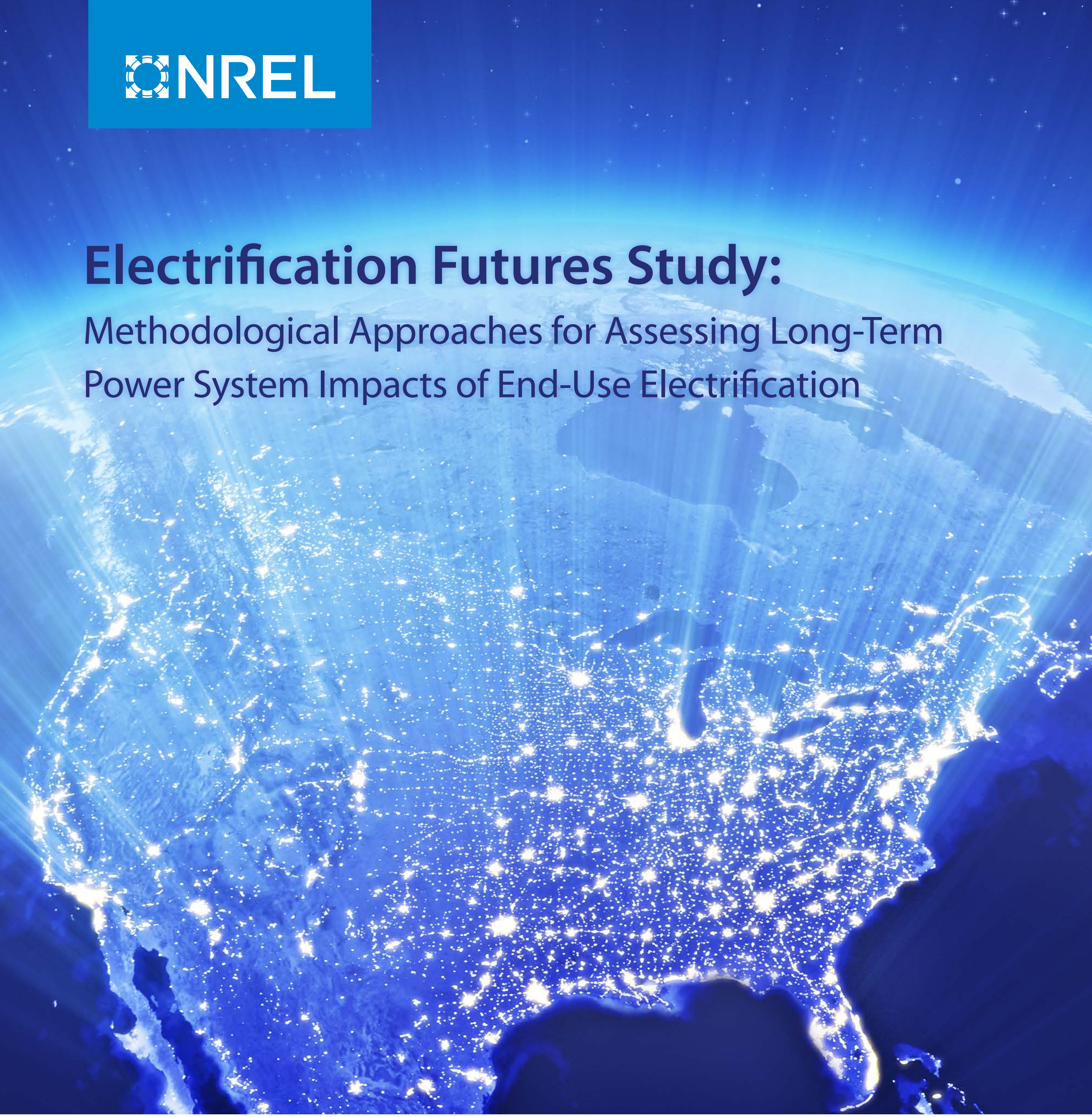
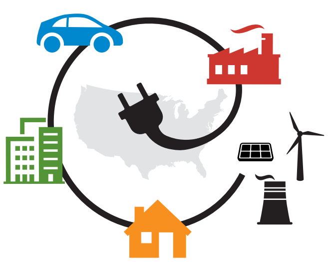


Electrification Futures Study:

Methodological Approaches for Assessing Long-Term Power System Impacts of End-Use Electrification

Yinong Sun,[1] Paige Jadun,[1] Brent Nelson,[2] Matteo Muratori,[1] Caitlin Murphy,[1] Jeffrey Logan,[1] and Trieu Mai [1]

[1] *National Renewable Energy Laboratory*
[2] *Northern Arizona University*



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[1] *National Renewable Energy Laboratory*
[2] *Northern Arizona University*

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Errata

This report, originally published in July 2020, has been revised in January 2021 to update the peak demand values listed in Table 3. The original table incorrectly listed peak demand for scenarios with an assumed level of demand-side flexibility.

Preface

This report is one in a series of Electrification Futures Study (EFS) publications. The EFS is a multiyear research project to explore potential widespread electrification in the future energy system of the United States. Electrification is defined as the substitution of electricity for direct combustion of non-electricity-based fuels used to provide similar services.

The EFS is specifically designed to examine electric technology advancement and adoption for end uses in the major economic sectors of the United States, electricity consumption growth and load profiles, future power system infrastructure development and operations, and economic and environmental implications of electrification. Because of the expansive scope and the multiyear duration of the study, research findings and supporting data will be published as a series of reports, with each report being released on its own time frame. The table below lists the reports published to date from the series.

Published reports to date from the Electrification Futures Study series
1. Jadun, Paige, Colin McMillan, Daniel Steinberg, Matteo Muratori, Laura Vimmerstedt, and Trieu Mai. 2017. *Electrification Futures Study: End-Use Technology Cost and Performance Projections through 2050*. NREL/TP-6A20-70485.
2. Mai, Trieu, Paige Jadun, Jeffrey Logan, Colin McMillan, Matteo Muratori, Daniel Steinberg, Laura Vimmerstedt, Ryan Jones, Benjamin Haley, and Brent Nelson. 2018. *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States*. NREL/TP-6A20-71500.
3. Hale, Elaine, Henry Horsey, Brandon Johnson, Matteo Muratori, Eric Wilson, Brennan Borlaug, Craig Christensen, Amanda Farthing, Dylan Hettinger, Andrew Parker, Joseph Robertson, Michael Rossol, Gord Stephen, Eric Wood, and Baskar Vairamohan. 2018. *The Demand-Side Grid (dsgrid) Model Documentation.* NREL/TP-6A20-71491.
4. Sun, Yinong, Paige Jadun, Brent Nelson, Matteo Muratori, Caitlin Murphy, Jeffrey Logan, and Trieu Mai. 2020. *Electrification Futures Study: Methodological Approaches for Assessing Long-term Power System Impacts of End-Use Electrification.* NREL/TP-6A20-73336. [this report]

This report is the fourth publication in the EFS series, and it provides detailed descriptions of major methodological modifications to the power system model that can be used in future EFS studies, in order to better reflect key impacts of electrification. The levels of electrification underlying the changes needed to power sector modeling are derived from the second report (Mai et al. 2018), coupled with various assumptions about prominent drivers that influence the future generation mix on the bulk power system.

Follow on studies can leverage these new capabilities to explore the potential impacts of electrification on power sector evolution. As a result, this report is limited only to methodological development and implementation in modeling and does not explore electrification impacts more broadly. The methodological approaches presented in this report can be used to assist researchers performing their own electrification analyses and to document the modeling upgrades.

More information, the supporting data associated with this report, links to other reports in the EFS, and information about the broader study are available at www.nrel.gov/efs.

Acknowledgments

The Electrification Futures Study (EFS) is led by researchers at the National Renewable Energy Laboratory (NREL) but relies on significant contributions from a large collaboration of researchers from the U.S. Department of Energy (DOE), Evolved Energy Research, Electric Power Research Institute, Lawrence Berkeley National Laboratory, Northern Arizona University, and Oak Ridge National Laboratory. We would like to thank all contributors for useful analysis, data, and input throughout the project.

A technical review committee of senior-level experts provided invaluable input to the overall study, with some committee members sharing thoughtful comments to this specific report as noted on the following page. Although the committee members offered input throughout the study, the results and findings from this analysis and the broader EFS do not necessarily reflect their opinions or the opinions of their institutions. The technical review committee is comprised of the following individuals:

Doug Arent (committee chair)
National Renewable Energy Laboratory

Sam Baldwin
U.S. Department of Energy

Steve Brick
Clean Air Task Force

Steve Clemmer
Union of Concerned Scientists

Laura Cozzi
International Energy Agency

Francisco de la Chesnaye
Electric Power Research Institute

Keith Dennis
National Rural Electric Cooperative Association

Carla Frisch
Rocky Mountain Institute

Arnulf Grübler
International Institute for Applied Systems Analysis

Howard Gruenspecht
Massachusetts Institute of Technology

Jonathan Hughes
University of Colorado Boulder

Michael Kintner-Meyer
Pacific Northwest National Laboratory

John Larsen
Rhodium Group

Bryan Mignone
ExxonMobil Research and Engineering Company

Granger Morgan
Carnegie Mellon University

Patrick Riley
GE Global Research

Joan Ogden
University of California Davis

Laurie ten Hope
California Energy Commission

Susan F. Tierney
Analysis Group, Inc.

This analysis benefited greatly from thoughtful comments and suggestions from several colleagues who generously reviewed either the entire report or portions of it in draft form, including:

- Amanda Myers (Energy Innovation)
- Wesley Cole, Stuart Cohen, Elaine Hale, and Jack Mayernik (NREL)
- Youngsun Baek and Sandra Sattler (Union of Concerned Scientists)
- Monica Neukomm, Sam Baldwin, and Jonah Steinbuck (U.S. Department of Energy)
- Jim McFarland (U.S. Environmental Protection Agency)

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Primary funding support for the EFS is provided by the DOE Office of Energy Efficiency and Renewable Energy Office of Strategic Programs. We especially thank Paul Donohoo-Vallett (DOE) and Steve Capanna (formerly DOE) for their support and leadership throughout the EFS and for this report.

List of Acronyms

AEO	Annual Energy Outlook
BA	balancing area
CBECS	Commercial Buildings Energy Consumption Survey
DOE	U.S. Department of Energy
EFS	Electrification Futures Study
EIA	U.S. Energy Information Administration
ENC	East North Central
HOGR	high oil and gas resource
HVAC	heating, ventilation, and air conditioning
LNG	liquefied natural gas
LOGR	low oil and gas resource
MTN	Mountain census division
NEMS	National Energy Modeling System
NG-CC	natural gas-combined cycle
NG-CT	natural gas combustion turbine
NREL	National Renewable Energy Laboratory
ORNL	Oak Ridge National Laboratory
PRM	planning reserve margin
ReEDS	Regional Energy Deployment System model
SCE	Southern California Edison
SIC	Standard Industrial Classification
VRE	variable renewable energy
W	watt

Abstract

The Electrification Futures Study (EFS) was designed to analyze the potential impacts of electrification, accounting for the complex dynamics between different segments of the U.S. energy system. The EFS uses several complementary modeling and analysis tools, and it relies on an overarching scenario analysis approach. Previous EFS reports defined a range of future cost and performance trajectories for electric end-use technologies (Jadun et al. 2017), which informed a variety of electrification scenarios (Mai et al. 2018). These "demand-side" scenarios are defined by different electric end-use technology adoption rates and, in turn, different levels and patterns of electricity demand. Comparison across these scenarios reveals alterations in the temporal and spatial patterns of electricity consumption, such that the magnitude and timing of peak demand are impacted in meaningful ways. Moreover, electrification expands opportunities for demand-side flexibility, which would further change the shape of electricity demand. In addition, increasing electrification also drives a reduction in end-use natural gas consumption which, in turn, influences the price of natural gas.

Assessing how these alterations in demand sectors would influence the corresponding buildout of the power system under widespread electrification requires their explicit representation in long-term planning models. The purpose of the present report is to document and demonstrate model development efforts we engaged in to improve our ability to represent interactions between electricity supply and demand under widespread electrification. These improvements were designed for and implemented in the National Renewable Energy Laboratory's Regional Energy Deployment System (ReEDS) model, which is a capacity expansion model that simulates the evolution of the U.S. electricity system through 2050.

This report summarizes three primary improvements that were implemented in ReEDS. First, we improved the representation of load shapes and peak demand to better capture how regional interactions—such as resource sharing between regions—could be impacted under widespread electrification. Second, we represented how changes in direct end-use natural gas consumption could impact the economics of natural gas-fired generation, through price elasticity effects. Third, we implemented a new model representation of flexible load that is dispatched endogenously within the model.

These improvements to ReEDS are intended to be employed in follow on work that will fully explore the impact of electrification on the power sector evolution. However, the data and methods documented in this report could also be adapted for other models with similar scopes and limitations, to improve their ability to assess future electric system scenarios under varying levels of electrification.

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1 Introduction

Electrification is the shift from any non-electric source of energy to electricity at the point of final consumption, and it is an emerging trend in energy markets around the world. Depending on the magnitude and extent of electrification, such a transition could have important implications for the future evolution of the power system. Alterations in the temporal and spatial patterns of electricity consumption as well as the overall magnitude of demand growth represent the primary impacts of electrification on bulk power system needs and economics. Such an impact could affect regional interactions by changing power transfers, influencing transmission expansion decisions, and potentially raising opportunities for capacity resource sharing between regions. Another potential impact of electrification is the reduction in end-use natural gas consumption, which could improve the economics of natural gas-fired power generation. Finally, demand-side flexibility could impact power system evolution and these impacts could vary with different level of electrification.

Given the interconnected nature of the U.S. energy sector, these direct effects of electrification in demand sectors would also influence the future evolution of the power system. Therefore, simulating electrification scenarios in power system models requires an explicit representation of how changes in the demand sectors would translate to different input assumptions for the power sector. The purpose of this report is to document model improvements that were designed and executed in the National Renewable Energy Laboratory's (NREL's) Regional Energy Deployment System (ReEDS) model in order to facilitate power sector analysis of electrification scenarios as part of the broader Electrification Futures Study (EFS). This section presents overviews of both the EFS and ReEDS, to provide context for the model development efforts that are detailed in Sections 2–4 of this report.

1.1 Overview of the Electrification Futures Study

The EFS is a multiyear research effort to explore the implications of increasing electrification on the U.S. energy system.[1] The study relies on a scenario analysis approach. The current report builds on prior EFS reports by beginning to extend the scenario analysis to the "supply-side" of the electricity system.

The primary purpose of this report is to present the methodological approaches applied to National Renewable Energy Laboratory's (NREL's) Regional Energy Deployment System (ReEDS) capacity expansion model in order to improve its ability to reflect electrification-related impacts on power system planning.[2] Given the methodological focus of this report, it should be viewed as a complement to the main ReEDS model documentation presented by Cohen et al. (2019). Section 1.2 provides an overview of the ReEDS model with particular emphasis on aspects of the 2018 final release version of the model prior to changes described in the latter sections of this report. Although this report focuses on modifications to the ReEDS model, the methods represented may also apply to other long-term power system planning models.

[1] For more information, see "Electrification Futures Study," NREL, https://www.nrel.gov/analysis/electrification-futures.html.
[2] See "Regional Energy Deployment System Model," NREL, https://www.nrel.gov/analysis/reeds/.

Note that this report focuses narrowly on the modeling methodological development and as such does not examine the impact of electrification on the power sector more broadly. Demand side electrification scenarios used here to test the methods are derived from Mai et al. (2018). Future supply-side electrification scenario analysis will rely on the model methods presented in the current report. Planned work will more comprehensively address major trends for the future U.S. electricity system and how these trends might impact—or might be impacted by—increased electrification; such impacts may include future capacity and generation mixes, associated infrastructure development, electric and energy system expenditures, fossil fuel and energy use, and air emissions.

1.2 Overview of the Model Structure

The ReEDS model (Cohen et al. 2019; Cole et al. 2018) serves as the analytic backbone of the EFS supply-side analysis.[3] ReEDS is a capacity planning and dispatch model that uses system-wide least-cost optimization to develop long-term electricity supply scenarios. The version of ReEDS used for our analysis models the power system in the contiguous United States through 2050.[4] Because ReEDS models the U.S. electricity system only, it relies on exogenously specified inputs for certain parameters that are affected by global dynamics and factors outside the bulk power system. Most notably, to inform its capacity expansion and dispatch decisions, ReEDS relies on exogenous assumptions for electricity demand and natural gas resource and pricing[5]—two factors that are influenced by the extent of end-use demand electrification. Because of these interactions and the model's scope, methodological developments were needed to improve ReEDS' ability to assess the impacts of electrification on power demand and natural gas power generation economics.

ReEDS is a sequential optimization model where the least-cost solution is found during every two-year solve period through 2050 (Figure 1). In each solve period, ReEDS finds the lowest-cost portfolio of generation, transmission, and storage options that meet numerous constraints, including grid requirements (e.g., electricity supply-demand balance, and reserves), policy requirements (e.g., state renewable portfolio standards), and resource constraints (e.g., geothermal resources, hydropower sites, and suitable land areas for wind and solar development). Investment in new capacity and the utilization of all (existing and new) capacity are endogenously co-optimized in the model based on the present value of electric system expenditures over a financial evaluation period (e.g., 20 years). Between each solve period, parameters are updated based on exogenous assumptions and decisions from the previous optimization; such parameters include technology cost and performance, fuel prices, demand growth, grid requirements, policy changes, and calculations and parameters associated with

[3] Consistent with Cole et al. (2018), we use the 2018 final release version of ReEDS as the starting-point version of the model. This report describes the deviations to this version for the EFS. In addition to ReEDS, the Distributed Generation (dGen) model (Sigrin et al. 2016) is used to generate the rooftop PV adoption levels assumed in our scenarios. No other distributed generation technologies are represented.
[4] This version includes simplified representation of net imports from Canada and Mexico. Other versions of ReEDS include explicit representation of the full North American power system and can be used to develop scenarios through 2100.
[5] As we describe below and in Section 3, ReEDS represents supply curves for natural gas that reflect the elasticity of prices and demand rather than fixed prices.

integration of variable renewable energy (VRE) technologies (namely capacity credit and curtailment of VREs).[6]

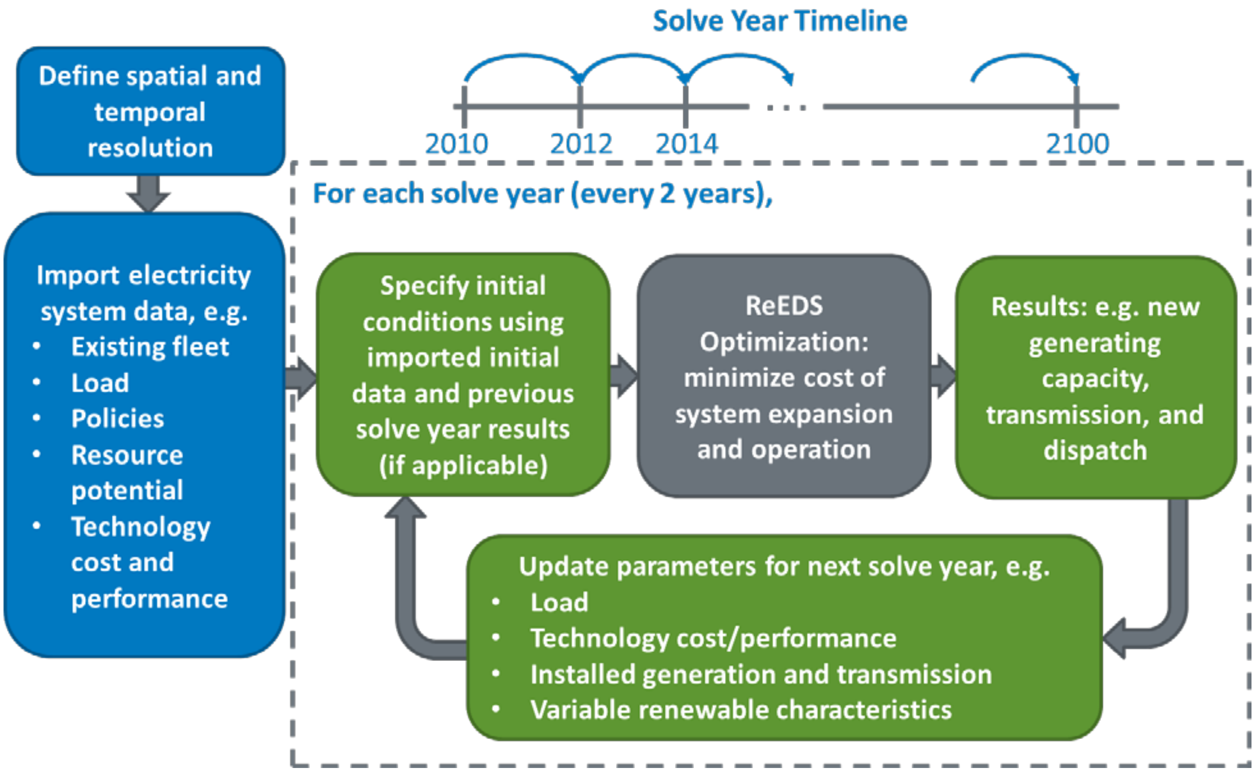

Figure 1. Schematic of the ReEDS model structure

Although the ReEDS model allows for simulations of the power system through 2100, the present analysis only explores power system evolution through 2050.

