu.

Comparison of Elasticities from Regression Approach to Literature Values

Technical literature tends to report the price elasticity of supply and the price elasticity of demand, which are estimates of the supply and demand, respectively, of a good given a change in price. In the formulation given by Equation [1], we attempt to estimate a value that is similar to the price elasticity of demand—we estimate a change in price given a change in demand. Therefore, we present here a comparison against the price elasticity of demand as the closest available proxy, noting however that it is not necessarily identical to estimates of β. Price elasticity of demand is typically negative but is reported here as a positive number for convenience.

External sources are varied and often vague in their estimates of price sensitivity of natural gas. Using the reported domestic NG market demand given for 2012 in AEO2014, the β values reported here yield an overall NG sector elasticity value of 0.36–0.92 (higher values of β correspond to lower elasticity values). Arora (2014) estimated the price elasticity of demand for NG to be 0.11–0.70, depending on the granularity and time horizon of the NG price data considered. Bernstein and Griffin (2006) examined the price elasticity of demand for residential NG usage, and they estimated the long-run elasticity to be 0.12–0.63 depending on the region. The Energy Modeling Forum at Stanford University reports NG price elasticity of demand for 13 different energy models (Huntington 2013). The reported elasticity ranges from 0 to 2.20 depending on the year, model, and scenario considered. For the NEMS model, which is used for the AEO, the elasticity ranges from 0.22 to 0.81 depending on the year and scenario (Huntington 2013).

The EPA's proposed Clean Power Plan included a projection that natural gas usage will increase by 1.2 quads in 2020, resulting in an 8%–12% increase in NG prices for the electric sector (Smith 2014). This corresponds to a β_{nat} of 0.38–0.51 in 2004\$/MMBtu/quad.

Constant Elasticity of Supply

The second method for representing gas price adjustments leverages a constant elasticity of supply curve for census division prices as a function of the quantities consumed. The general form of the equation relies on a reference price ($\bar{p}$), a reference quantity ($\bar{q}$), and a price elasticity of supply (ϵ)[77] to determine the endogenous price (p) based on an endogenous quantity (q) such that:

$$p = \bar{p}\left(\frac{q}{\bar{q}}\right)^{\epsilon}$$

When parameterizing for the census division representations, the supply curve should reflect the change in price given a change in the census division's quantity consumed in the electricity sector. To the best of our knowledge, no published studies estimate the elasticity of supply for natural gas specific to each sector and region. Therefore, the calibrated curve needs to consider the change in the census division's price given a change in the consumption of natural gas in the region's electricity sector with respect to other regions and sectors. To do this, the reference price, numerator, and denominator in the previous equation are adjusted to reflect the

---

[77] The default value of ϵ is assumed to be 0.76 from values estimated by Ponce and Neuman (2014)

consumption change only in the electricity sector. Explicitly, the constant elasticity of supply parameters are now indexed by census division (r) and sector $s \in \{electricity, industrial, residential, commercial, vehicles\}$). The equation used to populate the supply curve in the model becomes:

$$p_{ele,r} = \bar{p}_{ele,r} \left(\frac{\sum_{s' \notin ele,r' \notin r} \bar{q}_{s',r'} + q_{ele,r}}{\sum_{s,r} \bar{q}_{s,r}} \right)^{\epsilon}$$

A potential addition to this representation, included as a switch in the model, also includes national price adjustments as deviations from the reference point. By denoting the national price as $p_{ele,nat}$, the deviation from the benchmark price based on national quantities consumed in the electricity sector can be computed as:

$$\Delta p_{ele,nat} = \bar{p}_{ele,nat} \left(1 - \frac{\sum_{s' \notin ele,r} \bar{q}_{s',r} + \sum_r q_{ele,r}}{\sum_{s,r} \bar{q}_{s,r}} \right)^{\epsilon}$$

Seasonal Natural Gas Price Adjustments

We use natural gas futures prices to estimate the ratio of winter to non-winter natural gas prices to implement seasonal gas price differences in ReEDS. We chose futures prices for two reasons: (1) ReEDS represents a system with no unforeseen disturbances, which is similar to futures prices and (2) historical natural gas prices have fluctuated greatly since the deregulation of natural gas prices.

Figure 38 shows the cyclical nature of the natural gas futures prices. Figure 39 breaks the same prices out into seasons, showing that the non-winter seasons have nearly the same price while wintertime prices are consistently higher. Wintertime prices are on average 1.054 times higher than non-winter prices. The standard deviation of this price ratio is 0.004, indicating that the ratio shows very little year-to-year variation.
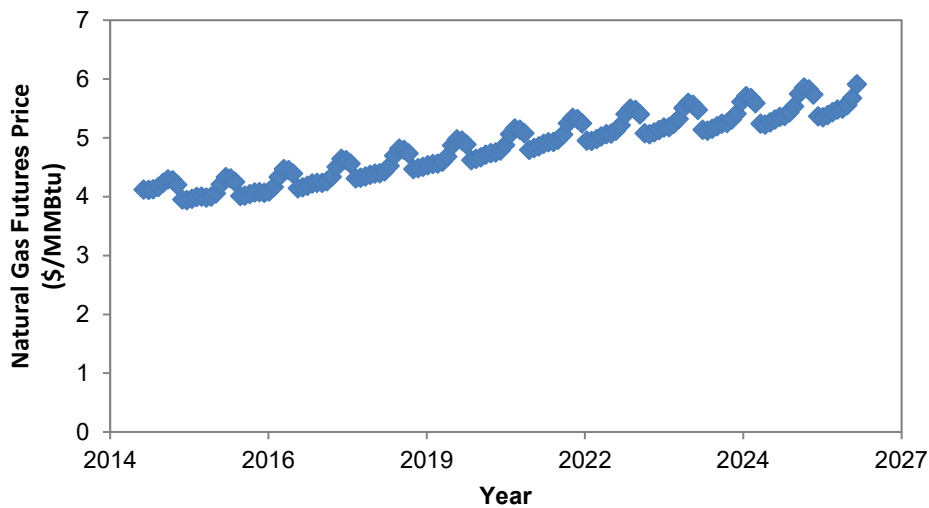
Figure 38. Natural gas futures prices from the New York Mercantile Exchange for July 10, 2014