Source: Cohen et al. 2019

Uniquely, ReEDS has higher spatial resolution than other leading national-scale capacity expansion models (Cole et al. 2017). Figure 2 shows a map of the model's spatial structure, which includes 134 model balancing areas (BAs)[7] and 356 renewable resource regions. The primary network structure in ReEDS is comprised of the BAs and the transmission lines connecting them. The model transmission lines shown in Figure 2 reflect the existing transmission interface capacities between BAs. Balancing areas are also where the aggregate capacity for each technology category is modeled. Renewable regions specify the amount and quality of developable wind and concentrating solar power resource. Other regional layers are used to specify other local constraints and requirements that impact the system-wide optimal solution. These larger regions are comprised of a collection of BAs to represent states and model regional transmission organization boundaries. For example, renewable portfolio standards and other state policies are modeled for states that possess such policies, and operating reserve

[6] Unless otherwise specified, the scenarios modeled include current policies as of spring 2018 only, including any legislated changes to the policy (e.g., expiration of federal renewable energy tax credits).
[7] Model BAs do not align with actual balancing authority area boundaries.

constraints are assumed for each of 18 model regional transmission organizations.[8] Overall, the highly disaggregated spatial structure in ReEDS allows us to assess the degree of trading—of multiple grid services including energy, capacity, and reserves—between regions.

Figure 2. ReEDS spatial structure

ReEDS' investment and dispatch decisions are also affected by the temporal structure of the model. The 2018 final release of ReEDS relies on 17 time-slices to reflect seasonal and diurnal variations in load and VRE production in the reduced-form dispatch decisions and power generation economics considered by the model.[9] For the EFS, we add a time-slice to better capture generation decisions during peak winter load hours. Furthermore, ReEDS has traditionally included an *annual* planning reserve constraint designed to enforce resource adequacy requirements for the system, which, for most regions, ensures sufficient installed capacity to meet summer peak demand hours. As electrification could change the timing of peak demand, we alter the model to consider *seasonal* planning reserve requirements, which improves ReEDS' ability to model the potential for sharing planning reserve provision resources between regions. Section 2 provides details about these model improvements.

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[8] Regional transmission organizations in the model closely overlap the actual footprints of regional transmission organizations and independent system operators where they exist, and they represent fictitious reserve-sharing groups for regions without restructured markets (see Cohen et al. 2019).
[9] As described in the ReEDS documentation (Cohen et al. 2019), the model includes additional calculations and parameters to capture *intra*-time-slice variations in load and VRE production.

Fuel prices and demand growth are two parameters that are heavily impacted by electrification. ReEDS relies on exogenous and fixed-price trajectories for coal and uranium but represents natural gas pricing using supply curves (Cole, Medlock, and Jani 2016).[10] The slope of the supply curves reflect the inverse price elasticity of demand (e.g., how an increase in electric sector consumption of gas would increase delivered prices for natural gas-fired generation), but in the 2018 final release version of ReEDS, they implicitly assume the same amount of gas is consumed outside the power sector across scenarios.[11] Seasonal patterns in natural gas prices are also reflected in ReEDS. Section 3 presents updates that were made to the representation of natural gas economics to better capture impacts of regional changes in non-electric natural gas consumption.

For demand growth, the 2018 final release version of ReEDS applies an annual load growth factor to each census division based on the U.S. Energy Information Administration's (EIA's) Annual Energy Outlook (AEO) 2018 reference case (Cole et al. 2018; EIA 2018a). This implementation assumes the *intra*-annual load shapes[12] remain constant over time, and it assumes annual demand in all states within a census division grow at the same rate. In this analysis, to better reflect potential changes in electricity consumption patterns driven in part by electrification trends envisioned in the EFS, we incorporate into ReEDS state-specific annual and hourly consumption from the demand-side scenarios reported in Mai et al. (2018) (see Appendix A)[13]. Demand-side participation can also impact electric system operation, and the impacts would become more significant with increasing electrification. To capture the potentially extensive interaction of demand-side participation and electrification, we include a new representation of demand-side flexibility based on the incorporated consumption profiles in ReEDS. Section 4 documents the data assumptions and modeling methodology used to represent different levels of flexible load with electrification.

In the EFS, we use the ReEDS model—including model developments presented in this report—to simulate a variety of scenarios of the contiguous U.S. electricity system through 2050. In this report, we only present select scenario results that highlight the effects of our methodological developments in ReEDS (documented here), without emphasis on the potential impacts of electrification on the bulk power system. Unless otherwise noted, the scenarios presented here use Base Case assumptions that are largely consistent with the Mid-Case of the *2018 Standard Scenarios Report* (Cole et al. 2018).

[10] Biomass feedstock supply curves are also used. The same biomass supply curves are used in all scenarios.
[11] This representation considers changes in non-power gas consumption over time as modeled in the AEO scenarios.
[12] The 2018 final release version of ReEDS relies on consumption patterns from 2012 for all years.
[13] The BA level consumption in ReEDS is adjusted using the corresponding state-specific consumption patterns.

2 Regional Interactions

The U.S. electricity system can be subdivided into several geographical levels representing differences between regions (Denholm, Sun, Mai 2019). These regional differences and the interconnection—both physical and institutional—between regions require power system models to account for interactions between regions. For example, regional coordination often refers to cooperation between BAs or other regional entities to perform consolidated operation of their joint assets through reserve sharing and coordinated scheduling (Greening the Grid 2015), and the model needs to reflect such practices. For the purpose of this report, and given the long-term modeling framework used, we describe how the model represents coordination and interactions in investment and utilization decisions relevant to all grid services, including energy as well as planning and operating reserves. Electrification can impact bulk power system needs and economics through alterations to the temporal and spatial patterns of electricity consumption, as well as the overall magnitude of demand growth. Such impacts could affect regional interactions by changing power transfers, influencing transmission expansion decisions, and potentially raising opportunities for capacity resource sharing between regions.

In this section, we briefly discuss regional interactions in electricity systems and how they could be impacted by electrification. We also present the model updates in ReEDS that are intended to improve the temporal representation of both energy and capacity resource sharing, especially with respect to peak demand. Scenario results are included to show the individual and combined impacts of these two updates on overall model results. Finally, we conclude the section with a discussion of limitations in our modeling methods.

2.1 Power System Regional Interactions

2.1.1 Review of Resource Sharing and Regional Interactions

Resource sharing and interregional coordination can yield economic benefits in planning and reliable operations of power systems. The value of sharing resources across larger geographic boundaries mainly comes from the geospatial diversity of both electricity demand and supply. This combination is also known as net-load diversity (Figueroa-Acevedo 2017). Electrical load varies across locations due to weather, time zone, behavior, and technological differences in consumption (e.g., use of electric heating systems). Supply also varies geographically, due to generation characteristics and system constraints, especially if VRE is largely deployed. These differences lead to opportunities to use a shared pool of resources to balance the system-level supply and demand or meet reserves rather than rely on only local resources.

These regional interactions, including resource sharing and interregional coordination, occur during both planning and operations of power systems. During power system planning processes, interregional coordination can help system planners make generation and transmission capacity expansion decisions with lower overall infrastructure and operating costs while achieving the same or even greater levels of reliability. Moreover, trading planning reserve provision resources between regions helps different regions meet their resource adequacy requirements (i.e., planning reserve margin [PRM] requirement) in a more economical way. During power system operations, energy resource sharing allows different regions to the meet supply-demand balance and essential reliability services (e.g., operating reserves) requirements, with resources that are less expensive than local ones.

Coordination across regions can be especially important for integrating VREs into the grid and maximizing their value. The sharing of reserves and energy can increase operational efficiency, improve system reliability, reduce system costs, and maximize the utilization of VRE generation (Greening the Grid 2015; Li and McCalley 2015; GMLC n.d.; GE Energy 2010, Bloom et al. 2016; NREL 2012; Milligan and Kirby 2007; Cochran et al. 2012). However, it is important to note that the benefits of regional coordination extend beyond VRE integration and, in fact, some degree of resource sharing has existed since the beginning of the modern power system when generation from VRE technologies was negligible. Furthermore, regional coordination would require a shift away from local control and would likely require greater complexity in managing the interactions between regional entities. Below, we describe how electrification might affect regional interactions and how the ReEDS model captures them.

2.1.2 Changing Regional Interaction Dynamics with Electrification

Electrification changes the temporal and spatial patterns of electricity consumption and the overall magnitude of demand growth; in turn, the opportunities for and value of resource sharing and regional interactions could be impacted by electrification.

Potential impacts of electrification on regional peak demand include increases in peak demand magnitude and shifts in the peak demand season from summer to winter in some regions. For example, Figure 3 shows the estimated peak demand magnitude and seasonal timing in the contiguous United States under different electrification scenarios of Mai et al. (2018). In cold climate regions such as the Northeast, winter peaks (blue wedges) increase with electrification due to increasingly electrified space heating. These electrification-induced impacts on regional peak demand raise regional PRM requirements and therefore require attention during the generation and transmission capacity planning process. The increased magnitude of peak demand during the winter season also suggests a growing potential for the beneficial sharing of both capacity and energy resource between interconnected regions with non-coincident peaks.

Figure 3. Peak load magnitude and seasonal timing by state for 2018 and 2050 for three electrification scenarios

The size of the circles represents the total electricity demand in gigawatts (GW) during the top load hour of the year. The wedges of each pie show the seasonal distribution of the top 100 hours with the highest demand by state. Seasons are defined as follows: summer includes June, July, and August; fall includes September, October, and November; winter includes December, January, and February; and spring includes March, April, and May. Data shown for 2018 are based on modeled estimates. The peak load shown does not include demand-side flexibility; see Section 4 for a discussion of the potential impact of demand-side flexibility on peak load.

Electrification also affects regional load shapes, requiring changes in regional interactions in a broader area. For example, Figure 4 shows load correlation coefficients between all pairs of 134 model BAs as a function of distance between BAs. The correlation coefficient is calculated for each pair of model BAs using their estimated hourly load profile in 2050. Correlations are shown for both the Reference (left) and High (right) electrification scenarios. The scatterplots show how correlations between load profiles typically decline with distance, thereby offering opportunities for resource sharing when proper transmission is available. In addition, the generally more-correlated profiles under High electrification, as shown by the shallower slope on the right scatterplot relative to the left one, suggest that to achieve the same degree of geospatial diversity in consumption patterns might require coordination over even greater distances in scenarios with widespread electrification.

One reason for the greater correlations under the High electrification scenario is the influence that building electrification has on load profiles. In particular, Mai et al. (2018) assume that (1) a greater shift toward electric heat pumps for space heating under the High electrification scenario and (2) heating demands are well correlated in both spatial and temporal dimensions. Furthermore, because the operational efficiency of heat pumps declines with temperature, the correlated space heating-induced electricity consumption can lead to stresses on broad areas in the system during extreme cold weather periods.

Figure 4. Correlation coefficients in 2050 hourly load profiles for model BAs under (left) Reference and (right) High electrification scenarios

Each dot represents a certain pair of model BAs across all 134 BAs; the x-axis shows the distance between the centroid point of the pair of BAs.

Higher demands from electrification could raise operating reserve requirements, which could require additional headroom and associated costs, but could also signal additional value for coordinated operations. The same effects apply to greater planning reserve requirements induced by electrification-driven higher peaks, but the magnitude of these effects can be even greater given their relevance to avoiding new capacity construction. Finally, if the electrified load is met with an increased contribution from VREs, higher levels of regional interactions may be cost-effective to help integrate VREs, as discussed in Section 2.1.1.

2.2 Implementation in ReEDS

Using a system-wide optimization modeling framework, ReEDS finds the lowest-cost portfolio of generation and transmission investment options (and the utilization of existing and new assets) that meets all grid and policy requirements for the system as a whole. This perspective reflects a system with full coordination and cooperation between regions.[14] The high spatial resolution of the model allows ReEDS to consider regional differences in load profiles, VRE profiles, reserve

[14] Note this system-perspective of full coordination in planning and operation is not consistent with current practice.

requirements, transmission limits, and capital and fuel costs in its least-cost investment and dispatch decisions.

ReEDS models regional interactions for both planning and operations simultaneously. When making investment decisions, ReEDS co-optimizes generation and transmission capacity investments. ReEDS also allows regional planning reserve provision contracts to meet PRM requirements. When modeling operation and dispatch, ReEDS models transmission flows to meet the supply-demand balance requirement within each balancing area. In short, the ReEDS model weighs the cost and benefit of local resources to meet grid system needs with resources of distant regions, and it can thus be used to demonstrate how regional interactions might change with electrification.

The modeled level of regional interactions highly depends on the temporal structure of the model and the method used to model load and VRE profiles. Finer temporal representation provides better evaluation of regional interactions because of load and generation profile diversity. To better represent the regional interactions with higher levels of electrification, two major model updates have been made to improve the temporal representation of both energy and capacity resource sharing, especially with respect to peak demand: (1) considering seasonal PRM instead of annual PRM and (2) directly modeling the winter peak for operations decisions. These improvements allow the model to better assess the impacts of electrification on the power system.

The 2018 final release version of ReEDS includes an *annual* planning reserve constraint designed to enforce resource adequacy requirements for the system, which ensures sufficient installed capacity to meet summer peak demand hours. However, this annual representation does not capture the seasonal timing changes of peak demand with higher levels of electrification. Therefore, we alter the model to consider seasonal planning requirements, based on the regional peak demand for each of the four seasons modeled in ReEDS. Specifically, we update the resolution of the following parameters from an annual to a seasonal level: regional peak load, VRE capacity credit, and planning reserve provision trading between regions.[15] This representation improves ReEDS' ability to model the potential for sharing planning reserve provision resources between regions, especially those that have different peaking seasons.

Furthermore, the 2018 final release version of ReEDS relies on 17 time-slices to reflect seasonal and diurnal variations in load and VRE production in the reduced-form dispatch decisions and power generation economics considered by the model. The model considers a representative day for each season (summer, fall, winter, spring) and four periods within each day (morning, afternoon, evening and night), plus a summer peaking time-slice that represents the 40 individual hours with highest load in summertime. Such a temporal modeling structure captures major load and generation features in the current, primarily summer-peaking U.S. system, but it fails to account for the effect of the increased magnitude and more frequent occurrence of winter peaks under widespread electrification. For this study, we add a time-slice to represent the 40

[15] Planning reserve provision requirements are applied at the level of the 134 model BAs, and the model (both the 2018 final release version and the one used for the EFS) allows planning reserve provision trading between BAs. However, the 2018 final release version is more constrained in how it represents these reserve requirements since it only has a single *annual* level.

individual hours with highest load in winter.[16] The new time-slice better captures generation and dispatch decisions during peak winter load hours, and it allows the model to better evaluate energy resource sharing opportunities between regions with non-coincident peaks.

2.3 Scenario Results

The two modeling updates (winter peaking time-slice and seasonal PRM requirement) allow ReEDS to better capture energy and capacity needs—as well as the potential for resource sharing to meet these needs—especially in scenarios where winter peak demands become more common. This section summarizes the impacts of each model change on the modeling results considering different electrification levels using Base Case assumptions.[17]

From a capacity perspective, changing from an annual to a seasonal planning reserve constraint helps the model more precisely represent the capacity needs of the system, as well as planning reserve provision trading between regions. With seasonal planning reserve requirements and planning reserve provision trading, the model is better able to capture how capacity from a single power plant can serve resource adequacy needs of multiple regions when the regional peak loads are imperfectly correlated *and* there is sufficient transmission capacity between regions. Under these conditions, the effective stringency of the planning reserve or resource adequacy requirements declines (compared to the case when only an annual requirement is represented), which would reduce overall capacity needs. Figure 5 shows that planning reserve provision needs decrease when changing from annual to seasonal PRM requirements.

Applying seasonal requirements results in about 131 GW in net summer planning reserve provision[18] reductions in 2048[19] under High electrification compared to when an annual planning reserve requirement is used, and the net reduction is 224 GW in winter. The results suggest seasonal planning reserve provision trading helps reduce capacity needs during non-correlated peaks. During the summer, some of the decline in natural gas-fired planning reserve provision is compensated by additional planning reserve provision from solar photovoltaics (PV). Because PV has a lower capacity credit than non-variable generators, installed capacity of PV is higher than its planning reserve provision. In winter, this additional installed PV capacity does not provide planning reserve provision services, as PV has near-zero capacity credit at these times when the solar resource is more limited and peak loads may occur during non-daylight hours. In fact, we find an overall reduction in planning reserve provision needs in winter with the seasonal

[16] We assume the top 40 hours occur in the evening and correspond to the period with the highest proportion of top load hours: in 2020, 70% of the top 100 winter load hours occur in the evening, and under high electrification, the proportion increases to 95% in 2050. However, it is important to note that there is significant uncertainty about the timing of this electrification-induced winter electricity consumption.

[17] The scenario results in this section are only used to demonstrate the impacts of certain model changes; they do not indicate any specific impacts of electrification.

[18] Planning reserve provision is defined as the installed capacity multiplied by the seasonal capacity credit for a certain technology. ReEDS assumes a capacity credit of 100% for all non-variable technologies and endogenously calculates the capacity credit for VRE technologies.

[19] Results shown here are modeled 2048 results, because planning reserve provision values are calculated after the solve year and 2050 results are not available in scenarios that run through 2050.

requirements (as opposed to the annual-only requirement) under both Reference and High electrification scenarios, although there are variations between regions.

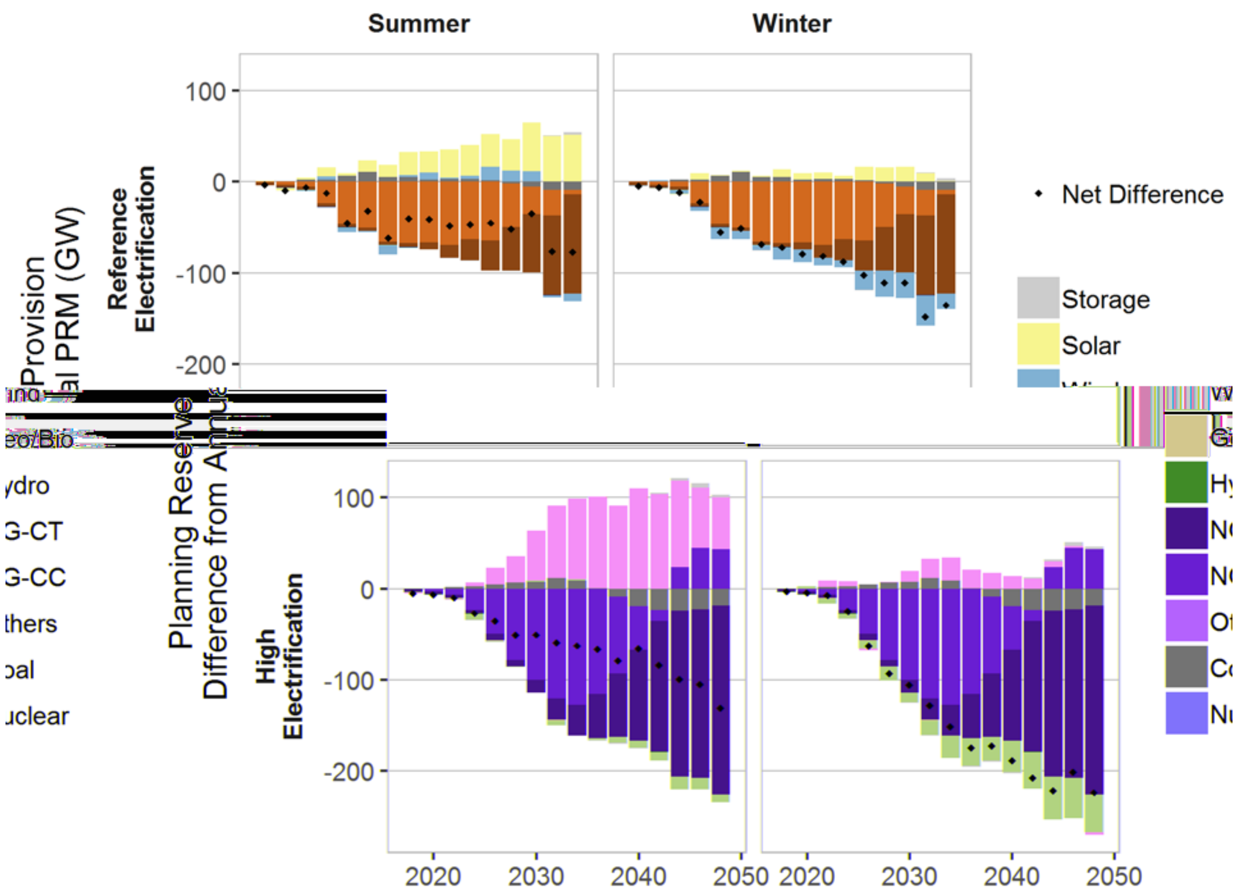

Figure 5. Planning reserve provision difference of seasonal PRM minus annual PRM in summer (left) and winter (right) under Reference (top) and High (bottom) electrification

Black dots represent the net difference of planning reserve provision when using seasonal PRM requirements compared to using annual PRM requirement. Negative values of these black dots show that planning reserve requirements decrease when changing from annual to seasonal PRM requirements

From an energy perspective, adding a winter peaking time-slice enables finer temporal resolution to represent energy provision during the winter season. Such detailed temporal representation helps better capture the operation and dispatch, as well as potential energy trading and resource sharing during winter peaks with electrification. Because the new peaking time-slice represents the 40 hours of highest load within a total of 2,880 winter hours, this additional time-slice has relatively minor impacts on overall capacity builds, generation, and system costs. Moreover, the directionality of these minor impacts varies across scenarios, suggesting that there is competition between the need for additional capacity and the potential for additional resource sharing (with neighboring regions that have non-coincident peaks) when considering winter peaks.

Figure 6 shows the time-slice dispatch by generation technology with and without a winter peaking time-slice under both Reference and High electrification in 2050. Under Reference electrification, the winter peaking time-slice has higher energy requirements than other winter season time-slices, but the requirements are still much lower than the summer peak time-slice.

The winter peak demand is largely met by generation from natural gas-combined cycle (NG-CC) and wind. Under High electrification, winter demand becomes peakier and has a similar level of energy requirement as the summer peak time-slice at a national level. Because solar resource availability is lower in winter than in summer, natural gas combustion turbine (NG-CT) generation is used to meet these winter peak demands.

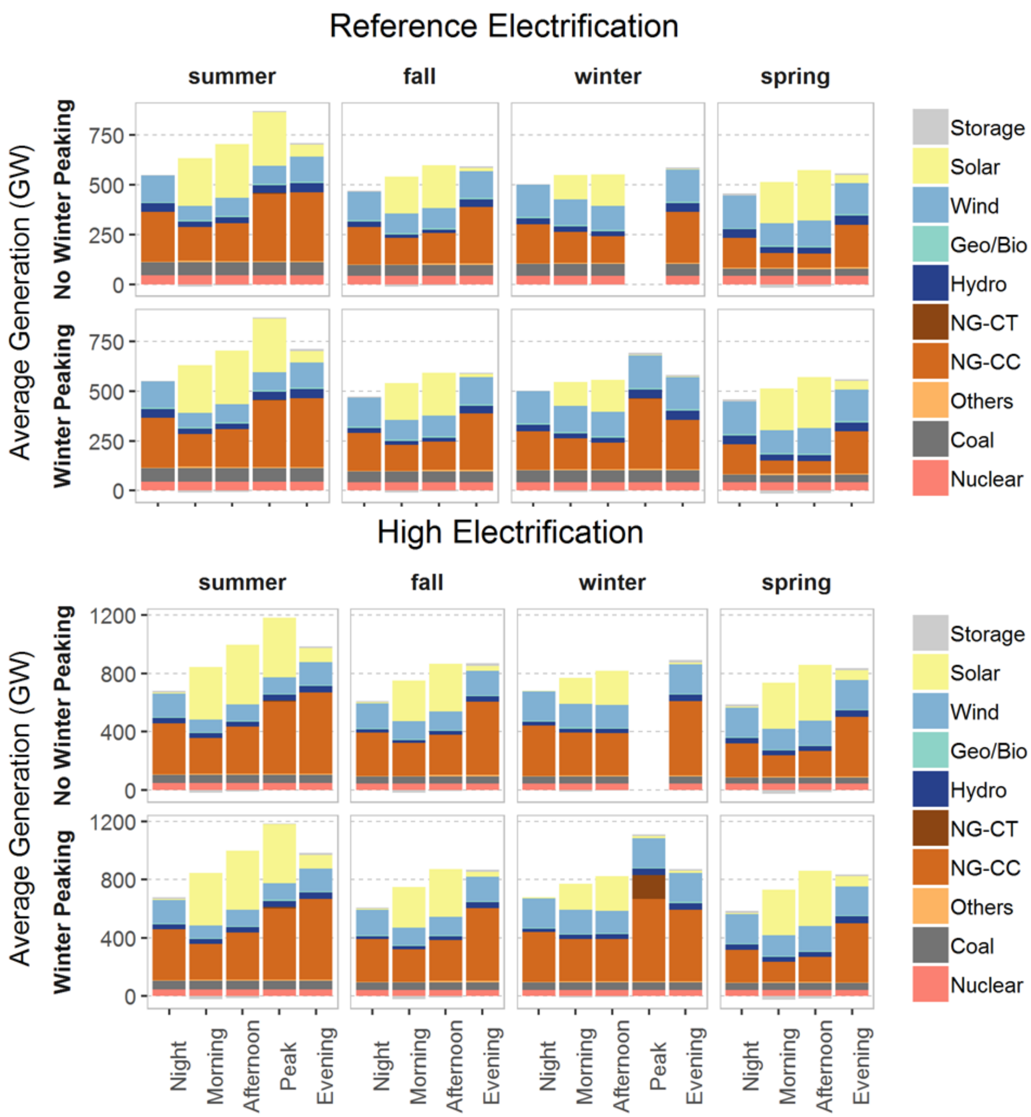

Figure 6. Difference in 2050 time-slice generation with and without winter peaking time-slice under Reference (top) and High (bottom) electrification

Though all time-slices are shown with equal widths, they represent different numbers of hours within a year in the model

The two model changes together provide a better representation of seasonal peak demand in ReEDS, and they unlock additional capacity and energy resource sharing opportunities between regions. For example, Figure 7 shows long-distance (interregional) transmission capacity increases from 2018 levels.[20] Changing from annual to seasonal PRM requirements increases the overall transmission capacity needs (orange and green lines). This is because the capacity builds within each region decrease due to increased flexibility in meeting reserve margin requirements, and additional transmission capacity is therefore needed to share resources. The winter peaking time-slice has minor impacts on overall transmission capacity under Reference electrification. However, this new time-slice leads to lower transmission builds under High electrification (orange and blue lines) with similar level of transmission flows (i.e., the utilization rate of transmission lines is higher with the winter peaking time-slice). These results suggest finer temporal resolution in representing system operation better captures energy resource sharing activities and reduces unnecessary transmission investments. When combining the two model updates, changing to seasonal PRM has a leading impact and results in an overall increase in transmission capacity investments (orange and purple lines).

The impacts of the two model changes are also reflected in electric system costs. A seasonal planning reserve constraint results in lower overall generating capacity investments and therefore leads to a reduction of about 3% of total system cost under High electrification, whereas the winter peaking time-slice has very minor net impacts on total system cost because the model change decreases transmission investments while also increasing fuel costs during operation.

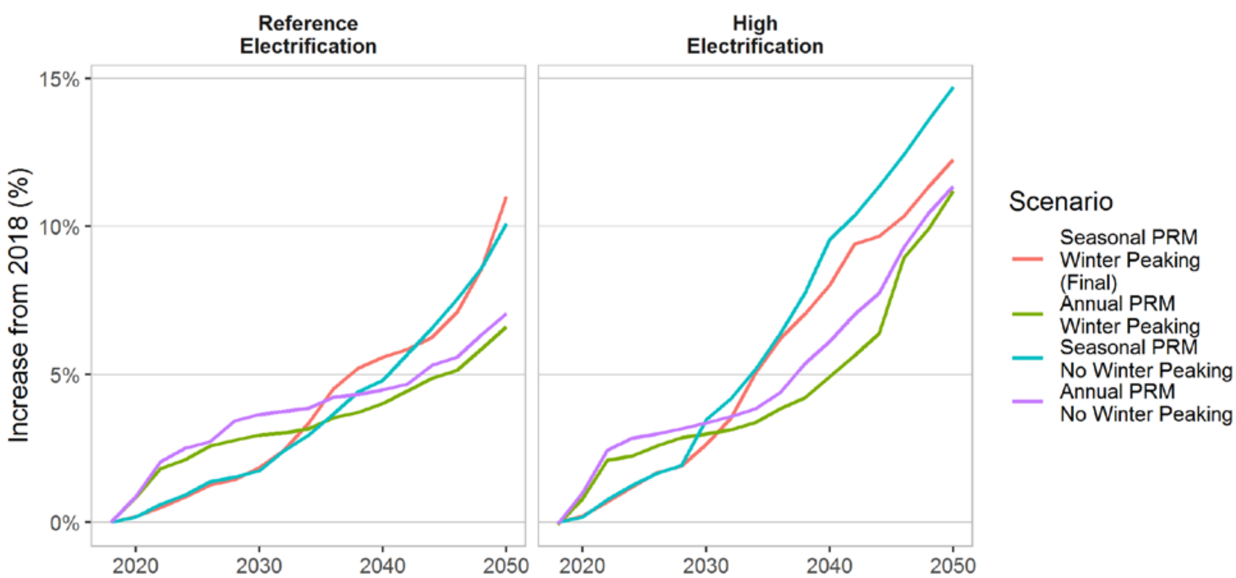

Figure 7. Increase in long-distance transmission capacity from 2018 levels under Reference (left) and High (right) electrification

2.4 Limitations of Modeling Regional Interactions

Regional interactions in the U.S. electricity system can be complex due to the multitude of geographic levels encompassing physical and institutional aspects of planning and operating the grid. These aspects are difficult to model within the context of the EFS due to the multidecade time frame of the study and its focus on potential transformational change in the power and

[20] Future work is intedend to more extensively explore the transmission-related implications for the EFS analysis.

energy system. Moreover, the ReEDS model used for the supply-side EFS scenario is not designed to capture all regional differences, particularly institutional ones. Furthermore, the ReEDS model, like any model, has limited spatial and temporal resolution that may imperfectly capture regional differences and interactions. The model changes presented in this section are intended to improve the representation in ReEDS, particularly on the temporal dimension; however, despite these improvements, much-higher resolution is likely needed to draw more-conclusive findings about transmission expansion, power transfers, and reserve sharing. Hourly production cost grid simulations of a subset of the EFS scenarios, including with flexible load (Section 4), are planned for coming EFS work.

Beyond the modeling and analysis limitations resulting from the model resolution as we note, several other limitations are related to regional interactions. First, the ReEDS modeling relies on a system-wide optimization for both investment and dispatch decisions. This system-wide perspective is not always consistent with the perspective of individual regional planning entities or operators. Although the optimization is constrained by local requirements and resource characteristics, it effectively assumes full coordination and no institutional barriers or implementation costs that directly prevent such coordination. In other words, a model BA could and does procure services from—and provide services to—other BAs if it makes economic sense to the system at large, even as it might impose additional costs to that BA, reduce or eliminate control by the BA, or forgo potential local non-power system benefits to the BA. Given this modeling framework, our analysis does not provide the appropriate counterfactual to estimate the incremental impacts of increasing coordination.

Moreover, ReEDS is an energy-economic model that does not fully reflect siting and permitting considerations, or other development challenges with new transmission infrastructure, which may be needed to maximize resource sharing in the future. The model includes regionally varying costs for new transmission, generation, and storage (Cohen et al. 2019), which are intended to reflect variations in labor and permitting costs, among other factors. However, due to the modeling resolution and source data limitations, the accuracy of such regional cost estimates for a particular project is inherently limited. Furthermore, how these costs and barriers might evolve over time is highly uncertain. On the other hand, we do not explicitly model large transmission overlays or new transmission technologies that could extend the possibilities for resource sharing beyond what is shown by our scenarios.

Also, technical factors affect transmission costs and capabilities. For example, we do not model AC power flow, which might introduce additional technical issues that could limit the potential for resource sharing or raise costs for sharing. With respect to electrification, the limited model resolution and lack of explicit behavioral representation prevents us from fully assessing the potential for, or limits to, coordination. For example, high spatial and temporal resolution techniques will be needed to accurately assess the value of consolidated operations to manage vehicle charging patterns, which vary with home and workplace charging depending on the region, day, hour, and mobility service.

3 Natural Gas Price and Consumption Dynamics

Natural gas serves a substantial and growing role in the U.S. energy system, especially with the emergence of hydraulic fracturing and horizontal drilling for oil and gas. Representing natural gas in energy-economic models requires modeling potential changes in gas and other fuels consumed across multiple sectors. In particular, widespread electrification could significantly alter natural gas economics—either directly by changing gas consumption and production or indirectly by affecting oil markets. With a focus solely on the U.S. power system, ReEDS cannot directly address these issues, especially in a bottom-up fashion. Nonetheless, modifications to ReEDS are implemented to improve its traditional treatment of natural gas—which implicitly assumes non-power consumption is constant for a given natural gas resource scenario—in assessing widespread electrification scenarios.

In this section, we present a brief overview of natural gas supply and demand trends in the United States and introduce model updates to better capture the impacts of electrification. We also present scenario test results that show the impacts of the new implementation, and key modeling limitations.

3.1 Natural Gas Economics

Natural gas economics are impacted by a complex set of factors that can make representation of natural gas in energy and electricity system models challenging. Our analysis focuses narrowly on how electrification might impact natural gas-fired power generation; however, it is important to recognize the complicated interactions at play with respect to the broader set of issues that might affect future natural gas production and consumption. Here, we provide context for and a discussion of these factors.

The shale gas revolution unleashed significant changes in the U.S. power sector over the past decade (Logan et al. 2012; MIT 2011; Middleton et al. 2017). Advances in hydraulic fracturing—and related exploration techniques and drilling practices—led to approximately 51% growth in production of dry natural gas between 2008 and 2018 in the United States, from both gas-only wells and oil wells that produce associated gas (EIA 2019a), as seen in Figure 8. In turn, demand for gas has increased, especially in the power sector. Annual natural gas-fired generation increased from just under 900 terawatt-hours (TWh) in 2008, to more than 1,460 TWh in 2018 (EIA 2019b), a 66% increase. Much of the increase in gas-fired electricity generation over this period offset the decline in coal-fired electricity generation, which fell from nearly 2,000 TWh in 2008 to about 1,150 TWh in 2018. The remaining decline in coal-fired generation over the period was offset by growth in renewables (mainly wind and solar), which doubled in generation from 2008, reaching 740 TWh in 2018 (EIA 2019b).

Despite increased demand, natural gas prices in the United States have remained relatively low since 2009 (Figure 8) as a result of abundant supply, even if short-term price spikes emerged in some regions due to extreme weather events, constrained pipeline supply, or low storage levels. Although future prices remain difficult to forecast accurately because of the dynamic nature of natural gas markets, policy, international events, and other factors, the accessibility of low-cost shale gas resources through new exploration and drilling techniques has led to expectations that future gas prices will remain low (EIA 2019c, NGSA 2018, CME Group 2019).

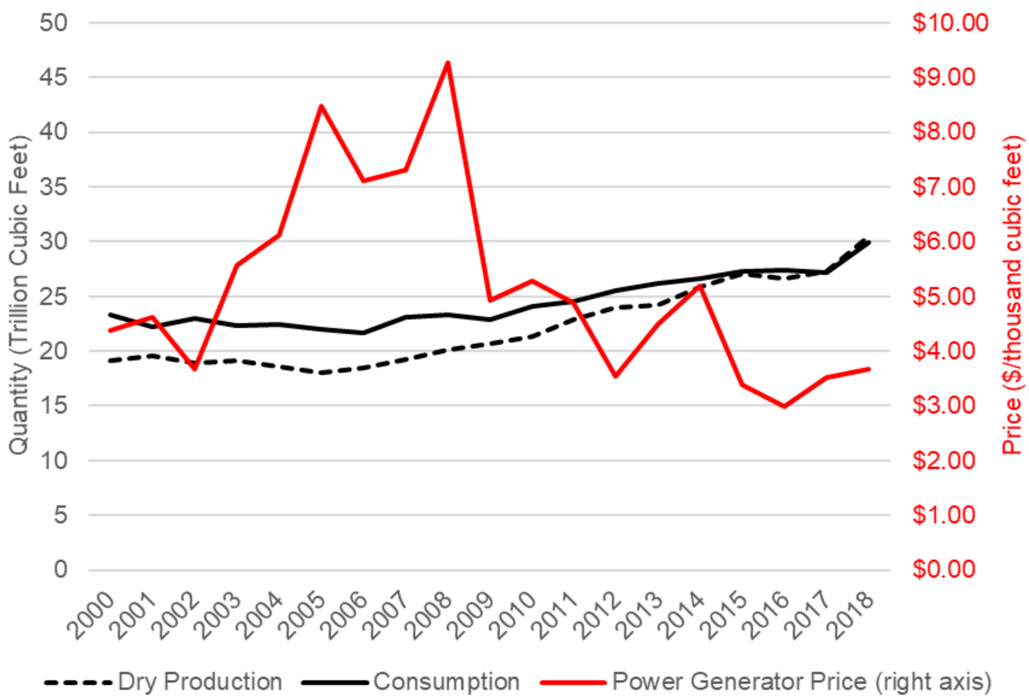

Figure 8. U.S. dry natural gas production and consumption (left axis) and average delivered price for electricity sector consumers (right axis)

Data Source: EIA 2019a
Natural gas prices for power generators are expressed in nominal terms (no adjustments for inflation) and include taxes.

As is the case with most commodities, natural gas demand is elastic to prices.[21] But unlike most other sources of energy, the demand for natural gas is relatively evenly distributed among multiple end-use sectors. In 2017, gas demand was nearly evenly split among power (34%), residential and commercial buildings (28%), and the industrial sector (35%).[22] Given this split, changes in gas demand in one sector can impact prices and economics in other sectors, which is not the case with other fuels. For example, coal and nuclear are both dedicated almost exclusively to electric power generation, while petroleum devotes roughly three-quarters of its resource to the transport sector and one-quarter to industry (EIA 2019a).

Electrification can affect natural gas consumption in all sectors, lead to changes in natural gas prices within each sector, and cause complex interactions between sectors. For example, direct replacement of natural gas-based technologies for space and water heating can lead to reductions in consumption of natural gas as a fuel in the buildings sectors. Adoption of electrotechnologies could also directly displace natural gas use for industrial applications. And less directly, electrification-driven reductions in demand for petroleum products in the transport sector could

[21] Price elasticity of demand is an economic measure that shows how consumer demand responds to changes in price of a commodity. The measure is calculated as the percentage change in quantity demanded in response to a one percent change in price. Price elasticity of demand is almost always negative, although it is often given in positive terms. Relatively low elasticities are considered inelastic—meaning consumers will not significantly change their demand despite rising prices—possibly because there are relatively few substitutes.
[22] The rest (3%) of gas demand was in the transportation sector.

lead to lower demand for natural gas in industries that rely on natural gas, such as refining. Adding to the complexity, a sizeable fraction of natural gas[23] is produced as "associated gas" in the process of drilling for oil. Transport electrification could reduce demand for petroleum production, which could in turn reduce the amount of associated natural gas produced; in isolation, this would tend to increase the overall price of natural gas. The global nature of those markets further complicates these dynamics (Ishwaran et al. 2017; Ahmad 2017).

Changes in natural gas demand—including from electrification—could also affect its temporal price profile. Historically, gas prices are higher during winter months, especially when storage or pipeline infrastructure is strained, which reflects increased demand for natural gas in space heating during those periods. Natural gas spot prices illustrated in Figure 9 are typically (but not always) higher in the winter months than in the warmer months in temperate regions. Shifts in temporal demand profiles associated with electrification could alter the price response of natural gas. Local demand for gas, along with constraints on pipeline and other gas infrastructure, can also result in significant regional variations in natural gas prices, as is also shown in Figure 9.

Other factors can also impact natural gas price dynamics. The level of liquefied natural gas (LNG) exports is one such variable. Between 2012 and 2018, the EIA commissioned five studies about the impact of LNG exports on the domestic energy sector and macroeconomic conditions, focusing primarily on the price impacts: EIA 2012a; NERA 2012; EIA 2014a; Cooper et al. 2015; NERA 2018. The most recent study (NERA 2018) examined the highest levels of potential LNG exports through a 54-scenario methodology that found the most likely range of LNG exports in 2040 lay between 20 and 40 billion cubic feet per day and that:

- "Increasing U.S. LNG exports under any given set of assumptions about U.S. natural gas resources and their production leads to only small increases in U.S. natural gas prices;" and
- "Available natural gas resources have the largest impact on natural gas prices. Therefore, U.S. natural gas prices are far more dependent on available resources and technologies to extract available resources than on U.S. policies surrounding LNG exports." (NERA 2018).

Finally, in the United States, natural gas prices are impacted by various federal, state, and local policies that are subject to change. For example, the "social license to operate" for gas producers is challenged in some regions of the country (Logan et al. 2012), while the potential for economic development benefits of natural gas might lead to local incentives for increased gas development. These trends are difficult to accurately predict, and their impacts on future gas prices are challenging to quantify.

[23] The EIA reports that in 2017 about 6.6 trillion cubic feet of gross natural gas withdrawals came from oil wells, while total gross natural gas withdrawals from gas wells, unconventional wells, oil wells, and coalbed methane wells were about 33.3 trillion cubic feet (EIA 2019d). Thus, approximately one-fifth of total natural gas production is "associated gas," although this fraction can vary significantly from year to year depending on relative market prices of the two fuels.

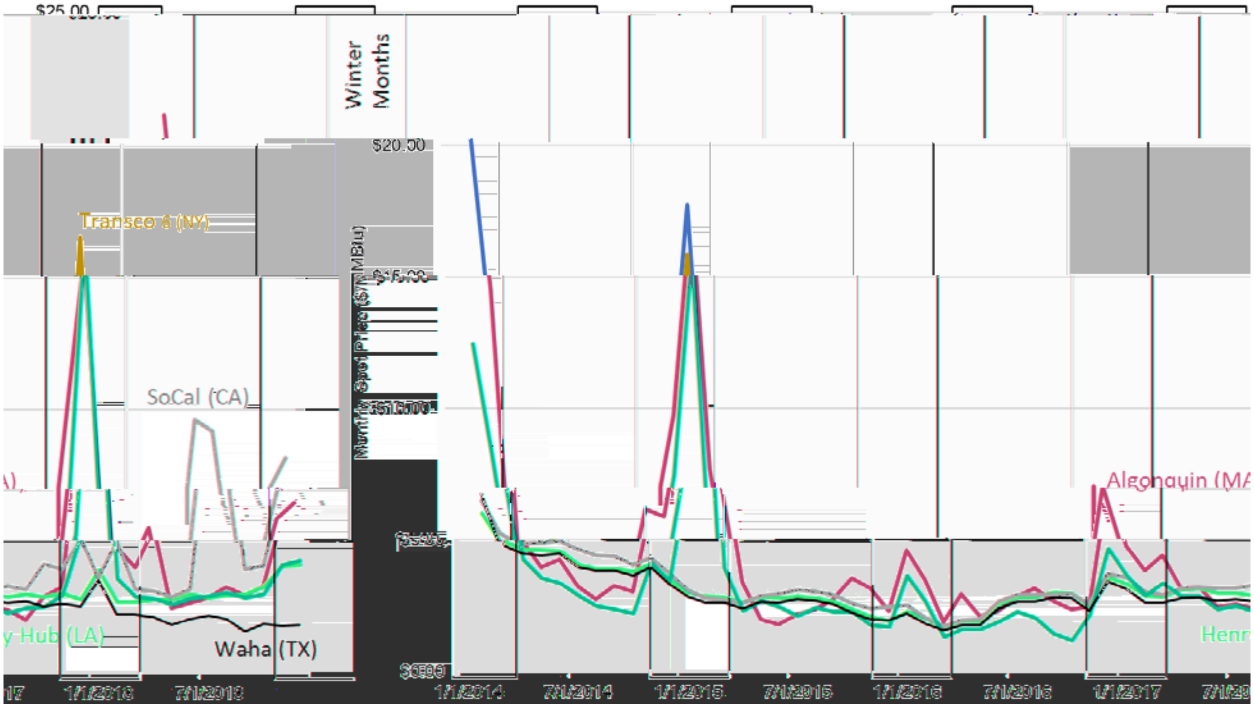

Figure 9. Temporal and spatial variations in select natural gas prices

Data source: Data from S&P (2019)

States where hubs are located are shown in parentheses.
Spot prices are expressed in nominal terms (not adjusted for inflation).