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The prices show the higher wintertime prices and the cyclical nature of the prices.
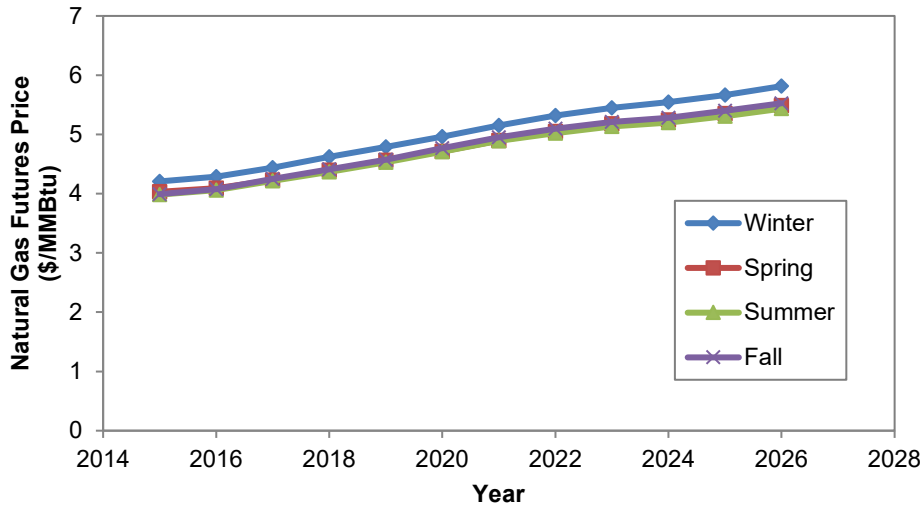
Figure 39. Natural gas futures prices from Figure 38 separated by season

Non-winter prices are nearly the same while wintertime prices are consistently higher.

A seasonal natural gas price multiplier is calculated in ReEDS based on the natural gas price ratio such that wintertime prices are 1.054 times higher than non-winter prices without changing the year-round average price. Mathematically, this can be expressed as

$$P_{year-round} = W_{winter}P_{winter} + (1 - W_{winter})P_{non-winter} \qquad [2]$$

$$P_{winter} = 1.054P_{non-winter} \qquad [3]$$

$$P_{winter} = \rho P_{year-round} \qquad [4]$$

$$P_{non-winter} = \sigma P_{year-round} \qquad [5]$$

where P is the natural gas price for the period indicated by the subscript, W_{winter} is the fraction of natural gas consumption that occurs in the winter months, and ρ and σ are the seasonal multipliers for winter and non-winter, respectively. The multipliers ρ and σ are determined by solving Equations [2] through [5].

Capital Cost Financial Multipliers

The financial multiplier represents the present value of revenue requirements necessary to finance a new investment, including construction financing, return to equity holders, interest on debt, taxes, and depreciation. The formula is based on (W. Short, Packey, and Holt 1995).

Financial Multiplier

$$\mathbf{3} \quad \mathbf{4} \quad \mathbf{5}$$

$$= CC_{mult} * fin_{mult} * \frac{1 - T * PV_{depr} * \left(1 - \dfrac{ITC_{eff}}{2}\right) - ITC_{eff}}{1 - T}$$

$$\mathbf{1} \quad \mathbf{2} \qquad\qquad \mathbf{6}$$

1. **Construction cost multiplier:** additional cost for finance construction
2. **Financing multiplier:** adjust required returns for diversifiable risk
3. **Depreciation Expense:** reduce the taxable income by the depreciation expense
4. **Depreciable Basis:** reduce the depreciable basis due to the investment tax credit
5. **Investment tax credit:** reduce the tax liability by the ITC
6. **Taxes:** additional revenues are required to pay taxes

Construction Cost Multiplier: The construction cost multiplier (CC_{mult}) captures the cost to finance the construction of the plant at construction interest rate i. We use a mid-year discounting and account for the deduction of interest payments for taxes.

$$CC_{mult} = 1 + \sum_t x_t \cdot \{(1 + i)^t - 1\} \cdot (1 - T)$$

The derivation of the construction cost multiplier is given below.

The total payment (*TP)* required to finance x percent of construction investment (*Inv*) at interest rate i in construction year t---where t is defined relative to the in-service date ($t=0$ is the final year of construction; $t=1$ is penultimate year of construction; etc.)---is the following:

$$TP_t = x_t \cdot Inv \cdot (1 + i)^t$$

Define the interest payment (*I*) in year t as a function of the total payment (*TP*) and the principal payment (*P*):

$$I_t = TP_t - P_t$$

$$= x_t \cdot Inv \cdot (1 + i)^t - x_t * Inv$$

$$= x_t \cdot Inv \cdot \{(1 + i)^t - 1\}$$

The tax savings (*S*) from interest deductions in year t at tax rate T is equal to:

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$$S_t = I_t \cdot T$$

Therefore, the absolute net change in the investment cost due to construction financing is the interest payments less the tax savings:

$$\Delta\ cost\ (absolute)\ = \sum_t I_t - S_t$$

$$= \sum_t I_t - I_t \cdot T$$

$$= \sum_t I_t \cdot (1-T)$$

$$= \sum_t x_t \cdot Inv \cdot \{(1+i)^t - 1\} \cdot (1-T)$$

Finally, the total relative change in the investment cost due to construction financing is:

$$\Delta\ cost\ (relative) =$$

$$= \left(Inv + \sum_t I_t - S_t \right) / Inv$$

$$= 1 + \frac{1}{Inv} \cdot \sum_t x_t \cdot Inv \cdot \{(1+i)^t - 1\} \cdot (1-T)$$

$$= 1 + \sum_t x_t \cdot \{(1+i)^t - 1\} \cdot (1-T)$$

Financing Multiplier: The financing multiplier (not to be confused with the financial multiplier) is an adjustment to reflect either higher or lower returns to capital, relative to the system-wide average return to capital. Conceptually, it is a multiplier that reflects the total present-value of a stream of higher (or lower) payments to capital, relative to what the payments would be at the system's average cost of capital. For example, if a technology's WACC ($WACC_{tech}$) is 7% and the system-wide WACC is 5% ($WACC_{sys}$), and the technology is being evaluated for a 20-year horizon (l) at a real discount rate of 5% (d_r), the financing multiplier (fin_{mult}) would be 1.25, per the equation below. This multiplier represents that the total present-value of the returns to capital for this technology must be higher (by an amount equal to 25% of the initial investment), relative to a technology with average financing terms. The difference is the technology WACC and system WACC represents the difference is returns to capital due to diversifiable risk.