Prices in Southern California spiked in the summer of 2018
due to constraints in underground storage capacity.

In conclusion, modeling and assessing future natural gas price behavior is complex because of (1) its cross-sectoral nature, (2) global and macro-economic effects, and (3) complexities related to production and infrastructure, such as pipeline availability, storage, and purchasing contracts. Because electrification can impact many of these factors, capturing their effects is needed to better understand how electrification might alter natural gas-fired power generation economics.

3.2 Implementation in ReEDS

The ReEDS model by itself does not explicitly include a bottom-up representation of the U.S. natural gas (NG) system, which is influenced by expectations of oil and gas resources, touches all sectors of the economy, and includes complex infrastructure and markets as discussed in Section 3.1. Rather, ReEDS uses a set of supply curves to approximate these complexities. In the 2018 final release version of ReEDS, natural gas prices are determined endogenously using supply curves to reflect the elasticity of natural gas demand and prices from estimated gas consumption in the power sector solely. These supply curves are informed by full economy-wide modeling in the EIA's National Energy Modeling System (NEMS).[24] Specifically, the EIA's

[24] "NEMS Documentation," U.S. Energy Information Administration, https://www.eia.gov/outlooks/aeo/nems/documentation/.

AEO natural gas price and consumption trajectories for the electric sector are used as the "set point" for ReEDS natural gas price-demand linkage (Cohen et al. 2019; Cole, Medlock, and Jani 2016; Logan et al. 2013). For example, if a ReEDS solution results in more power sector natural gas consumption than the AEO scenarios, the resulting natural gas price to the electric sector would be higher than the price reflected in the AEO, and vice versa.

For this traditional representation in ReEDS, the annual average delivered natural gas price for the electric sector in each census division is characterized by both the regional and national electric-sector natural gas demand:

$$\mathrm{P_{r,y}} = \alpha_{r,y} + \beta_{elec}^{nat} \times Q_{y,elec}^{nat} + \beta_{r,elec} \times Q_{r,y,elec} \ [1]$$

where:

- $\mathrm{P_{r,y}}$ is the price of natural gas in dollars per million British thermal units ($/MMBtu) in census division *r* and year *y*
- $\alpha_{r,y}$ is the intercept term of the supply curve[25]
- β_{elec}^{nat} is the inverse elasticity coefficient between electric sector natural gas prices and demand at the national level in units of $/MMBtu per quad
- $Q_{y,elec}^{nat}$ is the total national gas demanded by the electric sector (in units of quadrillion Btus or quads)
- $\beta_{r,elec}$ and $Q_{r,y,elec}$ are the inverse elasticity coefficient and electric sector consumption, respectively, in census division *r*.

National (β_{elec}^{nat}) and regional ($\beta_{r,elec}$) inverse elasticity coefficients are calculated through a regression analysis across an ensemble of AEO2014 scenarios (EIA 2014b)[26] to reflect changes in natural gas price driven by both national and regional electric sector natural gas demand, and the absolute prices $\mathrm{P_{r,y}}$ are impacted by the coefficient $\alpha_{r,y}$, which is calculated from AEO2018 scenarios at different resource levels (EIA 2018a). Typically, different gas resource scenarios from the AEO are represented by "differences choice" of the intercept terms. This method reflects natural gas resource, infrastructure, and non-electric sector demand assumptions embedded within the AEO modeling framework, but it does not explicitly consider how the changes in non-electric natural gas consumption would impact delivered prices for natural-gas fired generation. As a reference for later discussion, we call this method an Electric-Only Elasticity representation.

In the EFS, we updated the representation of natural gas price and demand dynamics in ReEDS to better capture changes in natural gas consumption outside the electric sector in different regions, especially under High electrification. Details of the data and representation can be found in Appendix B. In the updated representation, the delivered natural gas prices observed by the electric sector is similarly determined through regional supply curves, but they are price-

[25] These intercepts are determined such that if power sector consumption (in each census division and year) matches that of the AEO scenario, the same price is reached.
[26] The AEO2014 scenarios are the most recent set of AEO scenarios that contain a wide range of market scenarios for the regression analysis.

responsive not only to ReEDS natural gas consumption in the electric sector, but also to the consumption from outside the sector:

$$\mathrm{P}_{\mathrm{r,y}} = \alpha_{r,y} + \beta_{nat} \times \left(Q_{y,elec}^{nat} + Q_{y,nonelec}^{nat}\right) + \beta_r \times \left(Q_{r,y,elec} + Q_{r,y,nonelec}\right) \quad [2]$$

Where:

- β_{nat} is the inverse elasticity coefficient for national *energy sector*-wide natural gas demand
- β_r is the coefficient for the regional *energy sector*-wide natural gas demand in census division r
- $Q_{y,nonelec}^{nat}$ is national non-electric sector natural gas demand (in quads)
- $Q_{r,y,nonelec}$ is the regional non-electric sector natural gas demand.

All other terms are defined similarly to those in Equation [1]. In the EFS, non-electric sector natural gas consumption estimates are based on the modeled results of the demand-side scenarios from the EnergyPATHWAYS model (Mai et al. 2018). We call this method the Energy Sector-Wide Elasticity representation.

The national and regional elasticity coefficients in this representation are also calculated from the same ensemble of AEO2014 scenarios using a different regression model. The resulting new energy sector-wide β coefficients, together with electric-sector β coefficients from the previous method, are shown in Figure 10. For example, a β of \$0.2/MMBtu per quad means that if demand increases by one quad, the price will increase by \$0.2/MMBtu. Figure 10 shows that price responsiveness to energy sector-wide natural gas consumption in the New England, Mountain, Middle Atlantic and Pacific census divisions is lower than it is to electric sector natural gas consumption only, while the values for the other regions do not change much.

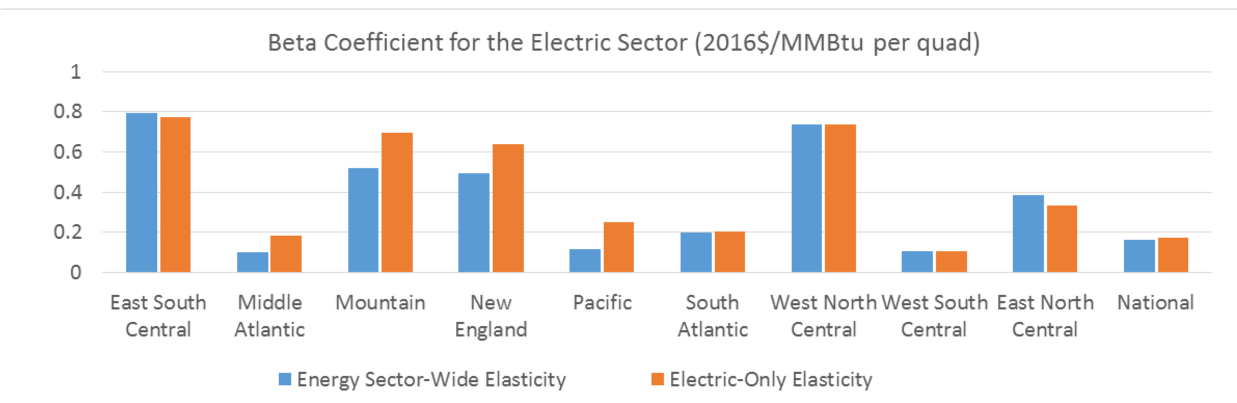

Figure 10. National and regional natural gas inverse elasticity parameters under the Energy Sector-Wide Elasticity representation and Electric-Only Elasticity representation

Though the elasticity coefficients are the same for different electrification scenarios, the intercept term ($\alpha_{r,y}$) includes adjustments by region and year to distinguish different gas resource scenarios and electrification levels. Because non-electric sector natural gas consumption for different electrification levels are exogenously defined from the demand-side modeling results, the two non-electric terms in Equation [2] can be effectively represented by $\alpha_{r,y}{}'$, as shown in

Equation [3]. Similarly, the prices under high and low oil and gas resource cases are also modeled by shifting the effective intercept terms (EIA 2018a).[27] Therefore, the effective alpha value ($\alpha_{r,y}{}'$) corresponds to the natural gas price at zero consumption in the power sector, and it can reflect how delivered natural gas price to power sector would change as a function of different resource and electrification scenarios.

$$\mathrm{P}_{\mathrm{r,y}} = \alpha_{r,y}{}' + \beta_{nat} \times Q_{y,elec}^{nat} + \beta_r \times Q_{r,y,elec}$$
$$\alpha_{r,y}{}' = \beta_{nat} \times Q_{y,nonelec}^{nat} + \beta_r \times Q_{r,y,nonelec} \quad [3]$$

Figure 11 shows how selected regional effective alpha values ($\alpha_{r,y}{}'$ in Equation [3]) shift by electrification levels and oil and gas resource levels. Under the High electrification scenarios, non-electric sector natural gas demand decreases (relative to Reference electrification), resulting in a potential reduction in the delivered natural gas price to the electric sector, which is reflected by the lower alpha values. Similarly, assuming a larger natural gas resource would lead to lower natural gas prices, which are represented by the lower alpha values.

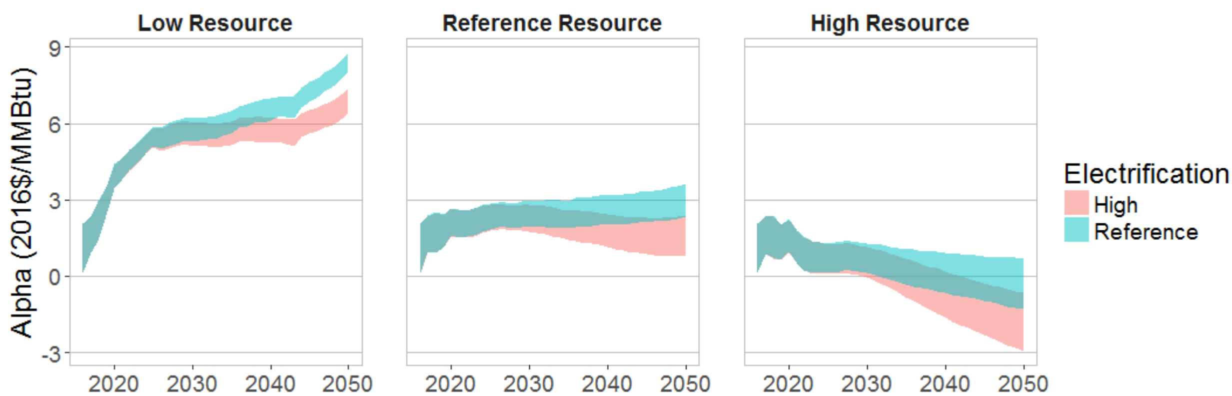

Figure 11. Effective alpha values for AEO Low Oil & Gas Resource, AEO Reference, and AEO High Oil & Gas Resource scenarios (from left to right), with shaded areas showing the range of different regional values across years

Effective alpha values (i.e., $\alpha_{r,y}{}'$ in Equation [3]) correspond to the natural gas price at zero consumption in the power sector

Finally, the natural gas fuel prices include a seasonal price adjustor, making winter prices higher than the natural gas prices seen during the other seasons (see Appendix C). It is important to note that electrification may change the relative seasonal delivered natural gas prices in different regions, but this potential impact is not fully captured in our modeling approach.

[27] Natural gas resource assumptions are derived from the AEO2018, including Reference, High Oil and Gas Resource, and Low Oil and Gas Resource cases.

3.3 Scenario Results

Under our supply curve representation for natural gas prices, the delivered natural gas price to the electric sector is a function of natural gas consumption of different end-use sectors. In particular, higher levels of electrification can impact delivered natural gas prices in two opposite directions: reductions in natural gas consumption in end-use sectors (e.g., through switching from natural gas-based heating technologies to electric heat pumps for space and water heating) could result in depressed natural gas prices, whereas increasing natural gas-based electricity generation to meet demands for the newly electrified loads would lead to higher natural gas prices. Compared to the Energy Sector-Wide Elasticity representation that captures both of these effects, the Electric-Only Elasticity representation reflects only the latter impacts and would therefore likely overestimate the delivered natural gas price to the electric sector under scenarios with increasing electrification. Comparing scenario results from the two different natural gas supply curve methods reveals the implications of these inaccuracies for the scenario outcomes.

Under Reference electrification, the two methods result in similar outcomes with Base Case assumptions, as the magnitude of non-electric natural gas consumption in this case is similar to the AEO cases for which the underlying natural gas supply curve parameters were developed (Figure 12). However, under High electrification, delivered natural gas prices are higher when using the Electric-Only Elasticity method than using the Energy Sector-Wide Elasticity method, the difference of which is about $0.73/MMBtu in 2050. As a result, electric sector natural gas generation and consumption both increase by 26% when incorporating non-electric sector natural gas consumption impacts (relative to Electric-Only Elasticity representation) in 2050. Nearly all of the increase in natural gas consumption is through greater amounts of generation from NG-CC technologies. In fact, the Energy Sector-Wide Elasticity method results in greater deployment of NG-CC capacity as shown in Figure 12. In contrast, NG-CT capacity and utilization do not vary much between the two different methods. As expected, the treatment of natural gas prices has a less-significant impact on NG-CT competitiveness, as this technology is primarily used to provide capacity services rather than energy services.

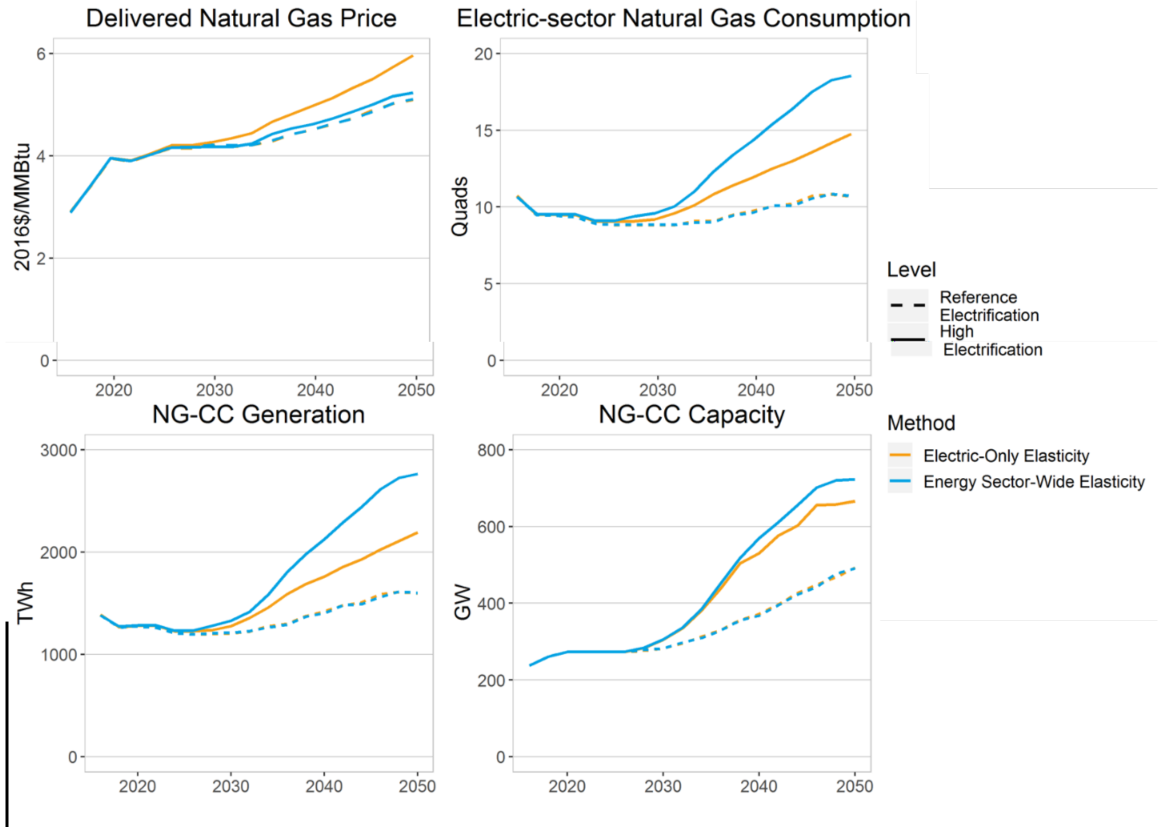

Figure 12. Natural gas delivered price to electric sector (top left), electric-sector natural gas consumption (top right), NG-CC generation (bottom left), and NG-CC capacity (bottom right) in Base Case scenarios, with Energy Sector-Wide Elasticity representation (in blue) and Electric-Only Elasticity representation (in gold)

Under High electrification, the greater amount of natural gas-fired capacity and generation with the more-comprehensive energy sector-wide method, is accompanied by a reduction in renewable energy capacity and, to a lesser extent, coal-fired capacity (Figure 13). In 2050, using the Energy Sector-Wide Elasticity method results in about 56 GW more NG-CC capacity than using the Electric-Only Elasticity method. Along with this increase in NG-CC capacity is a reduction of 188 GW capacity from wind and solar and an 11-GW greater coal retirement with the Energy Sector-Wide Elasticity method. Generation change shows similar trends. These differences in capacity and generation results between the two methods are also reflected in the system costs. Using the Energy Sector-Wide Elasticity method increases non-RE generator investments and fuel costs, but at the same time reduces total renewable investment, O&M costs, and transmission capacity needs, resulting in net changes in system costs of less than 1%.

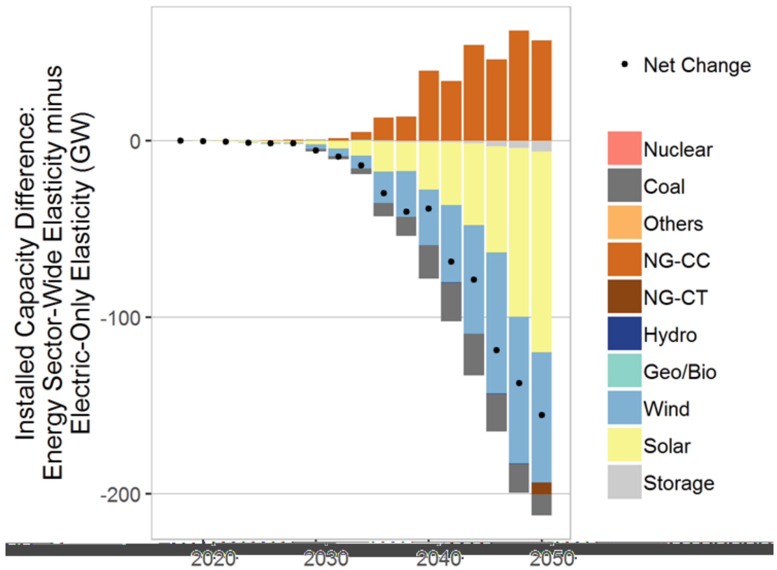

Figure 13. Difference in installed capacity when using the Energy Sector-Wide Elasticity method, as opposed to the Electric-only Elasticity method

Though the Energy Sector-Wide Elasticity representation has limitations (see Section 3.4), these findings suggest that analysis of power system evolution with electrification needs to consider these dynamic factors in fossil fuel prices or else they may inaccurately reflect the economics of power generation technologies—namely by overestimating the cost of natural gas-fired generation and thereby overestimating the economic deployment of other generation sources.

3.4 Limitations of Modeling Natural Gas Economics

As a power sector-only model, ReEDS is inherently limited in its ability to represent the U.S. natural gas system, and some care is therefore needed when interpreting the quantitative conclusions from the ReEDS analysis. Because two-thirds of gas consumption currently occurs outside the power sector, and changes in this consumption—which might occur from widespread electrification—can impact delivered gas prices to power plants, modeling of electrification requires some consideration of these effects.

In particular, ReEDS does not model natural gas supply resources, infrastructure, or delivery mechanisms using bottom-up representations. Instead, regression analysis and parameter calibrations are based on the AEO scenarios, which are developed by the energy sector-wide NEMS model and its more-complete representation of the natural gas system. Because of this reliance on NEMS outcomes, any limitations of NEMS would apply here as well. Furthermore, our methods reduce the complexities from NEMS and apply them to the EFS scenarios to further approximate natural gas supply and demand dynamics. Importantly, our representation does not fully capture the impacts on natural gas distribution companies and, thereby, prices to direct consumers of gas. A reduction in the volume of gas by some consumers might lead to a decline in prices for other consumers, as traditional economic theory holds that as demand decreases prices should decrease. At the same time, however, capital expenses associated with natural gas storage and delivery may need to be covered over a smaller customer base, thereby raising rates for consumers or negatively impacting distributors (Aas et al. 2019). These feedbacks, and the interactions between them, are not fully captured in our supply curves. Readers should recall, however, that the supply curves do capture the overall market impacts of varying natural gas demand outside the power sector: lower demand in those sectors results in lower market prices for the power sector, and vice versa (Logan et al. 2013).

Other scope-related limitations of our modeling include the omission of potential changes in LNG exports or other global trading opportunities.[28] In addition, the scenarios in the EFS consider direct end-use electric-only technologies, but they do not consider growth in all possible technologies, including those fueled by natural gas. This scope excludes opportunities for compressed natural gas vehicles and hybrid natural gas-electric space and water heating technologies. Growth in these and similar natural gas-fueled technologies might decrease the amount of electrification in our scenarios and impact the natural gas supply curves in the ReEDS modeling.

Beyond scope-related issues, we acknowledge other modeling limitations with respect to how we capture the economics of natural gas in our power-sector modeling. First, ReEDS is a deterministic model that may not perfectly reflect more-complex investment decision-making, which often includes assessment of volatility in future prices and associated hedging strategies.[29] Second, seasonal variations in natural gas prices are captured through static multipliers that reflect historical seasonal consumption patterns. The multipliers may become inconsistent with future consumption patterns, especially with electrification-driven changes to those patterns. Third, the EFS analysis is conducted in series, with the electricity "demand-side" scenarios (Mai et al. 2018) used as input for the development of the power sector "supply-side" scenarios. A more-direct reflection of economic equilibrium conditions would require modeling the supply- and demand-sides simultaneously and interactively.

Finally, another important shortcoming of our representation is that we do not explicitly model associated gas. Associated gas accounts for approximately one-fifth of total natural gas output (EIA 2019d) and creates a linkage between oil and gas markets. Changes in the demand for oil could thus impact the availability of natural gas and could affect economics. In particular, the potential for electrification to reduce demand for petroleum-based fuels (primarily in transportation in our scenarios) could have notable impacts on the economic supply of natural gas. All else being equal, a reduction in natural gas supply would result in higher delivered gas prices than those represented in our modeling. This result is further complicated by the global nature of oil markets and interactions between countries and industries.

[28] The AEO scenarios underlying our natural gas supply curve parameters consider LNG exports.
[29] ReEDS has limited foresight for future natural gas prices in its capital investment decisions (for new NG-CC capacity).

4 Demand-Side Flexibility

ReEDS and other national-scale electricity capacity expansion models primarily or exclusively represent supply-side options to meet semi-static power system needs; that is, electricity demand is taken as an exogenous input and supply systems are sized to match such demand. Although exceptions exist, changes to the demand-side in capacity expansion models are typically represented using exogenous assumptions or in a separate model module.[30] This limited scope mirrors the historical development in utility planning and restructured markets where demand-side participation has been limited for most of the history of the U.S. bulk power system (Cappers et al. 2013; Borenstein, Jaske, and Rosenfeld 2002; Greening 2010). However, increased interest in demand response (DR) resources and demand-side participation in electricity markets more broadly have opened the possibility of much more extensive interactions, possibly at shorter timescales, between electricity consumers and producers through market, pricing, or other mechanisms. Widespread electrification is also supporting these trends, especially for end uses that have significant intrinsic flexibility, such as electric vehicles (Hale et al. 2018).

In this section, we (1) review existing demand-side management programs and existing demand response studies; (2) present the representation of demand-side flexibility using load shifting in the ReEDS model; (3) report select scenario results; and (4) highlight limitations in our modeling and identify future research needs around the interaction of demand-side flexibility and electrification.

4.1 Flexibility Potential

4.1.1 Literature Review of Existing Demand Response Programs

Power systems planning is evolving from the non-RE premise that generation is dispatched to match an inelastic demand toward more integrated systems with greater participation from traditionally passive consumers. Interest in flexible demand, or DR, has increased in part as VRE technologies displace non-variable generation, and as distributed energy resources and advanced real-time communication solutions become ubiquitous (Walawalkar et al. 2010). In this context, DR is defined as the ability of an electrical load to respond to a signal from the power system and either shed load or change its power-time profile (e.g., reduce peak power or load shifting in time). In this report, DR is shown to significantly impact bulk power system requirements and operations. DR can support the bulk power system with minimal impact on the service provided by electrified end uses. For example, electric vehicle charging postponement can be accomplished without impacting driving and mobility needs, but simply by leveraging time during which vehicles are already plugged in.

While traditionally power system planning focused on generation and transmission systems, DR efforts date to the 1970s (Lampropoulos et al. 2013). Initial DR involved direct control of loads or electrical equipment and frequency-controlled load shedding (e.g., low frequency

[30] For example, in the U.S. EIA's National Energy Modeling System (NEMS) model, the Electricity Market Module (EMM) is separate from modules that estimate commercial, residential, and industrial energy and electricity demands (EIA 2009).

power-line communications have been used since the 1970s in Europe to remotely control residential water heaters (Delgado 1985)). In the 1980s, utilities started introducing incentives to motivate consumers in reshaping electricity use. These incentives included price-based control, such as time-of-use electricity rates (Delgado 1985). Advances in communication options, adoption of VRE resources, and new electrified end uses, most notably electric vehicles, are allowing DR to mitigate potential integration challenges, especially at the distribution level (Muratori 2018), and provide new values for the grid.

Today, several studies provide quantitative assessment of the overall level of DR available in different areas, their potential applications, and their related values. Nationally, several entities gather and publish data and/or reports on the size, prevalence, usage, and trends of DR programs, including the EIA (2018b), FERC (2018), NERC (2018a, 2018b), SEPA (2018), and others. Numerous other studies have examined opportunities and impacts for DR and flexible loads, including for:

- The industrial sector, especially direct load shedding programs (Shoreh et al. 2016; Samada and Kiliccote 2012; Wierman et al. 2015)
- Residential buildings, including appliances and heating, ventilation, and air conditioning (HVAC) systems (Tarish Haider, See, and Elmenreich 2016; Muratori, Schuelke-Leech, and Rizzoni 2014; Gelazanskas and Gamage 2014)
- Commercial buildings (Siano 2014)
- Electric vehicles, including smart charging of vehicles at residential or other locations and vehicle-to-grid technologies (Richardson 2013; Muratori and Rizzoni 2016; Yilmaz and Krein 2013; García-Villalobos et al. 2014; Zhang et al. 2018)
- Distributed energy storage (Hale, Stoll, and Mai 2016; Ma and Cheung 2016; Stoll, Buechler, and Hale 2017).

Kiliccote et al. (2016) reviewed the suitability of various end uses for DR applications across all sectors. The Brattle Group estimated the existing national capability of load flexibility and projected a tripling of cost-effective load flexibility potential from current levels by 2030 (Brattle Group, 2019). Other efforts have focused more specifically on the DR potential in a specific sector or geographic location. For example, Starke, Alkadi, and Ma (2013) identified the DR potential for various industrial sectors in the Western Interconnection, evaluating the size, controllability, relevant technology, and allowable adjustment duration of electric loads in each sector.

Alstone et al. (2017) characterized the cost, value, and peak savings potential of DR specifically in California, including the capability of fast-response DR to provide ancillary services. This study also defined a taxonomy for describing DR services with four categories: (1) *shape* for load modification through user responses to price or other signals, (2) *shift* for DR that changes load timing from peaks to times of surplus renewable generation, (3) *shed* for loads that can be curtailed to reduce peaks with sufficient notice, and (4) *shimmy* for dynamic load adjustment to manage disturbances in the seconds-hour timescale. The study used characteristic load profiles to forecast future loads and modeled DR supply curves based on a series of assumptions regarding future DR technology, customer acceptance, and costs. These supply curves were then used as inputs in a power system cost optimization model to determine the economic value of DR. This model estimated ~0.3% of daily energy consumption moves due to *shape* and another 2%–3% is available via *shift*. Zhang et al. (2018) show that full management electric vehicle load results in annual savings of several million dollars in generation system costs in California. Coignard et al (2018) show that one-way charging control of electric vehicles in California can achieve much of the same benefit of its Storage Mandate for mitigating renewable intermittency.

In addition to technical studies and data collection, multiple pilot projects have also been introduced to explore the value and technical feasibility and consumer engagement in DR programs (McKenna, Ghosh, and Thomson 2011; Torriti, Hassan, and Leach 2010; Faruqui, Sergici, and Sharif 2010; Faruqui and Sergici 2010). The method to model load flexibility proposed in this report builds on the insights discussed in these studies, in order to examine the impact of flexible load on the power system under different levels of electrification.

4.1.2 Characterization of Demand-Side Flexibility

4.1.2.1 Framework Overview

The representation of demand-side flexibility in our analysis is informed by the vast existing literature and data collected as part of multiple programs. However, our implementation is constrained by the ReEDS modeling framework, which is focused only on *load shifting* over hours. Accordingly, we define "flexible" loads to be those that could conceivably be shifted in time as a response to utility control, time-varying electricity pricing, or other incentives.[31] Load shifting has been assumed to not lead to changes in overall energy use, and we are not accounting for indirect effects of load rescheduling (e.g., HVAC postponement could result in overall load changes due to thermal dynamics, which are not accounted for here).

Our analysis focuses primarily on determining the *value* that flexibility could provide to the bulk power system under various scenarios as opposed to modeling the communication or business model requirements for implementing such flexibility, or the *cost*, which is the compensation required by final consumers to provide flexibility in their electricity consumption. Furthermore, as the demand-side inputs to our power sector models are taken from outputs of EnergyPATHWAYS model (see Mai et al. 2018), our demand-side flexibility characterization is based on the categorization and resolution of the subsectors in that model. We evaluate each of those subsectors to classify whether the subsector load is considered flexible and, if so, we then characterize the flexibility according to the following factors and estimate the amount of available flexible load (illustrated in Figure 14):

- **Potential Flexible Load:** Is the load flexible (i.e., can the load be shifted in time)? If so, what portion of a subsector load can be shifted (as a function of load characteristics and end-use technology distribution within the subsector)? This assessment is done at the subsector level to estimate total potential flexible load. For example, laptop charging was the only portion of the commercial office equipment subsector load that was assumed to be flexible, and thus only that share of the commercial building load was considered potentially flexible.

[31] More specifically, ReEDS "dispatches" the assumed flexible load by moving it to different time-slices to lower overall system costs as is explained in Section 4.2.

- **Technical DR Potential:**
  - **DR Timing:** During which time periods can the load be shifted? For example, commercial air conditioning systems were assumed to only be flexible during working hours.
  - **DR Direction:** How (i.e., in which direction) can the load the shifted? For example, loads could be anticipated (e.g., precooling), postponed (e.g., delay on electric vehicle charging), or moved in either direction (e.g., shifts in industrial production times).
  - **DR Duration:** For how long can the load be flexed? For example, a thermostat setpoint might be allowed to float outside thermal comfort bands for one hour, whereas residential clothes drying could be postponed for longer.
- **Customer Participation:** Finally, the "technical" DR potential is adjusted based on how many customers participate/engage in DR. Different participation rates are assumed for various scenarios. The potential flexible load is multiplied by the customer participation rate to determine the actual flexible load in each scenario. Details for these estimations are provided below.

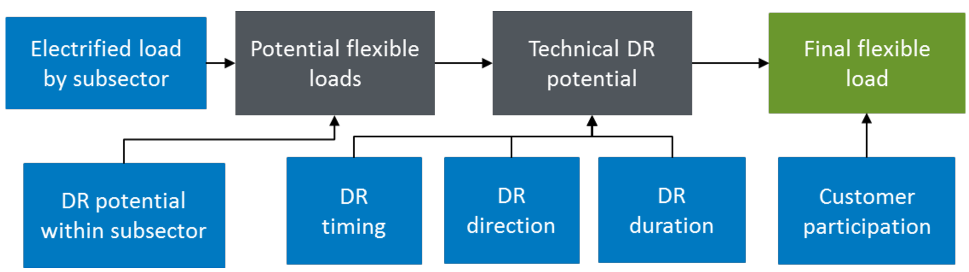

Figure 14. Flow chart of assumptions used to determine final flexible load used in modeling

Blue boxes indicate inputs and assumptions, gray boxes indicate intermediate outputs, and the green box represents the final output. The application of timing and duration constraints depends on temporal resolution of the model; see Section 4.2 for discussion of how duration is treated within the ReEDS modeling framework.

4.1.2.2 End-Use Technology Assumptions

Assumptions regarding the flexibility of subsector loads were made based on a mixture of expert judgment, reasonable proxies, and available literature and data sources. Appendix D provides details for all subsectors modeled.

Residential and Commercial

Heating, ventilation, and air conditioning (HVAC) loads were assumed to have one-hour flexible durations, roughly corresponding to a 30-minute precooling/preheating and then allowing the thermal setpoint to float outside thermal comfort bands for an additional 30 minutes afterward. This 30-minute duration was chosen to correspond to cycle times of air conditioners in some utility DR programs (e.g., SCE 2019). Commercial refrigeration was only allowed to precool, meaning load could only be shifted earlier in the day. Water heating was assumed to be more flexible in terms of duration (four hours for commercial and eight hours for residential) for when its electrical load could be shifted. Residential refrigerators and freezers were assumed to have flexible defrosting cycles that could be moved by eight hours.

Dishwashing was assumed to be delayable by up to eight hours, which corresponds to delaying overnight or over the workday. Washing and drying of laundry were also assumed to be flexible by up to eight hours. Among office equipment, only laptop charging was assumed to be flexible. The portion of the PC equipment load attributed to laptop charging was determined using available U.S. Environmental Protection Agency ENERGY STAR data on laptop/desktop/monitor energy consumption characteristics[32] and 2012 EIA CBECS microdata on laptop usage (EIA 2012b).

Industrial

Data on industrial load flexibility were adapted from the assessment of industrial DR by Starke, Alkadi, and Ma (2013); the authors of this Oak Ridge National Laboratory (ORNL) report (1) review industrial sectors' potential for DR and identify the resource capable of providing DR, the maximum allowable DR duration, (2) estimate the portion of the total electricity demand associated with the flexible resource, and (3) assess the flexible portion of the electricity demand of the resource. Where possible in our work here, we matched EnergyPATHWAYS subsector loads to the subsectors in Starke, Alkadi, and Ma (2013), with two exceptions. First, we assumed all thermal loads in the EnergyPATHWAYS industrial subsectors have the same flexibility characteristics as the electric furnace of Standard Industrial Classification (SIC) 32 in the ORNL report. Second, we assumed the machine drive subsector load has the same flexibility characteristics as the average of all sectors in the ORNL report. Agricultural subsector electrical loads in EnergyPATHWAYS consisted of only agricultural buildings and irrigation pumping. Assuming pumping loads were mostly flexible and agricultural buildings had flexibility characteristics similar to those of other commercial buildings, the potential flexibility of agricultural loads was estimated at 50%.

Transportation

Light-duty plug-in electric vehicle were assumed to have an allowable flexible duration of eight hours, which corresponds to having multiple charging options (e.g., workplace and home charging) or not needing to charge before every trip. For context, data from the Census Bureau's American Community Survey indicate that ~75% of people have commute times less of than 35 minutes,[33] which would be a sufficiently short duration (and corresponding distance) for most plug-in electric vehicles to complete a round-trip commute without needing recharge during a workday. To be conservative, 75% was adopted as the flexible portion (DR potential) of the light-duty vehicle electric load. Medium- and heavy-duty trucks were assumed to only be flexible during overnight charging, when the vehicles are assumed to be parked, and all electrified medium- and heavy-duty trucks are assumed to be potentially able to participate in DR (see participation rates assumptions in the following section).[34]

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[32] See "Computers," ENERGY STAR, https://www.energystar.gov/products/office_equipment/computers

[33] Based on a calculation using data from "American Community Survey (ACS)," U.S. Census Bureau, https://www.census.gov/programs-surveys/acs

[34] The allowable flexibility duration was assumed to be the difference between the number of hours in the time-slice (see Section 4.2) and the time required for complete charging, with the vehicle charging times taken from the representative vehicles listed in a previous EFS report (Jadun et al. 2017).

End-use technology assumptions for participation in DR are summarized in Table 1. Some dimensions are reported as ranges due to heterogeneity of assumptions for different end uses. Appendix D provides details on each end use modeled.

Table 1. Demand-Side Flexibility Assumptions by End-Use Subsector

Load	DR Potential	DR Timing	DR Direction	DR Duration
Residential HVAC	100%	All day	Either	1 hour
Residential appliances	17%–100%	All day	Either/postponement	8 hours
Commercial HVAC	100%	Work hours only	Either	1 hour
Commercial refrigeration	100%	All day	Anticipation	0.5 hours
Commercial office equipment	7%	Work hours only	Postponement	6 hours
Industrial	2%–100%	All day	Either	1–8 hours
Transportation (light-duty vehicles)	75%	All day	Either	8 hours
Transportation (medium and heavy-duty vehicles)[35]	100%	Night only	Postponement	4–7 hours

4.1.2.3 Participation Rate Assumptions

Customer participation rates are used to quantify the fraction of load that is allowed to be shifted in each scenario, and the rates represent the portion of consumers that will alter their consumption or allow it to be altered in each subsector. Actual participation rates will depend on the incentive structure in place and on consumer attitudes toward such programs. Early pilot studies show that electric vehicle consumers engage significantly in demand response programs and are willing to provide charging flexibility (Kaluza, Almeida, and Mullen n.d.). Other subsectors or end uses might experience lower participation due to greater impact on lifestyle or industrial operations (e.g., HVAC control) (Faruqui and Sergici 2010). We apply the participation rates to the technical DR potential within the respective subsector, as calculated from the DR potential, timing, and duration assumptions described above.[36]

Given the uncertainties with future participation in demand-side flexibility programs, we model three levels of flexibility—Current, Base, and Enhanced flexibility—which differ by the full participation rate that is achieved (Table 2, next page). Although all three levels are informed by existing programs and previous studies as described below, we acknowledge that there are significant uncertainties in future participation, and we do not claim that any set of assumptions is more likely than the other. Under Current flexibility assumptions, customer participation rates are estimated using current national customer participation in DR programs as a proxy, with data on residential, commercial, and industrial participation taken from 2016 EIA 861 survey data (EIA 2018b). Light-duty vehicles are assumed to be individually owned and to match residential participation rates, whereas medium-duty and heavy-duty vehicles are assumed to

[35] Buses are not included in this category.
[36] The participation rates do not represent the sales shares of flexibility enabled technology, for example, and we do not estimate stock turnover for this assumed technology.

be commercially owned and to match commercial participation rates. We assume Current participation remain constant through 2050.

In the Base and Enhanced flexibility cases, participation rates in each sector increase from current values in 2018 to a given participation level by 2050. Customer participation rates of 20% in 2050 for Base flexibility are meant to reflect the higher range of DR participation rates across states in the 2016 EIA 861 data (EIA 2018b); total DR participation rates by state ranges from 8% to 53% for the 10 states with the highest participation.[37] In the Enhanced scenario, we assume a 90% participation rate for light-duty vehicles based on a PG&E and BMW study in which vehicles were able to respond to over 90% of DR events (Kaluza, Almeida, and Mullen n.d.). Customers participation rates for medium- and heavy-duty vehicles, and the residential, commercial, and industrial sectors are assumed to reach 60% by 2050 to reflect the maximum end of current rates from the 816 EIA 861 survey data (EIA 2018b), which we assume to represent successful implementation of DR programs: the maximum rate by state is 53% (Delaware), and the maximum rates by state and sector are 63% (Maryland residential), 76% (California commercial), and 45% (Nevada industrial). These exogenously defined participation rates are used to bound a range of plausible scenarios rather than attempt to economically model customer participation scenarios as in Alstone et al. (2017) or the Brattle Group (Brattle Group, 2019). Use of smart devices, such as smart thermostats, may further improve customer participation rates—resulting in higher numbers than those estimated here—by enabling DR without causing additional inconvenience to the end user (Hargreaves, Nye, and Burgess 2013; Ramanathan and Vittal 2008).[38] Section 4.2 further describes how these flexibility assumptions are used to develop inputs for ReEDS, including the resulting effective percentage of load assumed to be flexible.

Table 2. Assumed Flexible Load Customer Participation Rates for Current, Base, and Enhanced Flexibility Scenarios

Sector	Current (2018–2050)	Base (by 2050)	Enhanced (by 2050)
Residential	6%	20%	60%
Commercial	5%	20%	60%
Industrial	7%	20%	60%
Transportation (light-duty vehicles)	6%	20%	90%
Transportation (medium- and heavy-duty vehicles)	5%	20%	60%

Under Base and Enhanced flexibility assumptions, participation rates start at Current levels in 2018 and increase linearly to the values shown by 2050.

[37] The average rate for the top 10 states is about 20%.
[38] Potential barriers to smart device adoption are analyzed by Balta-Ozkan et al. (2013).

4.2 Implementation in ReEDS

Demand-side flexibility in ReEDS is represented as load shifting between time-slices within a representative day.[39] For the EFS, we focus on several key model features to better understand the electric sector impacts of electrification under increased demand-side flexibility, including:

- Quantification of flexible load from EnergyPATHWAYS (see Mai et al. 2018) using the subsector assumptions described in Section 4.1.2
- Application of flexible load constraints controlling how load can be optimally shifted throughout the day (based on assumptions described in Section 4.1.2)
- Use of the endogenously optimized flexible load profiles within the model to estimate planning reserves, curtailment, and capacity values of VRE resources.