$$fin_{mult} = 1 + \left(WACC_{tech} - WACC_{sys} \right) \cdot \frac{1 - \frac{1}{(1+d_r)^l}}{d_r}$$

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To derive the above equation, begin with the definition of the capital recovery factor (CRF) for real discount rate (d_r) and economic horizon (l):

$$CRF = \frac{Annuity}{Present\ Value\ of\ Annuity} = \frac{1 - \frac{1}{(1 + d_r)^l}}{d_r}$$

$$Present\ Value\ of\ Annuity = \frac{1}{CRF} \cdot Annuity$$

Therefore, for every dollar invested in a technology, the absolute difference in required return is:

$$\Delta\ returns\ (absolute) = \$1 \cdot WACC_{tech} \cdot \frac{1}{CRF} - \$1 \cdot WACC_{sys} * \frac{1}{CRF}$$

Finally, the relative difference in required return per dollar invested is:

$$\Delta\ returns\ (relative) = \frac{\$1 + \Delta}{\$1} = 1 + \Delta$$

Depreciation Expense: The present value of depreciation (PVdepr) expense is computed based on the fraction of the plant value that is depreciable in each year. All investments use a MACRS depreciation schedule with f_t^{depr} representing deprecation fraction in year t. This depreciation is sheltered from taxes, which is reflected by the term $1 - T * PV_{depr}$ in the financial multiplier equation above.

$$PV_{depr} = \sum_t \frac{1}{(1 + d_n)^t} \cdot f_t^{depr}$$

Depreciable Basis: The eligible cost basis for MACRS depreciation expense is reduced by one-half the effective value of the tax credit:

$$PV_{depr} * \left(1 - \frac{ITC_{eff}}{2}\right)$$

Investment Tax Credit: The value of the ITC is reduced, to reflect the costs of monetizing it (m_{ITC}). The effective investment tax credit value (ITC_{eff}) reduces the tax burden of the investments.

$$ITC_{eff} = ITC \cdot m_{ITC}$$

Taxes: The denominator term of the financial multiplier equation, "1-T", reflects the additional revenues necessary to pay taxes. The tax burden is adjusted for depreciation expenses as well as the effective investment tax credit.

Weighted Average Cost of Capital: The technology-agnostic, nominal discount rate is represented as the average WACC. Where, d_f is the debt fraction, $rore_n$ is the nominal rate of return on equity, T is the effective tax rate, and I_n is the nominal interest rate on debt.

$$d_n = (1 - df) * rore_n + (1 - T) * df * I_n$$

Present Value of Direct Electric Sector Cost

The equations in this section are used to calculate the present value cost of building and operating the system for some defined economic analysis period. To calculate the present value of total system cost, the cost in each future year t is discounted to the initial year of the economic analysis period, t_0, by a social discount rate, d_{social}. The real social discount rate used here for present value calculation is different from the investment discount rate assumptions, or cost of capital (WACC) assumptions.

The present value, or PV in the equation, consists of two cost components: 1) the present value of all operational costs in the model for the analysis period, $PV_{operational}$, including fixed and variable operating and maintenance costs for all sectors, as well as fuel costs and 2) the present value of all new capital investments, $PV_{capital}$. The present value of energy system costs is then calculated as:

$$PV = PV_{operational} + PV_{capital}$$

Operational costs, $PV_{operational}$, and capital costs category, $PV_{capital}$, are discounted from year t by $\frac{1}{(1+d_{social})^{t-t_0}}$ for each year in the analysis period:

$$PV_{operational} = \sum_{t=t_0}^{t_f} C_{op,t} \times \frac{1}{(1 + d_{social})^{t-t_0}}$$

$$PV_{capital} = \sum_{t=t_0}^{t_f} C_{cap,t} \times \frac{1}{(1 + d_{social})^{t-t_0}}$$

where $C_{op,t}$ is the operational costs in year t, and $C_{cap,t}$ is the capital costs in year t. For all ReEDS system cost results, we assume the operational costs for the non-modeled year are the same as the closest model year.

In this present value calculation, the economic analysis period is 2018–2050. The social discount rate used for present value calculations, d_{social}, is assumed to be 7% (real). This is different from the WACC assumption for investment decisions.

Marginal Electricity Prices

ReEDS marginal "competitive" electricity prices are derived from the linear programming formulation.

In standard form, the primal formulation of a linear program is:

$$(P) \quad \min c^T x$$
$$\text{s.t.} \quad Ax \geq b$$

$$x \geq 0$$

The associated dual formulation of the primal is:

$$
\begin{aligned}
(D) \quad & \max y^T b \\
\text{s.t.} \quad & y^T A \leq c^T \\
& y \geq 0
\end{aligned}
$$

Consider a simplified formulation of the ReEDS model with a subset of constraints: (1) resource limits, (2) capacity limits, (3) supply/demand balance, (4) planning reserve margin requirement, (5) operating reserve requirement, and (6) national and/or state-level RPS requirements. The primal formulation is:

Parameters

$capcost_i$: capital cost of model plant i (\$/MW)
$vomcost_i$: variable O&M cost of model plant i (\$/MWh)
s_i: available supply of model plant i (MW)
$load$: electric load (MW)
cv_i: capacity value of model plant i (MW)
f^{prm}: planning reserve margin (unitless)
f^{or}: operating reserve requirement (unitless)
f^{RPS}: national and/or state-level RPS requirement (unitless)

Variables

C_i: capacity of model plant i (MW)
G_i: generation of model plant i (MWh)
OR_i: operating reserve allocation of plant i (MWh)

$$minimize \sum_i capcost_i \cdot C_i + vomcost_i \cdot G_i$$

Subject to:

$$C_i \leq s_i \quad \forall i \quad [1]$$

$$\frac{G_i}{8,760} + \frac{OR_i}{8,760} - C_i \leq 0 \quad \forall i \quad [2]$$

$$\sum_i G_i = load \quad [3]$$

$$\sum_i cv_i \cdot C_i \geq \frac{(1 + f^{prm})}{8760} \cdot load \quad [4]$$

$$\sum_i OR_i \geq f^{or} \cdot load \quad [5]$$

$$\sum_{i \in RE} G_i \geq f^{RPS} \cdot load \quad [6]$$

$$C_i, G_i, OR_i \geq 0 \quad \forall i \quad [7]$$

Constraints [1] define the resource limits for each model plant. Constraints [2] limit how capacity is allocated for each model plant (i.e., for energy or reserves). Constraint [3] requires the total generation supplied to equal the load. Constraint [4] ensures the total firm capacity meets the planning reserve margin requirement. Constraint [5] ensures the total operating reserves meet the operating reserve requirement. Constraint [6] requires that total generation from renewable technologies meets the state-level and national RPS requirements.