These features allow the model to endogenously consider how load flexibility might affect resource adequacy (by impacting both load shape, in particular load peak, and the capacity credit of VRE resources), operating reserve needs, and dispatch decisions including renewable curtailment (by changing the alignment of load and generation profiles), and how these effects factor into future investment and dispatch decisions. The remainder of this section details the implementation of demand-side flexibility in the ReEDS model.

The supply-side scenarios presented in this report rely on electricity consumption from the demand-side technology adoption scenarios from Mai et al. (2018) using the EnergyPATHWAYS tool. EnergyPATHWAYS estimates hourly electricity consumption profiles for each subsector represented by state. To develop load profiles for electrification scenarios, we calculate the incremental growth in the Medium and High electrification scenarios from Reference and add that load growth to the default load profile used in ReEDS. The ReEDS default profile is used for Reference electrification. Additionally, we use the hourly subsector distributions from EnergyPATHWAYS to determine subsector load and the subsector-specific flexibility potential and constraints based on the assumptions described above. See Appendix A for details about this methodology.

Flexible load inputs for ReEDS are determined from the adjusted load profiles described above, with the estimated portion of flexible load being based on assumed subsector DR potential, timing, duration, and customer participations rates (Section 4.1.2). The annual flexible load is calculated by multiplying the assumed portion of subsector flexible load by the total time-slice load, respecting the constraints on the timing of flexibility for each subsector (e.g., only nighttime load is assumed to be flexible for charging medium- and heavy-duty vehicles, which mainly operate during the day). The total possible flexible load by subsector is multiplied by the customer participation rates for the given year (Table 1). We then adjust this flexible load based on the time-slice definitions in ReEDS: the load shift duration is divided by the duration of the time-slice to estimate the fraction of load that can be shifted to another time-slice. For example, if a given load with a 30-minute shift duration occurs during a time-slice representing a four hour

[39] In the ReEDS model, each model year is disaggregated into 18 time-slices, where each of the four seasons is represented by 4–5 time-slices representing different diurnal periods. See Section 2.2 for details.

period, one-eighth of the load in the time-slice is assumed to be shiftable out of the time-slice.[40] Directional constraints are applied to each subsector to specify how load can be shifted throughout the representative model day. Finally, flexible load is aggregated by sector and flexibility direction ("postponement," "anticipation," "either") for inputs into ReEDS.

Figure 15 shows an example of how the hourly load data are translated into the ReEDS time-slice structure. It also shows an example of how the flexible portion of the load is dispatched in ReEDS—considering the constraints on flexibility and factors related to the generation mix (e.g., amount and profile of VRE generation). For example, among the five time-slices in the representative summer day, the summer peak time-slice (fourth time-slice) has around a quarter share of flexible load in the original, unoptimized load profile. After shifting determined in the model optimization, a large portion of this flexible load is shifted to other time-slices within the summer day (i.e., the black dot of this fourth time-slice is lower than the bar height, whereas the black dots in the first, second, and third time-slices increase).

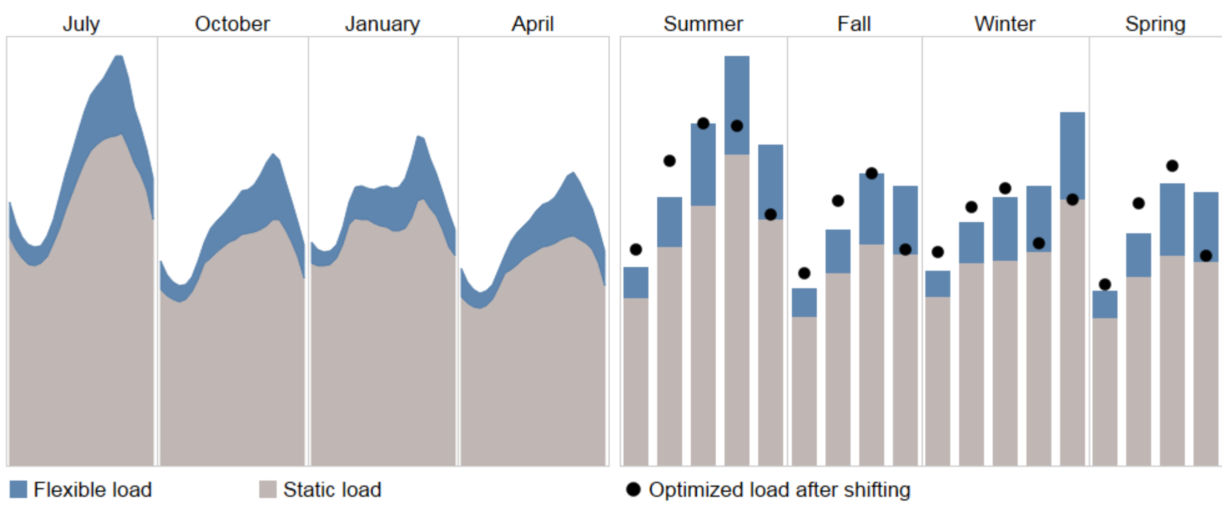

Figure 15. Representative input hourly load profile from EnergyPATHWAYS (left), input time-slice and optimized time-slice profile in ReEDS (right)

The optimized time-slice profile differs between scenarios, as it is an endogenous model decision. This example shows Enhanced flexibility.

To control how load shifting can occur within the model, we enforce two sets of constraints. The first set limits how load can be shifted across time-slices according to the noncontinuous time-slices representation in ReEDS and the assumed DR direction of flexible load. As ReEDS considers a representative day for each season, we only allow flexible load to shift throughout the representative day within each season, and not to shift across seasons. We also constrain load to move to only the appropriate time-slices based on the DR direction designation of anticipation, postponement, or either, where "either" is classified into daily (all time-slices) and

[40] The temporal resolution of ReEDS requires this approximation so as to not overestimate the load shifting potential. Higher temporal resolution modeling, such as is planned in the EFS, would eliminate the need for this scaling.

adjacent (only the previous and next time-slices). The second set of constraints ensures the peak load for a given solve year—used to determine planning reserves—increases if sufficient flexible load is moved to a particular time-slice. For example, if shifting load to an afternoon hour has operational cost savings for a region with high solar resource in summer, the optimization must also consider the potential impact on peak load due to this shift.[41]

Load shifting alters the underlying demand profile that must be met by the system, which in turn, affects system resource adequacy. In ReEDS, the hourly demand profile is used to calculate peak load, capacity credit of VRE resources, operating reserve requirements, and curtailment.[42] To account for the impact of flexible load on these parameters, we adjust the hourly load profile used in the ReEDS optimization with the endogenously optimized flexible load profile for each solve year.[43] ReEDS solves for the optimal load shifting at the time-slice level, so to disaggregate flexible load to an hourly profile, we assume the total megawatt-hours (MWh) of flexible load shifted to a time-slice are allocated evenly to each hour represented within that time-slice.[44] The resource adequacy and system operation parameters described above are then calculated with the adjusted hourly load profile that includes the optimized flexible loads.

The dispatch decisions for flexible load in ReEDS are based on the overall objective function and the constraints in the model: to minimize the total system-wide costs, subject to power sector constraints as well as the demand-side flexibility constraints described above. Note that this system perspective may not align with the consumer perspective. Absent incentives to align individual consumers' behavior with the optimized system perspective, our method would likely overestimate the extent of the flexibility available from the demand side. This and other limitations associated with our approach are discussed in Section 4.4.

Demand-Side Flexibility Potential for the EFS

The final demand-side flexibility potential for the EFS scenarios is determined from the electricity consumption of the demand-side scenarios documented by Mai et al. (2018), the flexibility assumptions in Section 4.1.2, and the EnergyPATHWAYS-to-ReEDS translation input described above. The set of demand-side scenarios include three levels of electrification, referred to as Reference, Medium, and High electrification, and three levels of end-use technology

[41] The ReEDS linear optimization is modeled at the time-slice level; therefore, the inter-time-slice variability of the shifted load is not captured and the impact on peak load may not be estimated correctly. For example, the model considers shifted load at the aggregated time-slice level, so the effect on peak load is estimated as the average of shifted load across all hours in the time-slice. In reality, load varies within the time-slice, so the actual peak after shifting may higher than the original peak plus the average of the shifted time-slice load.

[42] Detail on how ReEDS estimates these parameters is provided by Frew et al. (2017) and Zhou, Cole, and Frew (2018).

[43] Because the optimization module in ReEDS is linear, parameters that capture the impacts of flexible load are updated in between optimization iterations. Specifically, in each year we estimate the amount of flexible load that must be added to the baseline load profile by scaling the flexible load profile (shape) determined in the previous solve year so that the total electricity consumption matches the amount of flexible electricity available in the current year.

[44] The translation between time-slice to hourly resolution is a simplification that will be examined in future analysis in the EFS using higher-fidelity models.

advancement, referred to as Slow, Moderate, and Rapid advancement. Table 3 shows the annual and coincident peak load for these scenarios without any assumed flexibility.[45]

We apply subsector flexibility assumptions from Section 4.1.2 to estimate the amount of flexible load for each electrification scenario at three levels of flexibility: Current, Base, and Enhanced. Figure 16 shows the total flexible load and the ratio of flexible load to total load for each flexibility scenario and each of the three electrification scenarios (with Moderate end-use technology advancement). Under Enhanced flexibility, flexible load makes up 8% of total load under Reference Electrification and 17% under High. In each flexibility scenario, higher electrification levels lead to higher proportions of flexible load, suggesting that the end uses electrified in these scenarios have greater potential to contribute to system flexibility. This result is largely driven by electrification in transportation, which has the highest share of flexible load by sector (Table 4). In the Reference scenario in 2050, each 1.00 MWh increase in load from the previous year comes with a 0.07 MWh increase in flexible load under the Base flexibility case, and 0.25 MWh in the Enhanced case. Under High electrification, the corresponding flexible load increases are 0.12 MWh (Base) and 0.53 MWh (Enhanced) per MWh total load growth.

Table 3. Annual Load and the Peak Load for Electrification and Technology Advancement Scenarios[a]

	Electrification	End-Use Technology Advancement	Annual Demand [TWh]	Peak Demand [GW]
2018			3,710	670
2050	Reference	Rapid	4,760	850
		Moderate	4,790	860
		Slow	4,840	880
	Medium	Rapid	5,660	1,080
		Moderate	5,800	1,130
		Slow	6,030	1,220
	High	Rapid	6,460	1,250
		Moderate	6,700	1,320
		Slow	7,060	1,450

For consistency, 2018 estimates are based on modeled results and not historical data.

[a] Demand values represent end-use demand. The total amount of generation required in the model will exceed these values because of transmission and distribution losses. Transmission losses are endogenously represented in the model and depend on the amount (and distance) of energy transfers. Distribution losses are simply assumed to be 5.3% in all years and scenarios.

[45] As described in Section 4.2, we apply the incremental load growth from the scenarios in Mai et al. (2018) to the default ReEDS load profile to determine the load profiles used in this analysis. Therefore, the resulting values shown in Table 2 differ slightly from those presented in Mai et al. (2018).

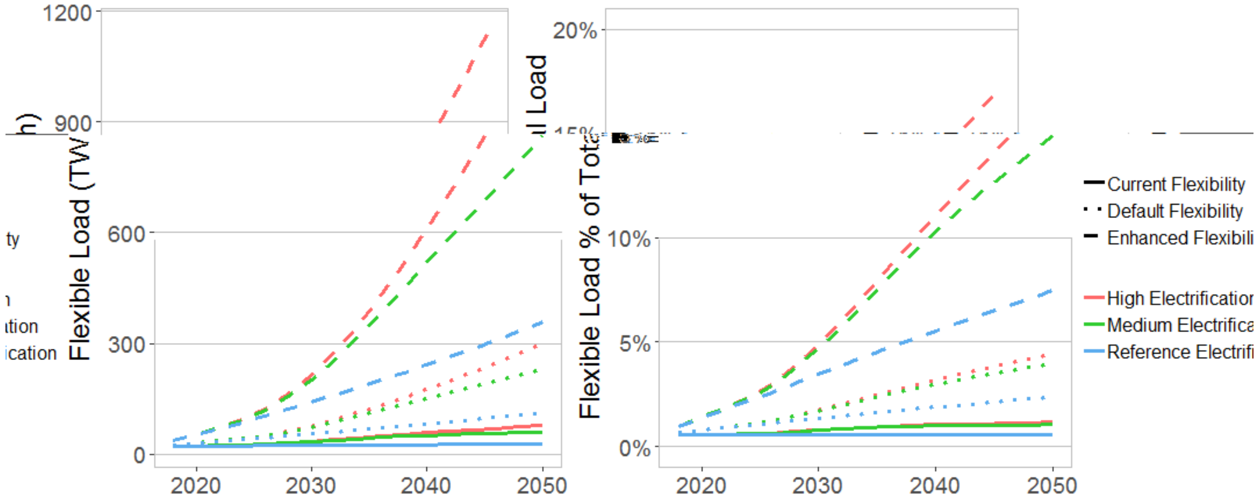

Figure 16. Total flexible load (left) and flexible load share of total load (right)

Only moderate end-use technology advancement cases are shown.

Table 4. Percentage of Sectoral and Total Load Assumed Flexible in 2050 By Flexibility Scenario

	Reference Electrification			High Electrification		
Sector	**Current**	**Base**	**Enhanced**	**Current**	**Base**	**Enhanced**
Transportation	4%	13%	58%	3%	12%	51%
Residential	1%	4%	13%	1%	4%	12%
Commercial	<1%	1%	2%	<1%	1%	3%
Industrial	1%	2%	5%	1%	2%	5%
Total	**1%**	**2%**	**7%**	**1%**	**4%**	**17%**

The share of flexible load within each sector depends on both the subsector level consumption and flexibility assumptions. For example, within the transportation sector, the High electrification scenario has higher shares of medium- and heavy-duty vehicles, which we assume to be less flexible than light-duty vehicles. Similarly, within the residential sector, space heating makes up a higher share of consumption under High electrification, which we assume to be less flexible than water heating and air conditioning.

The potential impact of load shifting on peak load is highlighted in Table 5, which shows the portion of flexible load in the winter and summer super-peak time-slices modeled in ReEDS (see Section 2). The table shows the unoptimized load, before any shifting has occurred, and it provides an upper-bound estimate for the potential reduction of system capacity under increased demand-side flexibility. The extent to which this potential is reached depends on how this load gets optimally shifted within the model, considering the impacts on capacity requirements, as well as on operating reserves and dispatch costs. And, of course, moving demand from one time period to another could make demand greater in the new period, therefore the peak reduction potential suggested by Table 5 is likely higher than what can be realized.

Table 5. Percentage of Summer and Winter Super-peak Load Assumed Flexible in 2050 by Flexibility Scenario

	Reference Electrification			High Electrification		
Super-peak Time-slice	**Current**	**Base**	**Enhanced**	**Current**	**Base**	**Enhanced**
Summer	<1%	3%	9%	2%	6%	21%
Winter	<1%	3%	8%	2%	6%	22%

The assumed load flexibility is driven by the electrification of various end uses in each scenario. Figure 17 and Figure 18 show the distribution of flexible load across the top 15 subsectors for the Base flexibility case for the Reference and High electrification scenarios in 2050. Under Reference electrification, 58% of the flexible load is from the residential sector, and the remaining 19%, 13%, and 11% are attributed to the industrial, commercial, and transportation sectors respectively. The High electrification scenario, as described in Mai et al. (2018), assumes higher penetrations of plug-in electric vehicles, especially in the light-duty segments. This growth of plug-in electric vehicles leads to flexible load in the High electrification scenario that is dominated by light-duty vehicles, which make up over 64% of the flexible load. The distribution of flexible load by subsector is similar in the Enhanced flexibility case; the absolute quantity of flexible load increases as a result of the higher participations rate assumptions across sectors. And light-duty vehicles make up a larger portion of the flexibility potential (15% under Reference Electrification, 72% under High) because of the higher customer participation rate of 90% (compared to 60% in other sectors). Appendix D includes similar details for all subsectors and flexibility scenarios.

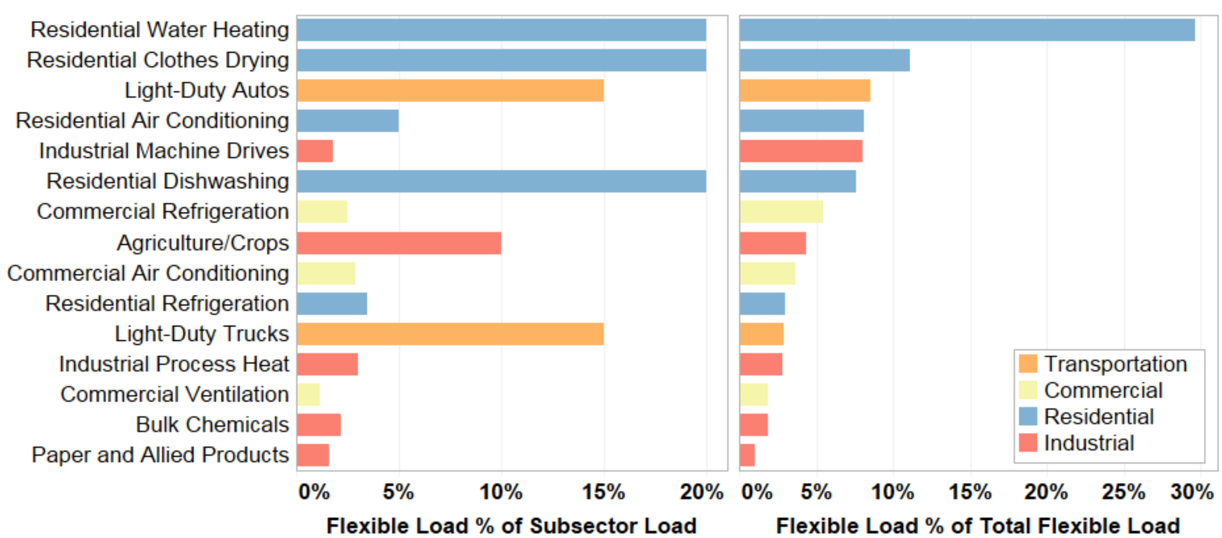

Figure 17. Flexible load by top subsectors for Reference electrification and Base flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible.
The right panel shows the percentage of total flexible load attributed to the respective subsector.

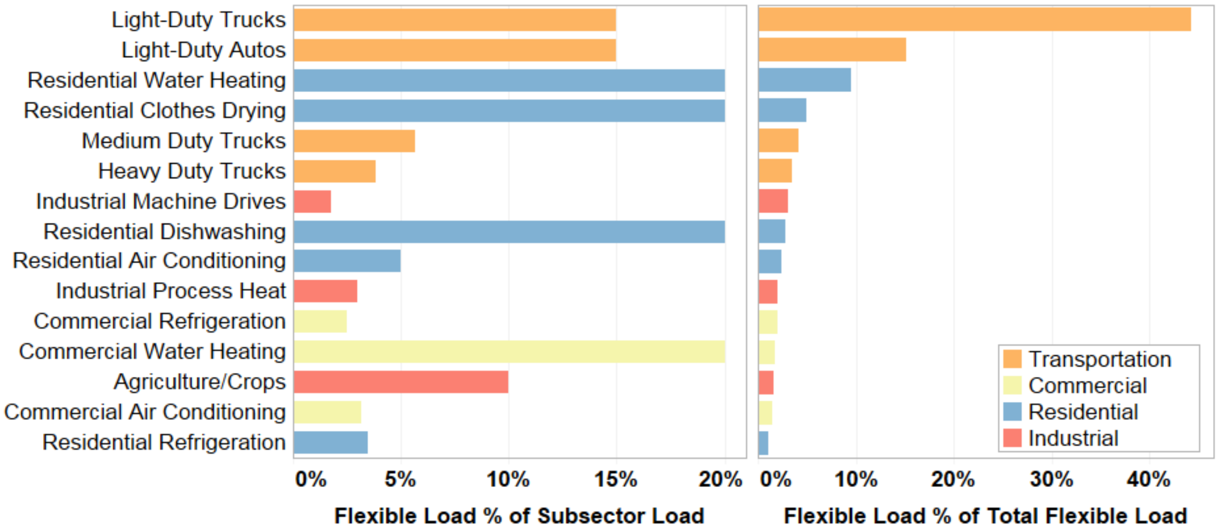

Figure 18. Flexible load by top subsectors for High electrification and Base flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible.
The right panel shows the percentage of total flexible load attributed to the respective subsector.

In addition to the total quantity of flexible load, different levels of end-use electrification also impact the distribution of flexible load across various duration and timing levels (Figure 19).[46] As described above, the residential sector accounts for most flexible load under Reference electrification. Almost 70% of the total flexible load, which primarily includes residential water heating, dishwashing, and clothes drying, can be shifted 4–8 hours. The remaining 30% of flexible load—made up mostly of load for residential and commercial air conditioning, commercial refrigeration, and industrial machine drives—can be shifted less than 1 hour.[47] Under High electrification, most additional flexible load is attributed to the transportation sector. As a result, the distribution of flexible load is more heavily weighted toward the assumed load shifting duration of electric vehicles; over 75% of the flexible load can be shifted 7–8 hours, while 13% of load can be shifted less than 1 hour. Given the time-slice representation in ReEDS, we note that the representation of the shorter duration flexible loads is imperfect, as load can be shifted from one 4–8 hour time-slice to the next (which may not be possible when modeling at the hourly or subhourly time scales).

[46] Appendix D includes all subsector-level assumptions about the direction and duration of flexible load.
[47] Most of the remaining flexible load in the Reference electrification case has a duration of 24 hours (11% of load, mostly from residential clothes drying) and 12 hours (11% of load, from light-duty vehicles).