From the dual formulation of the primal, the objective function is:

$$y^T b = y_1 \cdot s + y_2 \cdot 0 + y_3 \cdot load + y_4 \cdot \frac{(1 + prm)}{8760} \cdot load + y_5 \cdot f^{or} \cdot load + y_6 \cdot f^{RPS} \cdot load$$

Reformulating the primal with Constraints [3], [4], [5], and [6] "linked" with a "load" variable, L, an alternative, but equivalent, primal formulation is the following:

$$minimize \sum_i capcost_i \cdot C_i + vomcost_i \cdot G_i$$

Subject to:

$$C_i \le s_i \quad \forall i \quad [1]$$

$$\frac{G_i}{8760} + \frac{OR_i}{8760} - C_i \le 0 \quad \forall i \quad [2]$$

$$\sum_i G_i - L \ge 0 \quad [3']$$

$$\sum_i cv_i \cdot C_i - \frac{(1 + f^{prm})}{8760} \cdot L \ge 0 \quad [4']$$

$$\sum_i OR_i - f^{or} \cdot L \ge 0 \quad [5']$$

$$\sum_{i \in RE} G_i - f^{RPS} \cdot L \ge 0 \quad [6']$$

$$C_i, G_i, OR_i \ge 0 \quad [7]$$

$$L = load \quad [8']$$

From the dual formulation of the alternative primal, the objective function is:

$$y^T b = y_1 \cdot s + y_2 \cdot 0 + y_{3'} \cdot 0 + y_{4'} \cdot 0 + y_{5'} \cdot 0 + y_{6'} \cdot 0 + y_{8'} \cdot load$$

Equating the dual objective functions from the two equivalent primal formulations, we find that the marginal off the linking constraint [8'] is a blending of all constraints containing the "load" variable, including, constraints [3], [4], [5], and [6]:

$$y_{8'} \cdot load = y_3 \cdot load + y_4 \cdot \frac{(1 + f^{prm})}{8760} \cdot load + y_5 \cdot f^{or} \cdot load + y_6 \cdot f^{RPS} \cdot load$$

$$y_{8'} = y_3 + y_4 \cdot \frac{(1 + f^{prm})}{8760} + y_5 \cdot f^{or} + y_6 \cdot f^{RPS}$$

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Therefore, we define the marginal off the linking constraint [$y_{8'}$] as the "all-in" marginal price of electricity (i.e., change in total cost [objective function] given a small change in load). This marginal electricity price includes the energy price, capacity price, operating reserve prices, and potential RPS prices. Marginal electricity prices are reported at BA level with different requirement categories. These prices can be aggregated at different regional level, weighted by corresponding requirement quantities for certain category.

Demand Module

In this section, we discuss the underlying data and structure of the demand model. The main exogenous inputs include reference levels of energy service demand, existing device stock and new stock totals, and characteristics of new devices. Much of our data comes from EIA's National Energy Deployment System (NEMS), and its Annual Energy Outlook (EIA 2017a). Table A-1, which is referred to throughout the rest of this section, summarizes the end uses and device types modeled in ReEDS.

Table A-1. End Uses and Devices Modeled in ReEDS

End-use	Service units	Device types	Device options
Space heating	BTU	Electric radiator	1 efficiency level
		Air-source heat pump	3 efficiency levels
		Ground-source heat pump	2 efficiency levels
Space cooling	BTU	Central air conditioning	3 efficiency levels
		Room air conditioning	3 efficiency levels
		Air-source heat pump	3 efficiency levels
		Ground-source heat pump	2 efficiency levels
Clothes washing	Cycles	Clothes washer	2 efficiency levels
Dishwashing	BTU	Dishwasher	2 efficiency levels
Water heating	BTU	Electric water heater	5 efficiency levels
		Solar water heater	1 efficiency level
Cooking	Unitless	Cookstove	1 efficiency level
Clothes drying	BTU	Clothes dryer	2 efficiency levels
Refrigeration	Unitless	Refrigerator – top freezer	3 efficiency levels
		Refrigerator – bottom freezer	2 efficiency levels
		Refrigerator – side-by-side	2 efficiency levels
Freezing	Unitless	Chest freezer	2 efficiency levels
		Upright freezer	2 efficiency levels
Lighting	Lumens	General service light bulb	Incandescent, CFL, LED
		Reflector light bulb	Halogen, CFL, LED
		Exterior light bulb	Incandescent, halogen, LED, high-pressure sodium
		Linear fluorescent light bulb	T12, T8, LED
Miscellaneous	Unitless	Generic	1 efficiency level
Furnace fans	Unitless	Generic	1 efficiency level
Secondary heat	Unitless	Generic	1 efficiency level

CFL: compact fluorescent lamp; LED: light-emitting diode

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Energy Service Demand

For the residential buildings sector, electricity demand in ReEDS is derived from energy service demand and the composition of devices used to meet that demand, while it is directly specified for the commercial buildings and industrial sectors. In this section, we discuss how we calculate reference levels of demand, including how we identify the hours that contribute to the summer peak time-slice (H17, Table 1, page 14). We also discuss our sources for demand elasticities. Currently, ReEDS only includes a detailed representation of energy service demand for the residential buildings sector. We model 13 end uses in the residential sector, which are listed in Table A-1 alongside the units we use for service demand. End-use categories that do not have explicit service units are denoted in the table as "unitless". For these categories, service demands are treated as relative quantities but do not have any physical interpretation.

Reference Levels

Reference demand levels are needed to parameterize demand curves. This requires several sources of data, including electricity consumption values (obtained from the AEO), capital stock characteristics for residential buildings (also from the AEO), and hourly load shapes (obtained from Steinberg et al. (2017) for residential and commercial buildings and from Hostick et al. (2012) for industrial facilities). Preparing the data requires the steps described below. Because of lack of data, we must make several simplifying assumptions, such as that each BA within a state observing the same load shape and load shapes remains constant for all years.

Residential

Our calculation of reference service demand levels for residential buildings requires two primary inputs: electricity consumption and average efficiency levels. Here, we discuss the details of this calculation and the key assumptions that we make. Fundamentally, the calculation is of the form:

$$Service\ consumption = Electricity\ consumption \cdot Average\ efficiency$$

where average efficiency is denoted in terms of number of service units (e.g., lumens) per unit of electricity (e.g., watt-hours), though several steps are needed to prepare the raw data first.

Service consumption in ReEDS is defined by end use, device type, BA, income class, time-slice, and year. The raw energy consumption data from AEO is disaggregated by end use, device type, building type, census division, and year.[78] The average efficiency data are indexed over the same elements, with additional base year data for 2009. Preparing the data requires the following steps:

1. **Add consumption from distributed generation (DG) to the energy consumption levels.** Because of the way NEMS results are reported, the reported energy consumption levels omit consumption of DG. Therefore, we have to add these values to the raw totals. Following NEMS convention, 65% of solar PV DG is applied to central air-conditioning in single-family housing, while the remainder is applied to miscellaneous end uses in

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[78] The end uses and device types correspond to those listed in Table. Building types include single-family housing, multi-family housing, and manufactured housing. The AEO data covers all years from 2010 to 2050.

single-family housing. All other DG is credited to miscellaneous end uses in single-family housing.

2. **Calculate lighting efficiencies.** In contrast to other end uses, NEMS does not report a true efficiency metric for lighting. Instead, average lighting efficiency levels over time are reported in watts. To convert these values to lumens per watt, we divide the total lumen level of a baseline device by the average wattage for each category. For general service, reflector, and exterior lighting, the baseline device is an incandescent bulb. For linear fluorescent lighting, the baseline device is a T12 bulb.[79]

3. **Calculate relative efficiencies for certain end uses.** For electric stoves, refrigerators, freezers, and clothes washers, efficiencies are converted to a relative scale by dividing the average efficiency value by the corresponding base year efficiency value. This means the efficiency value in the base year will be equal to one, and average efficiency values in subsequent years will be less than one, provided average device efficiency improves over time.

4. **Multiply energy consumption by average efficiency and aggregate service consumption over building types.** To obtain service levels for each end use, device type, building type, census division, and year, we multiply energy consumption by average efficiency. Because ReEDS does not separately model different building types, service consumption is aggregated over the NEMS building types.

5. **Disaggregate service consumption by BA and income class.** The last step in preparing reference service consumption levels is to disaggregate along temporal, spatial, and income dimensions. The spatial and income disaggregation is informed using population data obtained from SNL Financial in 2017. Using county-level counts of households in each income class, we first calculate the number of households per income class in each BA. We then divide this value by the total number of households in each census division (because service consumption has been calculated at the census division level) to obtain the proportion of households belonging to each BA-income class combination in each census division. This proportion is multiplied by the service consumption values obtained from the previous step to generate service consumption by end use, device type, income class, BA, and year.

6. **Disaggregate service consumption by time slice.** The final step is to disaggregate service consumption into time-slices by multiplying service consumption by a load-shape factor for each time-slice. The profiles provide end-use load-shape proportions for each hour by state, which are translated to the time-slice level and applied to the appropriate BAs and end uses in the service consumption data. This process requires us to identify the hours that contribute to the peak time-slice (H17, Table 1, page 14), which is described in the Peak Electricity Demand section below.

Commercial and Industrial

Currently, electricity consumption for the commercial and industrial sectors are modeled at an aggregate level, without specifying end-use service consumption and devices. To calculate

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[79] Our use of base year general service incandescent bulbs assumes energy use of 60 watts with an efficiency of 14 lumens per watt, for a total of 840 lumens per bulb. And our use of baseline bulbs for reflector, linear fluorescent, and exterior lighting assume 650 (65×10), 2,880 (40×72), and 1,136 (71×16) lumens per bulb respectively.

reference levels of electricity consumption for these sectors, we combine historical and projected electricity demand estimates with demographic data from SNL Financial. The data preparation steps are as follows:

1. **Add consumption from DG to the energy consumption levels.** For commercial buildings, the first step is to subtract the quantity of DG sales to the grid from total DG. Then, following NEMS convention, 12% of DG is applied to cooling, 13% to ventilation, 16% to lighting, and the rest (59%) to "miscellaneous."[80] The accounting for industrial facilities does not require DG to be added back in.

2. **Disaggregate electricity consumption to the BA level**. Commercial and industrial electricity consumption is disaggregated spatially in two steps. To disaggregate from the census division to the state level, we calculate historical state proportions of census division consumption using EIA data (EIA 2017a). For model years before 2016, we use year-specific proportions, while for model years in 2016 and beyond, we fix the proportions at the 2016 values. To disaggregate consumption from the state to the BA, we use population proportions for commercial buildings and the fraction of state land that each BA contains for industrial facilities.

3. **Disaggregate electricity consumption to the time slice level.** For commercial buildings, hourly load shapes are applied for BAs and end uses, while industrial load shapes are not specified by end use. The profiles provide end-use load-shape proportions for each hour by state, which are aggregated up to the time-slice level and applied to the appropriate BAs and, for commercial buildings, end uses in the electricity consumption data. Finally, commercial building consumption is aggregated across end uses to generate reference demand. As was the case for residential buildings, this step requires us identify the hours that contribute to the peak time-slice (H17, Table 1, page 14), which is discussed next.

Peak Electricity Demand

We calculate peak electricity demand by combining electricity consumption and load shapes for each sector. The data preparation steps, which are listed below, mirror the steps used to construct reference demand levels.

1. **Add consumption from DG to the energy consumption levels and aggregate to the appropriate level.** Adding DG follows the same procedure as described in the first step in the Residential and Commercial and Industrial sections above. Once DG totals are applied, energy consumption for residential and commercial buildings are aggregated by census division, end use, and year. There is no end-use index for industrial facilities.

2. **Disaggregate electricity consumption to the BA level.** For residential buildings, this step is the same as Step 5 from the Residential section, except there is no disaggregation along the income dimension. For the commercial and industrial sectors, this step is the same as Step 2 from the Energy Service Demand: Commercial and Industrial section above.