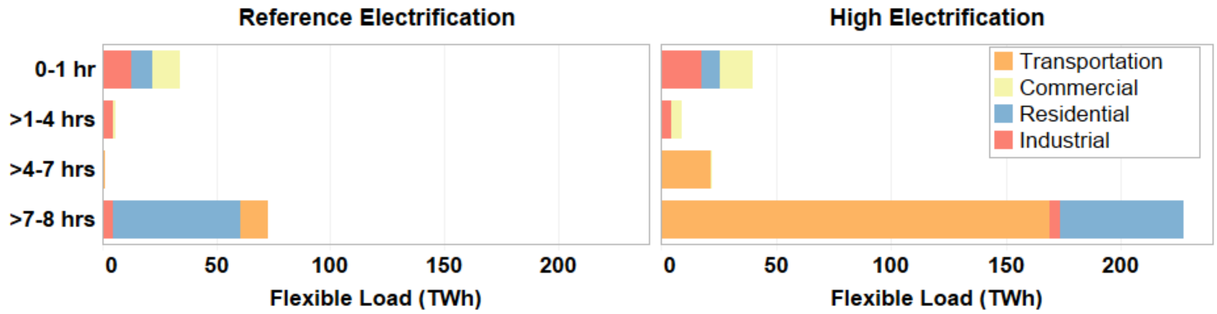

Figure 19. Flexible load by duration for Reference (left) and High electrification (right) with Base flexibility in 2050

As with total load, the absolute amount of flexible load varies by time of day, season, and region, depending on the adoption of end-use electric equipment. The variation is primarily driven by the changing levels of service demand—and as a result, changing levels of flexible load—across these temporal and geographic scales, as we do not vary flexibility assumptions seasonally or regionally. In general, with greater electrification, flexible load makes up the largest portion of total load in the afternoon and evening hours, which is mostly because the higher plug-in electric vehicle charging occurs during that time. As expected, there is also greater flexibility from commercial end uses in the workday time-slices (morning and afternoon). Seasonally, a slightly higher proportion of flexible load is attributed to the residential sector in the winter and summer months, resulting from the potential flexibility in heating and cooling applications. This increase in winter flexibility from the residential sector is more pronounced on a regional level, as colder climate regions in the Northeast have higher proportions of heating loads than warmer climates.

4.3 Scenario Results

Demand-side flexibility has the potential to affect the evolution of the power system by influencing investment and dispatch decisions. The representation of flexible load discussed here—including estimation of total flexible load, load shifting constraints, and the effects on system resource adequacy—allow us to estimate these potential impacts. Future work will more fully explore power sector implications from demand-side flexibility under a range of scenarios, including those with increased electrification. In this section, we summarize key results enabled by the modeling updates implemented for demand-side flexibility.

The flexible load implementation in ReEDS, which implies a system perspective, is used to assess the value of demand-side flexibility, given the assumed potential. The system benefits of flexible load include enabling of more efficient economic dispatch and reductions of capital expenditures to meet planning and operating reserves. These benefits are realized by better aligning electricity demand with the availability of lower-cost generation and reducing peak load. These changes in demand profiles, particularly during peak or stressful periods, could lead to a reduction in reserve requirements and a corresponding reduction in new capacity investments to meet reliability and resource adequacy requirements.

To illustrate the impact of demand-side flexibility, we compare scenario results across two primary dimensions: flexibility level (Current, Base, and Enhanced) and electrification level

(Reference and High). Results of this comparison show that increasing the amount of demand-side flexibility reduces the overall amount of capacity requirement for all electrification levels. Figure 20 summarizes the capacity and generation findings for Base and Enhanced flexibility. Total capacity in 2050 decreases by 1% with Enhanced Flexibility compared to Base under Reference electrification, and it decreases by 6% under High electrification.

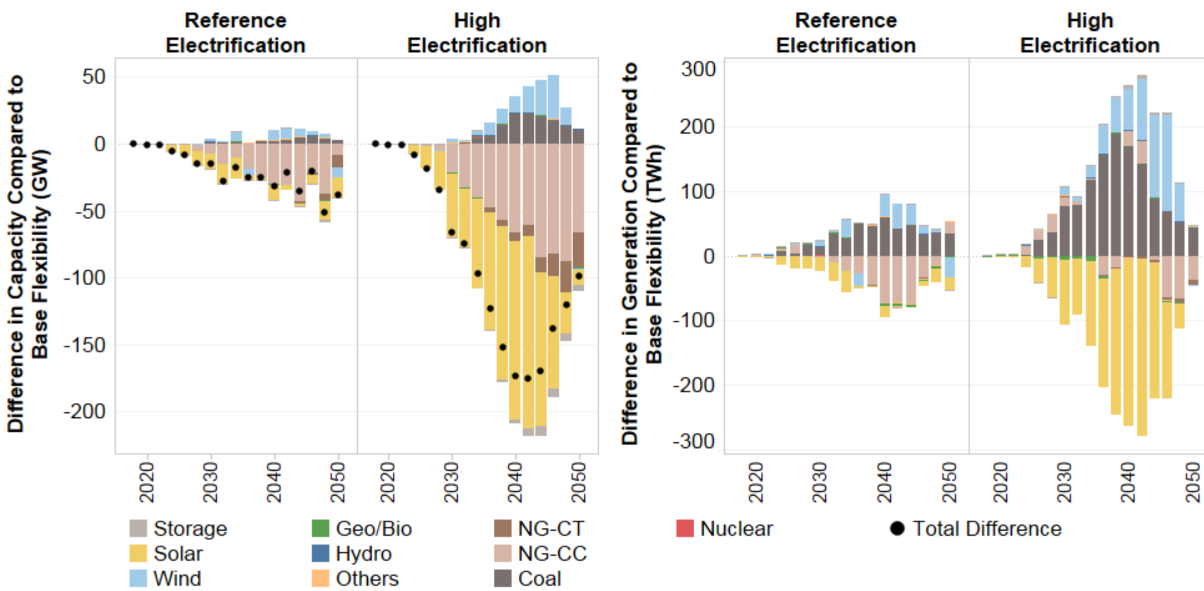

Figure 20. Difference in 2050 capacity (left) and generation (right) of Enhanced flexibility from Base flexibility for Reference and High electrification

Increasing demand-side flexibility also affects the optimal dispatch decisions. The modeling changes allow load to be shifted economically to utilize existing assets, particularly coal-fired generators in the near term, which have higher capacity and generation under higher flexibility. Increased enablement of load shifting also reduces the curtailment rate of VRE generators by better aligning load with the VRE resource. In our current modeling implementation, demand-side flexibility competes with energy storage, which generally results in reduced storage capacity with increased flexibility (both in absolute terms and as a percentage of solar capacity).

Figure 20 shows the impacts of demand-side flexibility on *annual* generation, but optimal load shifting varies both diurnally and geographically. In general, load is shifted from the evening and afternoon time-slices, when inflexible load usually peaks, to the overnight and morning hours. However, these decisions vary by region, depending on the resource availability and flexible load profiles. Figure 21 shows the difference in time-slice dispatch by generation technology between the Enhanced and Current flexibility cases under High electrification for select census divisions chosen to illustrate the variations in optimal load shifting decisions with different regional generation mixes.[48] For example, increased flexibility leads to a more optimal dispatch of generating units in the East South Atlantic and East North Central census divisions: lower peak load allows for lower natural gas capacity requirements and for higher dispatch of existing coal-fired generators, which benefit from increased utilization factors and lead to overall cost decreases. In contrast, increased flexibility in the Pacific division results in a higher reliance on solar PV and storage technologies, as load is shifted to the morning and afternoon hours to take advantage of the available PV resource and reduce curtailment. In the Mountain region, flexibility enables expansion of wind generation. These examples show that the impacts of demand-side flexibility can vary significantly by region but consistently lead to a reduced need for the marginal (and more expensive) generation in each region and to increased utilization of existing generation capacity in the region or relying on more cost-effective new generation sources.

[48] A map of the census divisions can be found in Figure A-1 (Appendix A).

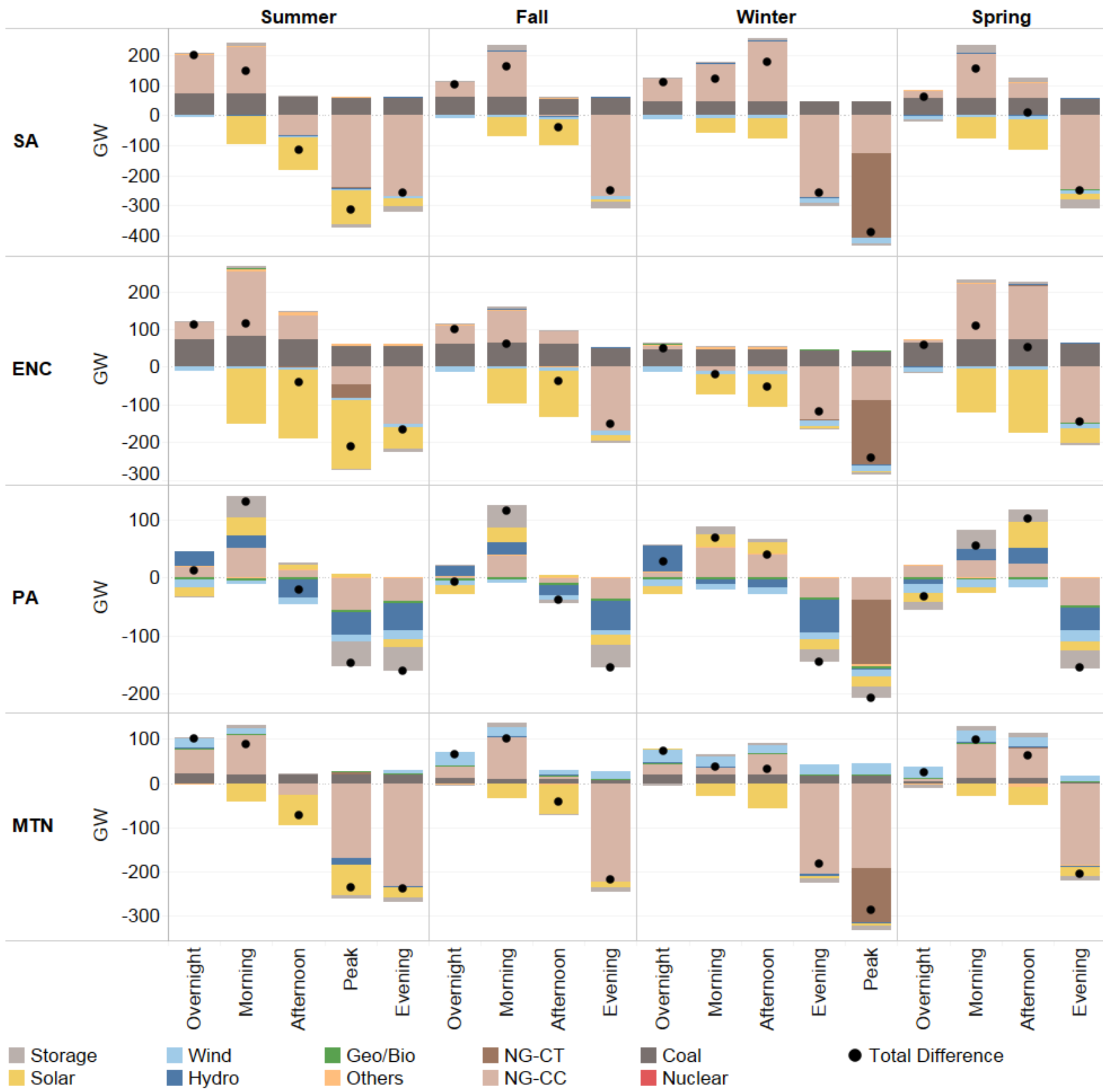

Figure 21. Difference in 2050 time-slice generation (Enhanced flexibility less Current flexibility) for High electrification for select census divisions

SA: South Atlantic division (District of Columbia, Delaware, Florida, Georgia, Maryland, North Carolina, South Caroline, Virginia, and West Virginia

ENC: East North Central division (Illinois, Indiana, Michigan, Ohio, and Wisconsin)

PA: Pacific division (California, Oregon, and Washington)

MTN: Mountain division (Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Utah, and Wyoming)

4.4 Limitations of Modeling Demand-side Flexibility

Understanding the limitations of our demand-side flexibility implementation is necessary to appropriately interpret our findings and to use them to guide future research and inform decision-making. The extent to which demand-side flexibility will be available and realized is highly uncertain. In particular, there are significant uncertainties surrounding the level of consumer willingness and capability to (1) participate in bulk power system planning and operations and (2) respond to incentives aimed at changing their power consumption.

The limited (short-run) price demand elasticity today might suggest little consumer participation to the bulk power system in the future; however, automated DR systems that minimally impact lifestyle and commercial operations, and an increasing value of demand-side flexibility, might suggest the opposite. The current situation reflects a combination of consumer ambivalence to supply-side changes through limited pricing signals (and limited impact of electricity bills on most residential customers) as well as technical and regulatory barriers to such participation. However, some of these barriers are changing due to changes to market rules and the increased ubiquity of information and communications technologies. Due to sizeable uncertainties over several decades, we model a wide range of participation levels in our parameterization of demand-side flexibility, from current participation of 5%–7% (Current flexibility case), 20% participation (Base flexibility), and 90% participation (Enhanced flexibility) across end-use technologies. In the EFS, we explore this range of possible future amount of flexible load to understand the value of this flexibility and inform further studies.

To achieve large-scale demand-side flexibility, technical barriers remain in terms of availability of automated DR-enabled technologies and appliances (i.e., technologies that can alter their power consumption without direct human intervention within predetermined bounds), reliable communication system that convey price or other signals, and control systems capable of realizing and managing large-scale DR. Several hardware and software advancements are required to realize the level of flexible load modeled here, particularly in the Enhanced flexibility cases.

Moreover, our analysis does not specify a mechanism to enable flexibility from end-use technologies. Possible mechanisms include pricing signals (e.g., properly designed time-of-use rates or real-time pricing), utility incentive programs, utility owned and/or controlled equipment, or aggregators and virtual power plants. Many of these mechanisms are either currently in place or are being explored in multiple regions (FERC 2018, SEPA 2018); however, there may be yet-to-be-developed mechanisms that could further facilitate demand-side flexibility. Many of these mechanisms might require supporting infrastructure, updated communication protocols, development and/or changes in technology and consumer behavior that we do not fully analyze or consider. As a result, none of our assumed levels of demand-side flexibility should be interpreted as predictions or forecasts.

In modeling demand-side flexibility in ReEDS, we apply a system-wide perspective to operate the flexible load. Our implementation applies constraints on when and how much the flexible load can be "dispatched." Although end user behavior and preferences are considered in our design of the constraints to flexibility, this approach may not align with actual end user preferences and might therefore misestimate the achievable flexibility of electricity consumption. In the EFS, we assume several constraints on the overall amount of load flexibility, including consumer participation and technology capability for load to be shifted and participate in DR, either by changing behavior or leveraging automated systems. Furthermore, for some grid services, a high degree of confidence may be needed for utility planners to count on demand-side flexibility as a resource that is equivalent to supply-side options. Lower expectations for, or confidence in, the availability and responsiveness of the flexible load may reduce their benefits. For example, we model that flexible load can reduce the need for planning reserve requirements, but planners may not estimate the same capacity credit for the shiftable load due to their expectations or experience with demand-side resources. More research is needed to assess different perspectives and pilot programs, and implementation studies are required to fully understand and realize the potential value of demand-side flexibility and design effective programs for utilities to tap and rely on those resources.

In addition to the level of demand-side participation, other important caveats are related to our representation of the *technical* capabilities of end-use technologies to provide grid services. These limitations include the model resolution, where "load-shifting" is modeled using the reduced-form 18 time-slices per year in ReEDS. Our parameterization is intended to account for load shifting at shorter timescales within this model structure; however, this representation is imperfect. Future planned analysis for the EFS will assess systems operation (including with demand-side flexibility) using hourly and subhourly modeling. Moreover, as described above, we represent demand-side flexibility through the lens of load shifting only—which impacts investment and operational decisions—but a wide range of other capabilities are not reflected in our analysis. For example, we do not directly model interruptible load (reduction in electricity demand at certain times without shifting to other times), vehicle-to-grid or building-to-grid capabilities for providing short timescale operating reserves, or other similar capabilities. Lastly, the flexibility treatment assumes a narrow set of technology options that do not cover all possibilities. For example, we do not model thermal energy storage in buildings, behind-the-meter battery storage or backup generation, or multiday charging flexibility from longer-range electric vehicles.

Our analysis of demand-side flexibility, including system cost measures, does not include all costs to enable the levels of flexibility assumed. For example, we do not consider additional cost for DR-ready end-use technologies, control systems, information and communications costs in either the model or any of our cost estimates. Moreover, we do not consider administrative or consumer compensation (incentives) costs. Nor do we consider potential maintenance or other costs that might affect equipment operated in a flexible manner (e.g., damage from more-frequent cycling). As a result, the scenario framework is designed to estimate the "technical" value of demand-side flexibility rather than assess the costs of enabling this flexibility. Similar with costs, however, we do not consider all potential sources of value of demand-side flexibility, such as potential value to the distribution system through potential equipment upgrade deferral or congestion relief. Finally, in assessing the value of demand-side flexibility, or any source of flexibility, it is well acknowledged that the incremental value to the grid depends on what is assumed for other sources of flexibility (Brinkman et al. 2016); these other sources include power plant flexibility, storage technologies, and institutional and market flexibility. More research is needed on the trade-offs between different sources of flexibility and their roles in future power systems.

Though it is important to acknowledge these limitations and caveats, our methodology for representing demand-side flexibility is intended to advance modeling of demand-side capabilities in long-term power system models such as ReEDS. The scenario results provide initial estimates of the potential value of electrification-enabled demand-side flexibility to guide future research, including in future analysis within the broader EFS. These initial findings indicate there may be sizeable system benefits with demand-side flexibility, including benefits in lowering the estimated cost and mitigating challenge of meeting a higher electrification future.

5 Conclusions

This report documents the improvements made to the ReEDS long-term capacity expansion model for the EFS supply-side scenario analysis. The improvements are designed for a more self-consistent representation of the impacts of end-use electrification in power system investment planning and dispatch. The model updates to ReEDS include the following changes that help improve the model's capability to represent the complex impacts of electrification, even within its electric sector-only framework:

- Improved temporal representation of planning reserve requirements and winter peak demand to capture regional interactions with widespread electrification,
- Changes to natural gas supply and demand dynamics representation to consider impacts of natural gas consumption changes across end-use sectors, and
- A new model representation of demand-side flexibility to investigate the role of demand-side participation in bulk power system planning and operation under higher level of electrification.

Electrification impacts the opportunities for, and value of, resource sharing and regional interactions particularly through changes in peak demand magnitude and seasonal timing. To better capture electrification-induced impacts on peak demand and load shapes, we updated the planning reserve constraints from an annual basis to a seasonal basis, which also allows seasonal planning reserve provision trading between regions. We also added a winter peaking time-slice to capture the dispatch decisions during increased winter peaking periods with electrification. The change to seasonal planning reserve requirements reduces overall system capacity, especially natural gas-combustion turbine capacity needs for resource adequacy. Adding a winter peaking time-slice has relatively minor impacts on overall capacity and generation pattern, but doing so helps the model capture generation and dispatch decisions during the winter season. The combination of both changes allows ReEDS to better capture the impacts on transmission capacity and operation with higher and shifted peak demands with widespread electrification.

Electrification also shifts natural gas consumption from end-use sectors to the electric sector. It is important to consider these changes in natural gas consumption, as well as the resulting changes in natural gas fuel price, when investigating the impacts of electrification on power system planning and operation. We updated natural gas supply curves in ReEDS from an Electric-Only Elasticity representation to an Energy Sector-Wide Elasticity representation to better capture the impacts of decreased natural gas price due to reductions in non-electric sector natural gas consumption. Therefore, the new representation reduces the delivered natural gas price to the electric sector, and it increases electric-sector natural gas plant generation and fuel consumption under High electrification scenario.

Finally, electrification expands opportunities for demand-side flexibility, which would further change the shape of electricity demand. By including a new representation of flexible load in ReEDS, we can assess the value of this source of flexibility under a wide range of future conditions with different electrification levels. Our scenario results show that flexible load can help reduce the need for new capacity additions and enable more efficient system operations. These benefits are found to be larger with increased electrification as both (1) the amount of available flexibility increases with electrification and (2) the value of flexibility is greater with the higher peaks from the electrified loads. Future work is planned to explore a more complete analysis of the impacts of demand-side flexibility in the context of the EFS scenarios.

Although the changes to ReEDS help advance the model by more accurately representing the impacts of electrification to bulk power system decisions, there are numerous limitations to our approach and substantial uncertainties associated with it, as we discuss throughout the report. These limitations and uncertainties highlight possible electrification-related modeling research needs. The present report and the broader EFS provide initial modeling methodologies and data to inform these future research needs, including:

- **Efficient Planning and Operations:** Meeting electricity demand and other grid services in an electrified future will challenge infrastructure development for the bulk power system. Understanding how these challenges can be mitigated—such as through resource sharing and increased flexibility—is crucial to achieving these possible futures efficiently and at low cost.
- **Natural Gas Systems:** Our analysis focuses on the impacts of electrification on the power system evolution, but electrification would also have significant impacts on direct use and supply of natural gas as well as on the dynamic interactions of these two complex systems. Understanding how electrification might affect the natural gas industry and related infrastructure is needed for a comprehensive assessment of the impact of widespread electrification on the future energy system.
- **Electrification-Driven Loads and Load Shapes:** Electrification can introduce changes to overall electricity demand and load shapes, including new sources of demand (e.g., plug-in electric vehicles), that can have far-reaching impacts on power system planning. Understanding this future load shape, which will be affected by technology choice, consumer behavior, infrastructure deployment, macroeconomic changes, electricity rate structures, and other factors, is critical for evaluating the impacts of electrification.
- **Demand-Side Participation and Consumer Behavior:** Although electricity already plays an integral role in modern U.S. society, electrification could increase the reliance on the power system in all parts of the energy system with a greater number of consumers. As the importance of the power system grows, electric consumers may play a more active role in electricity markets under widespread electrified futures, which calls for a better understanding of the possibilities and challenges of these interactions.