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[80] Although ReEDS does not currently model commercial demand at the end-use level, the end uses used to create load shapes include heating, cooling, water heating, ventilation, cooking, lighting, refrigeration, office equipment (computers and non-computers), and miscellaneous.

3. **Disaggregate electricity consumption to the hourly level.** For commercial and residential buildings, hourly load shapes are applied for BAs and end uses, while industrial load shapes are not specified by end use.

4. **Aggregate electricity demand across sectors, compute peak load, and identify H17 hours.** The final step begins by aggregating sectoral consumption levels to obtain total consumption by BA, hour, and year. The top 40 hours within the H3 time-slice are then assigned to H17 (Table 1, page 14), with the top hour representing peak demand.

Currently, the calculation of peak demand and identification of the peak time-slice is not performed dynamically within a ReEDS solve, primarily because of their data-intensive natures. Future work will focus on updating these elements dynamically in response to changing demand conditions.

Elasticities

Though the economics literature is replete with estimates of the price elasticity of electricity demand, few studies have attempted to estimate the price elasticity of service demand for specific end uses. This is perhaps due to the substantial data requirements needed to perform such an analysis, specifically household-level information on appliances, electricity consumption for specific end uses, and utility rate schedules.[81] Therefore, we take a conservative approach to parameterizing our energy service demand curves, tending toward lower elasticity values, with the expectation that future work will lend better insight into appropriate elasticity values. Our default elasticity assumptions are presented in Table A-2.

For the industrial and commercial sectors, we use the short-run electricity demand elasticities estimated by Paul, Myers, and Palmer (2009). Because we do not currently model service demand for the industrial and commercial sectors, the elasticities are consistent with our modeling approach. For the residential sector, we use the corresponding short-run elasticity value from the same study for end uses for which we do not have service elasticity estimates. For the remaining end uses, we use estimates from a variety of studies. Though the empirical techniques differ, all are designed to estimate service elasticity for a particular end use. We also assume the elasticities for furnace fans and secondary heating are the same as those estimated for primary space heating.

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[81] Several studies, including Reiss and White (2005) and Zhang (2016), estimate end-use electricity demand elasticities using total household electricity consumption via conditional demand analysis. Though these studies do not account for device efficiency, preliminary work at NREL using similar techniques that attempts to account for device efficiency suggests that doing so does not change the results significantly.

Table A-2. Default Electricity and Energy Service Demand Elasticity Values

Sector	End Use	Elasticity value	Source
Residential	Space heating	-0.26	Dubin and McFadden (1984)
	Space cooling	-0.20 †	Rapson (2014)
	Clothes washing	-0.06	Davis (2008)
	Dishwashing	-0.13	Paul, Myers, and Palmer (2009)
	Water heating	-0.26	Dubin and McFadden (1984)
	Cooking	-0.13	Paul, Myers, and Palmer (2009)
	Clothes drying	-0.13	Paul, Myers and Palmer (2009)
	Refrigeration	-0.13	Paul, Myers and Palmer (2009)
	Freezing	-0.13	Paul, Myers and Palmer (2009)
	Lighting	-0.40	Guertin, Kumbhakar, and Duraiappah (2003)
	Miscellaneous	-0.13	Paul, Myers, and Palmer (2009)
	Furnace fans	-0.26	Dubin and McFadden (1984)
	Secondary heat	-0.26	Dubin and McFadden (1984)
Commercial	All	-0.11	Paul, Myers, and Palmer (2009)
Industrial	All	-0.16	Paul, Myers, and Palmer (2009)

† This value represents the midpoint between room and central air conditioning elasticities for the non-California U.S. sample

Capital Stock

ReEDS explicitly models the evolution of the capital stock of energy service devices for 10 end uses in the residential buildings sector. In this section, we describe how the initial, preexisting stock of devices is determined, how the capital stock evolves over time, and the technology options available to consumers. We also discuss our assumed distribution of discount rates by income class. Table A-1 lists the modeled device types associated with each service demand category and the options for each device type. For some end uses, the capital stock is not explicitly tracked (denoted in the table as having a "Generic" device type). For these end uses, users still have the option to model efficiency improvements, though this is not the default. Currently, our default technology options correspond to the options represented in the NEMS data files. A key assumption we make for modeling the residential capital stock is that devices are retired, or scrapped, according to exogenous survival rates. The lifetime (in years) of each device is assumed to follow a Weibull distribution, with scale parameter α and shape parameter β; examples of survival functions are illustrated in Figure 40.[82] An alternative approach, which could be pursued in future iterations of the model, would be to make the scrappage rate responsive to device prices.

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[82] The survival function is defined as $S(x) = 1 - F(x)$, where $F(\cdot)$ is the cumulative distribution function of device lifetime.
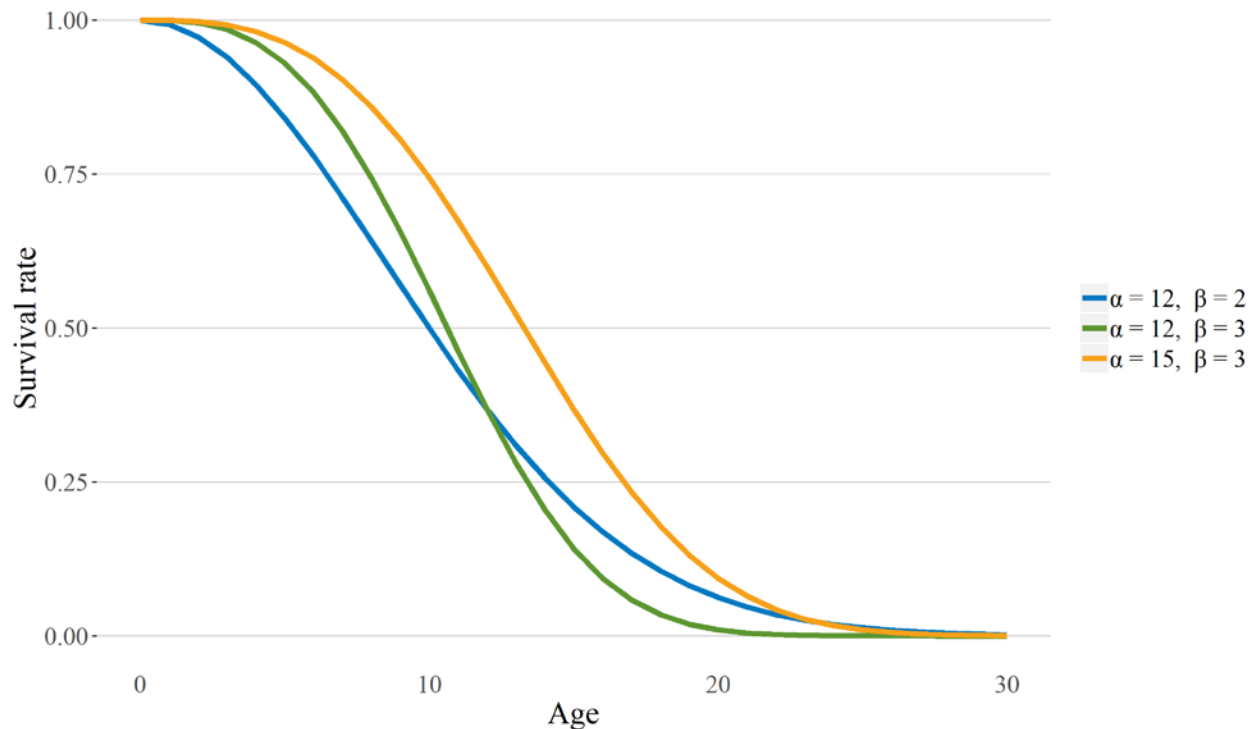
Figure 40. Examples of survival rates for different scale and shape parameterizations

Initial Stock

To model the evolution of the stock of end-use devices, we need to characterize the initial stock in the model. We project the phaseout of these devices using exogenous cumulative retirement fractions. The primary source of these data is the AEO, which we supplement with demographic data from SNL Financial from 2017. The data processing steps are as follows:

1. **Calculate retirement fractions for lighting.** Though we have AEO data on cumulative retirement fractions for the initial stock for most device types, light bulbs are an exception. To address this, we calculate Weibull distribution parameters for light bulb lifetimes (in years) using light bulb lifetimes (in hours) from NEMS for all the bulb type categories identified in the third column of Table A-1Table.[83] Imposing the assumption that all bulbs in the initial stock are purchased in 2009,[84] we use the survival functions to calculate cumulative retirement fractions for each year from 2010 to 2050.

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[83] Calculating these parameters requires several steps. First, from NEMS data files, we obtain shares of general service lighting assumed to be used 0.5, 1.5, 2.5, 4.5, 8.0, and 10.0 hours a day (i.e., lighting is separated into six bins, each with an assumed daily use level). These shares are used to calculate empirical annual survival rates assuming a one-hour lifetime. For example, if 65% of bulbs are assumed to be used 0.5 hours per day and 16% of bulbs are assumed to be used at least 1.5 hours per day, 65% of bulbs remain after $1/1.5 \div 365 = 0.002$ years and 0% remain after $1/0.5 \div 365 = 0.005$ years. Fitting a Weibull survival function to the empirical survival rates yields a scale parameter of 0.00277384 and a shape parameter of 1.74169. To construct a survival function for a light bulb with a lifetime of x hours, the scale parameter is equal to 0.00277384x and the shape parameter remains the same. Because we do not have binned data on other lighting categories, we use the same scale and shape parameters.
[84] This assumption means our model will tend to understate the pace at which the initial stock of bulbs is replaced, depending on the accuracy of our survival functions.

2. **Calculate remaining stock of devices in each year.** To calculate the remaining devices from the initial stock in each year, we multiply the initial stock counts by the cumulative retirement fractions for each device. Before this calculation can be done, we must first disaggregate the base stock of light bulbs into type categories (e.g., incandescent and LED.) based on shares from NEMS data files.

3. **Disaggregate initial stock by BA and income class.** The final step in preparing the initial stock data is to disaggregate the devices spatially and by income class. The process for this step is identical to the disaggregation of reference service demand described in Step 5 from the residential Energy Service Demand section above.

New Device Purchases

In ReEDS, new device purchases are made to replace scrapped devices and to meet new demands reflecting dynamics such as population growth. Consumers can choose from among device technology options that differ according to their capital costs, efficiency levels, and, in the case of light bulbs, lifetimes.[85] AEO is the data source for total device counts from 2010 to 2050. The process for determining the number of new device purchases is as follows:

1. **Disaggregate total device counts by BA and income class.** The first step in determining the number of new device purchases is to disaggregate the total device counts spatially and by income class. The process for this step is identical to the disaggregation of the initial stock described in Step 3 from the Capital Stock: Initial Stock section above.

2. **Calculate the exogenous device requirement for each year.**
   We define the exogenous device requirement as the difference between the total device counts and the number of devices remaining from the initial stock. Because both those quantities are exogenous to the model, we can calculate this quantity outside of the optimization.

3. **Calculate the number of new device purchases in each year.** The number of new device purchases in a given year is equal to the exogenous device requirement for that year minus any devices remaining from purchases in prior years, not including the initial stock. Because the number of devices remaining from prior-year purchases depends on which devices were purchased, this step occurs within the optimization of the model.

Discount Rates

The key differentiating factor in the decision-making of consumers of different income classes is the assumed discount rate used in assessing present and future costs of purchasing and operating devices. Train (1985) provides reviews that estimate discount rates for energy durables, including several that estimate negative relationships between income and discount rates. More recently, Newell and Siikamäki (2015) estimate a relationship between income and discount rate for energy efficiency decisions using survey responses. We parameterize our model using their regression results—from Model 1 in their Table A6—which estimate a constant of 0.334 and a coefficient on the log of income of -0.035. Table illustrates our default income class and discount rate assumptions. For the first 11 income classes, we assume income levels equal to the midpoint of the range (with zero representing the lower bound on income) to calculate the discount rates

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[85] Future model developments could incorporate other factors affecting consumer device choices, such as the color rendering index of light bulbs or the orientation of refrigerators and freezers.

for each class. For the top, open-ended income class, we follow a procedure from Parker and Fenwick (1983) to calculate an income level based on a distributional assumption. Denoting the lower bound of income class bin i by x_i and the number of individuals in bin i by n_i, the income value for the top bin is estimated by:

$$x_{12} = \frac{v}{v-1}$$

$$v = \frac{\log(n_{11} + n_{12}) - \log(n_{12})}{\log(x_{12}) - \log(x_{11})}$$

We use the national, rather than county, values for n_i to calculate v.

Table A-3. Default Assumptions for Discount Rates by Income Class

Income range from SNL	Income for model	Discount rate
<15,000	7,500	26.3%
15,000 – 24,999	20,000	22.9%
25,000 – 34,999	30,000	21.5%
35,000 – 49,999	42,500	20.2%
50,000 – 74,999	62,500	18.9%
75,000 – 99,999	87,500	17.7%
100,000 – 124,999	112,500	16.9%
125,000 – 149,999	137,500	16.2%
150,000 – 199,999	175,000	15.3%
200,000 – 249,999	225,000	14.4%
250,000 – 499,999	375,000	12.7%
≥500,000	1,119,391	8.6%

Differences from the 2018 Model Version

Table A-4Table A-4 summarizes the key differences from the 2018 model version. Table A-5 summarizes the key differences in the dGen model, which is used to provide the rooftop PV input projections for ReEDS.

Table A-4. Key Differences in Model Inputs and Treatments for ReEDS Model Versions

Inputs and Treatments	2018 Version (June 2018)	2019 Version (July 2019)
Architecture	Heritage ReEDS	ReEDS 2.0
Fuel prices	AEO2018	AEO2019
Demand growth	AEO2018	AEO2019
Generator technology cost, performance, and financing	ATB2018[a]	ATB2019[a]
Tax credit penalty	Estimated using a change in equity fraction that was proportional to the tax credit (Mai et al. 2015)	Set at one-third of the value of the tax credit (Bolinger 2014)

Inputs and Treatments	2018 Version (June 2018)	2019 Version (July 2019)
Wind supply curves and profiles	Based on a 2016 vintage wind turbine	Based on an estimated 2030 vintage wind turbine (Wood Mackenzie 2018; Stehly et al. Forthcoming)
Existing fleet, retirements, and prescribed builds	ABB Velocity Suite from May 2018	NEMS plant database from AEO2019
Storage capacity credit	Varies based on storage and PV penetration (Frew 2018)	Varies based on load shape, wind, PV, and storage penetration
Storage curtailment recovery	If storage charges during a time-slice with curtailment, it reduces curtailment by 1 MWh for every 1 MWh it charges.	If storage charges during a time-slice with curtailment, it reduces curtailment by 0.5 MWh for every 1 MWh it charges.[b]
Transmission distances	Calculated using the straight-line distance between the geographic centroids of BAs	BA centroids were moved to the highest population area within the BA; distances between these new centroids were calculated by tracing actual transmission pathways that connected the centroids.
AC-DC-AC interties	Existing interties represented and allowed to be expanded	Existing interties represented, but expansion of interties is not allowed
Clean energy policies	Not included	Included for California, Massachusetts, New Mexico, Washington state, and the Xcel portion of Colorado
Renewable portfolio standards and carveouts	Updated as of May 2018	Updated as of July 31, 2019
State storage mandates	Updated as of May 2018	Updated as of July 31, 2019
Canadian imports	Set exogenously based on Canada's Energy Future 2016 (NEB 2016)	Set exogenously based on Canada's Energy Future 2018 (NEB 2018)
Thermal unit representation	Coal units grouped into four bins per BA, all other units grouped into a single bin per BA, with representative costs and heat rates per bin	All unit types grouped into four bins per BA, with representative costs and heat rates per bin
Planning reserve margin	Planning reserve margin ramped down from current levels to NERC reference levels by 2025 (Reimers, Cole, and Frew 2019)	Planning reserve margin set at NERC reference levels for all years, except ERCOT in 2018 and 2019 is set to actual values because the actuals were lower than the NERC reference levels
NOx ozone season limits	Not represented	Included

[a] As noted in the scenario descriptions, the default cost recovery period is 20 years in ReEDS and 30 years in the ATB.

Table A-5. Key Differences in dGen Model Versions

Inputs and Treatments	2018 Version	2019 Version
Demand growth	AEO2018	AEO2019
Technology cost	ATB2018	ATB2019
Tariff set	Curated in January 2018	Curated in January 2019
Tariff selection	Residential agents are assigned a curated default (most applicable) tariff from among those available in their class.	Residential agents are assigned a curated default (most applicable) tariff from among those available in their class
Agent rooftop area	Set to equal observed county values and estimated residential/non-residential breakdown (Gagnon et al. 2016; Sigrin and Mooney 2018)	Set to equal observed county values and estimated residential/non-residential breakdown (Gagnon et al. 2016; Sigrin and Mooney 2018)
Solar economics metric	Simple payback period	Simple payback period
System sizing	Systems are optimally sized based on the tariff, roof size, and consumption	Systems are optimally sized based on the tariff, roof size, and consumption
Sampling rate	Ten statistically representative consumers per sector per county were sampled	Ten statistically representative consumers per sector per county were sampled
State net energy metering, policies	Updated in March 2018	Updated in March 2019[a]

[a] If states have no mandated NEM expiry dates, a distributed solar penetration threshold was implemented, which was determined from values of peer states.

ReEDS Model Contributors

All NREL contributors to the ReEDS model are listed below.

Jon Becker	Eduardo Ibanez	James Richards
Ross Beppler	Paige Jadun	Anna Schleifer
David Bielen	Charles Kang	Walter Short
Nate Blair	Venkat Krishnan	Ben Sigrin
Max Brown	Anthony Lopez	Travis Simpkins
Wesley Cole	Trieu Mai	Ramteen Sioshansi
Paul Denholm	Andrew Martinez	Elina Spyrou
Victor Diakov	Dana Max	Dan Steinberg
Kelly Eurek	Maureen McDaniel	Patrick Sullivan
Will Frazier	Matt Mowers	Aaron Townsend
Bethany Frew	David Mulcahy	Caroline Uriarte
Nathaniel Gates	Caitlin Murphy	Nina Vincent
Sameera Gudladona	John Nangle	Tibebe Woldeyesus
Maureen Hand	Scott Nicolson	Ella Zhou
Donna Heimiller	Hyungseon Oh	Owen Zinaman
Jonathan Ho	Andrew Reimers	Matt Zwerling