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Appendix A. Methodology for Translating EnergyPATHWAYS Outputs to ReEDS

For inputs into ReEDS, we adjust the hourly load profiles from the demand-side technology adoption scenarios in Mai et al. (2018) that were modeled in EnergyPATHWAYS. The ReEDS model is calibrated to a default load profile that includes electricity demand for all sectors.

Directly using the EnergyPATHWAYS load profiles would require additional data and calibration, because not all subsectors are covered (e.g., combined heat and power). Therefore, to ensure consistency, we use the ReEDS default profile for the Reference electrification scenario and scale the default profile based on the incremental growth of electricity consumption in the EnergyPATHWAYS Medium and High electrification scenarios; [49] Figure A-1 (next page) summarizes the applied methodology. The translation from EnergyPATHWAYS outputs to ReEDS inputs consists of the following steps:

1. Disaggregate the ReEDS default profile into subsectors based on the state- and hourly-level load from the Reference electrification scenario[50]
2. Calculate the incremental growth between the Reference electrification scenario and the Medium and High electrification scenarios by state, hour, and subsector
3. Apply the incremental growth by state, hour, and subsector to the disaggregated ReEDS default profile to obtain the final electrification scenarios.

This methodology results in slight discrepancies of annual load compared to those reported in Mai et al. (2018): the 2050 annual electricity consumption for Reference, Medium, and High electrification scenarios differ from Mai et al. (2018) by 1%, 2%, and 3%, respectively.[51]

[49] The ReEDS default profile is used for Reference electrification and Moderate technology advancement. Scaling is used for the other technology advancement scenarios.
[50] The ReEDS default profile is aggregated across sectors; thus, mapping to EnergyPATHWAYS output requires disaggregation into subsectors.
[51] Estimates are reported for Moderate technology advancement.

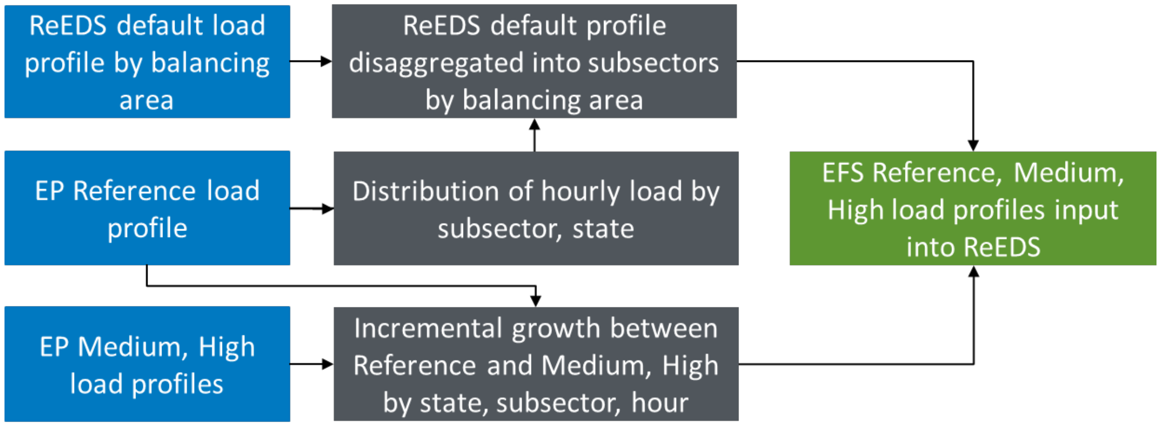

Figure A-1. Flow chart of assumptions used to determine load profiles used in modeling

Blue boxes indicate inputs and assumptions, gray boxes indicate intermediate outputs, and the green box represents the final output (i.e., input to ReEDS). EP = EnergyPATHWAYS.

Appendix B. Natural Gas Supply Curves

The ReEDS model by itself does not explicitly model the U.S. natural gas system, which touches all sectors of the economy and includes complex infrastructure and markets. Rather, a supply curve representation is a used to approximate the natural gas system. For more information on the impact of natural gas representation in ReEDS, see Cole et al. (2016).

Based on previous ReEDS supply curve methods that model the electric sector natural gas price in each region as a function of regional and national electric natural gas demand, the updated method in this study also considers non-electric sector natural gas demands. The supply curves are parameterized from AEO2014 (EIA 2014) scenarios for each of the nine EIA census divisions (see Figure B-1). The AEO2014 scenarios are the most recent set of AEO scenarios that contain a wide range of market scenarios. We extract the regional delivered natural gas price for the electricity sector, as well as regional and national energy sector-wide natural gas consumption by all sectors for the 31 AEO2014 scenarios.

Figure B-1. The nine census divisions defined by EIA

Source: EIA 2016, Figure F1: United States Census Divisions
A regional supply curve was created in ReEDS for each of these census divisions.

The AEO2014 scenarios were used to estimate parameters for the following natural gas price-consumption model:

$$\mathrm{P}_{\mathrm{r,y}} = \alpha + \alpha_r + \alpha_y + \alpha_{r,y} + \beta_{nat} \times \left(Q_{y,elec}^{nat} + Q_{y,nonelec}^{nat}\right) + \beta_r \times \left(Q_{r,y,elec} + Q_{r,y,nonelec}\right) \quad \text{[A-1]}$$

Where:

- $P_{r,y}$ is the price of natural gas (in \$/MMBtu) in census division *r* and year *y*
- $\alpha_{r,y}$ is the intercept term of the supply curve with adjustments made based on region and year
- β_{nat} is the coefficient for national energy sector-wide natural gas demand ($Q^{nat}_{y,elec}$ for electric sector and $Q^{nat}_{y,nonelec}$ for non-electric sector, in quads)
- β_r is the coefficient for the regional energy sector-wide natural gas demand ($Q_{r,y,elec}$ and $Q_{r,y,nonelec}$) in census division *r*.

Note that the α parameters in Equation [A-1] can be represented using only $\alpha_{r,y}$. Nine of the 31 AEO2014 scenarios were removed as outlier scenarios. These outlier scenarios typically included cases of low or high natural gas resource availability, which are useful for estimating natural gas price as a function of supply but not for estimating natural gas price as a function of demand—for given supply scenarios.

The national and regional energy sector-wide β terms are reported in Figure B-2. Similar to the previous Electric-Only Elasticity calculation, we made a specific post-hoc adjustment to the regression model's outputs for one region; the β_i term for the West North Central division was originally an order of magnitude higher than the other β_i values because the West North Central usage in the electricity sector is so low (0.05 quad[52] 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 β_i for West North Central that is close to that of East North Central. We therefore manually adjusted the West North Central β_i term to be 0.6 (in 2004\$/MMBtu/quad), and we recalculated the alpha terms with the new beta term to achieve the AEO2014 target prices. The situation in West North Central whereby such a small fraction of natural gas demand goes to electricity is unique; we do not believe that the other regions warrant similar treatment.

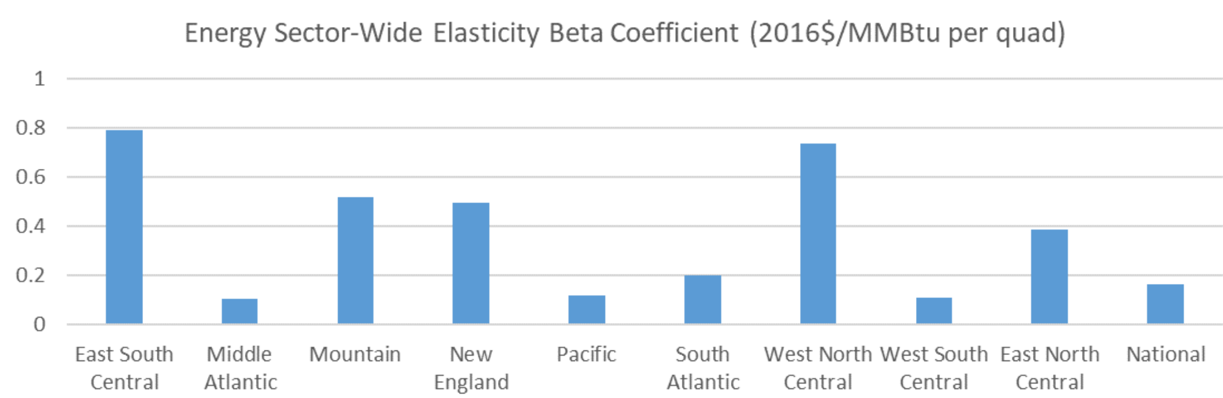

Figure B-2. Beta values for census divisions

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

The α values are calculated using natural gas price and consumption data from AEO2018 reference scenario. Prices under high and low oil and gas resource cases are modeled through an intercept shifter calculated from AEO2018 high and low oil and gas resource scenarios, which can be merged with $\alpha_{r,y}$. Because non-electric sector natural gas consumption ($Q_{y,nonelec}^{nat}$ and $Q_{r,y,nonelec}$) for different electrification levels are exogenously defined from EnergyPATHWAYS modeling results in this study, the two non-electric terms in [A-1] can also be merged into $\alpha_{r,y}$. Therefore, α values can reflect how natural gas price would change as a function of electric sector demands under different resource and electrification scenarios.

In addition to the natural gas supply curve representation, ReEDS includes targeted fuel price foresight for new natural gas capacity investments. Specifically, the effective investment cost for new natural gas combined cycle capacity includes an extra term representing the present value of the difference between flat natural gas prices and expected future natural gas prices.

Comparison 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 [A-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 will be reported here as a positive number for the sake of convenience.

External sources are varied and often unclear in their estimates of price sensitivity of natural gas. Using the reported domestic natural gas market demand given for 2012 in AEO2014, the β values reported here yield an overall natural gas 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 natural gas to be 0.11–0.70, depending on the granularity and time horizon of the natural gas price data considered. Bernstein and Griffin (2006) examined the price elasticity of demand for residential natural gas 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 reported natural gas price elasticity of demand for 13 different energy models (EMF 2013), with the reported elasticity ranging from 0.00 to 2.20, depending on the year, model, and scenario considered. For NEMS, which is used for the Annual Energy Outlook, the elasticity ranges from 0.22 to 0.81, depending on the year and scenario (EMF 2013).

Appendix C. Seasonal Natural Gas Price Adjustments

We use natural gas futures prices to estimate the ratio of winter to non-winter natural gas prices. We choose futures prices because (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 C-1 shows the cyclical nature of the natural gas futures prices. Figure C-2 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.

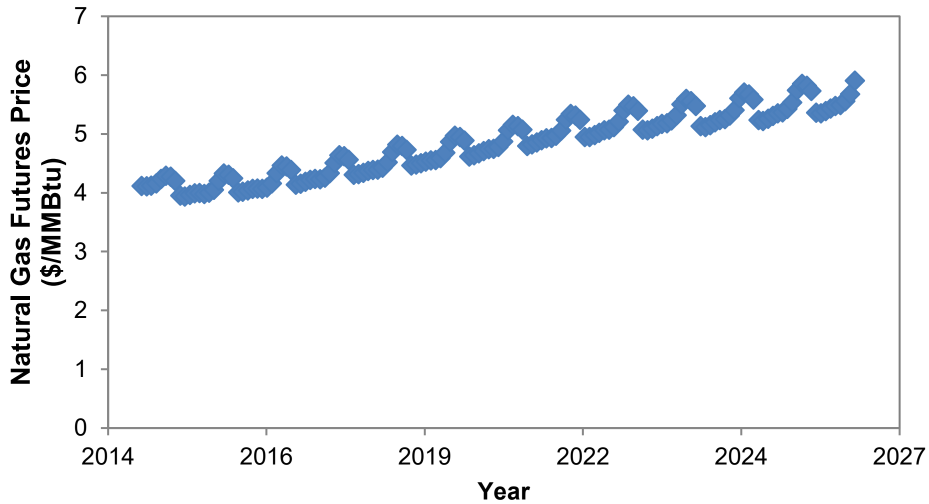

Figure C-1. Natural gas futures prices from the New York Mercantile Exchange for July 10, 2014

The prices show the higher wintertime prices and the cyclical nature of the prices.

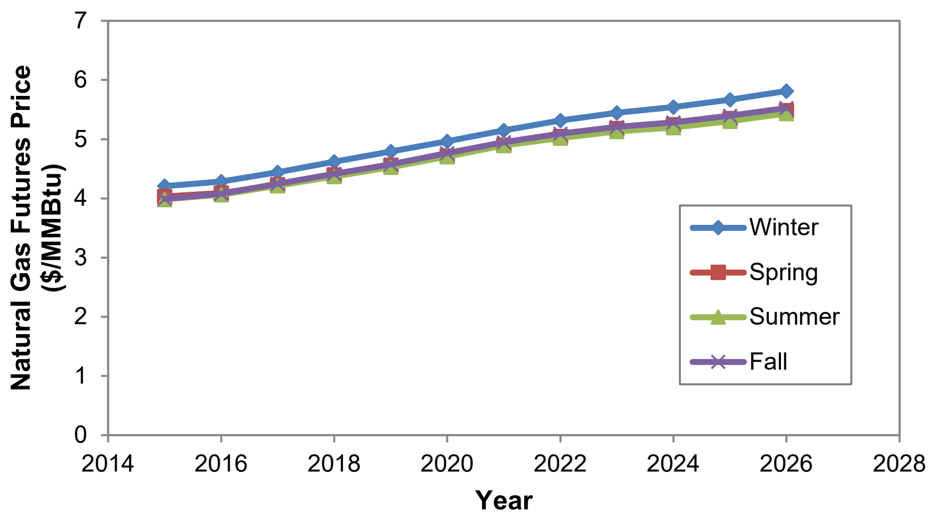

Figure C-2. Year-round natural gas futures prices from Figure C-1 separated by season

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:

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

$$P_{winter} = 1.054 \times P_{non-winter} \quad [A\text{-}3]$$

$$P_{winter} = \alpha P_{year-round} \quad [A\text{-}4]$$

$$P_{non-winter} = \beta P_{year-round} \quad [A\text{-}5]$$

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
- α and β are the seasonal multipliers for winter and non-winter respectively.

The multipliers α and β are determined by solving Equations [A-2] through [A-5].

Appendix D. Demand-Side Flexibility Assumptions

We characterize and quantify load shifting potential based on subsector-level assumptions about the timing, direction, and availability of load flexibility (see Section 4). This appendix provides details on the subsector levels assumptions that factor into the sectoral totals used in ReEDS. Table D-1 summarizes the total flexible load by sector in 2050 for three flexibility scenarios: Current, Base, and Enhanced. Tables D-2 through D-4 describe the assumptions about DR potential within a subsector, DR timing and duration, and the estimated DR available based on ReEDS time-slice constraints. Assumptions are based on a combination of expert judgment and a literature review.

Table D-1. Amount and Percentage of Flexible Load in 2050, by Sector and for Total Load

Electrification Level	Demand-Side Flexibility Level	Transportation Load	Residential Load	Commercial Load	Industrial Load	Total Load
Reference	Current	4 TWh (4%)	13 TWh (1%)	3 TWh (<1%)	8 TWh (1%)	27 TWh (1%)
	Base	12 TWh (13%)	65 TWh (4%)	14 TWh (1%)	22 TWh (2%)	113 TWh (2%)
	Enhanced	55 TWh (58%)	195 TWh (13%)	42 TWh (2%)	65 TWh (5%)	357 TWh (7%)
High	Current	52 TWh (3%)	11 TWh (1%)	4 TWh (<1%)	10 TWh (1%)	77 TWh (1 %)
	Base	191 TWh (12%)	62 TWh (4%)	20 TWh (1%)	27 TWh (2%)	299 TWh (4%)
	Enhanced	825 TWh (51%)	187 TWh (12%)	60 TWh (3%)	80 TWh (5%)	1,151 TWh (17%)

Totals may not equal sector totals due to rounding.

Table D-2. Summary of Demand-Side Flexibility Assumptions for Residential End Uses

Subsector	Flex from[a]	Flex to[a]	Duration (hours)[b]	DR Portion of Subsector[c]	DR Available[d]	Explanation
air conditioning	all	adjacent	1	100%	25%	precooling and setpoint floating[e]
clothes drying	all	daily	8	100%	100%	assume backup set of clothes available[f]
clothes washing	all	daily	8	100%	100%	assume backup set of clothes available[f]
dishwashing	all	next	8	100%	100%	delay either overnight or during workday[g]
freezing	all	adjacent	8	17%	17%	adjust defrost timing; 500-W defrost and 120-W compressor; 30-minute defrost every 10 hours of operation[h]
refrigeration	all	adjacent	8[i]	17%	17%	adjust defrost timing; 500-W defrost and 120-W compressor; 30-minute defrost every 10 hours of operation[h]
space heating	evening	adjacent	1	100%	20%	preheating and setpoint floating[e]
water heating	all	daily	8	100%	100%	tank storage[j]

[a] "Flex from" describes the DR timing (i.e., during which time periods load can be shifted). "Flex to" represents the DR direction and describes how load can be shifted to other time periods. The same definition applies to Tables D-3 through D-5.

[b] "Duration" describes how long the flexible load can be advanced or postponed. The same definition applies to Tables D-3 through D-5.

[c] "DR Portion of Subsector" represents the portion of subsector load that is assumed to be flexible. The same definition applies to Tables D-3 through D-5.

[d] "DR Available" is an adjustment for cases where the assumed duration is shorter than the ReEDS time-slice. The same definition applies to Tables D-3 through D-5.

[e] Hong et al. 2013

[f] Expert judgment

[g] Stamminger 2009

[h] Synthesized judgment from articles on defrost element size, defrost operational parameters, and power draw during operation

[i] The estimated portion of flexible load was based on a calculation of how much refrigerator energy consumption is related to defrost. Energy used for compressor operation is not considered flexible.

[j] Moreau 2011; Fuentes, Arce, and Salom 2018

Table D-3. Summary of Demand-Side Flexibility Assumptions for Commercial End Uses

Subsector	Flex from	Flex to	Duration (hours)	DR Portion of Subsector	DR Available	Explanation
commercial air conditioning	workday	adjacent	1	100%	25%	precooling and setpoint floating[a]
commercial refrigeration	all	previous	0.5	100%	13%	precooling[b]
commercial space heating	workday	adjacent	1	100%	25%	preheating and setpoint floating[c]
commercial ventilation	workday	adjacent	0.5	100%	13%	temporary delay in ventilation timing[d]
commercial water heating	all	adjacent	4	100%	100%	storage tank[e]
office equipment (PCs)	workday	next	6	7%	7%	flexible 7.5-W laptop charging with dock; desktop and monitor, 15 W each[f]

[a] Yin et al. 2010

[b] Grein and Pehnt 2011

[c] Yin et al. 2010

[d] Olsen et al. 2013

[e] Expert judgment

[f] Duration assumption is based on expert judgment on modern battery life in new laptops. Power consumption comes from averaging EPA energy star data from multiple monitors and laptops. The fraction of office computers that are laptops is from 2012 CBECS microdata (see "2012 CBECS Survey Data," EIA, https://www.eia.gov/consumption/commercial/data/2012/index.php?view=microdata).

Table D-4. Summary of Demand-Side Flexibility Assumptions for Industrial End Uses

Subsector	Flex from	Flex to	Duration (hours)	DR Portion of Subsector	DR Available	Explanation[a]
agriculture/crops	all	daily	8	50%	50%	shift pumping times
aluminum industry	all	adjacent	4	2%	2%	shift production times
bulk chemicals	all	adjacent	4	11%	11%	shift production times
food and kindred products	all	adjacent	1	19%	5%	shift production times
glass and glass products	all	adjacent	2	21%	11%	shift production times
industrial boilers	all	adjacent	1	60%	15%	preheat and store; shift production
industrial curing	all	adjacent	1	60%	15%	shift production times
industrial drying	all	adjacent	1	60%	15%	shift production times
industrial machine drives	all	adjacent	1	36%	9%	shift production times
industrial process heat	all	adjacent	1	60%	15%	preheat and store; shift production
industrial space heating	all	adjacent	1	100%	25%	preheating and setpoint floating
iron and steel	all	adjacent	4	2%	2%	shift production times
paper and allied products	all	adjacent	2.13	15%	8%	shift production times
plastic and rubber products	all	adjacent	1	16%	4%	shift production times
transportation equipment	all	adjacent	3.14	17%	14%	shift production times
wood products	all	adjacent	1	22%	6%	shift production times

[a] Values are derived from Starke, Alkadi, and Ma (2013).

Table D-5. Summary of Demand-Side Flexibility Assumptions for Transportation End Uses

Subsector	Flex from	Flex to	Duration (hours)	DR Portion of Subsector	DR Available	Explanation
light-duty autos	all	daily	8	75%	75%	percentage of daily commutes that could go round-trip with a plug-in hybrid electric vehicle[a]
light-duty trucks	all	daily	8	75%	75%	percentage of daily commutes that could go round-trip with a plug-in hybrid electric vehicle
medium-duty trucks	night	next	6.5	100%	81%	percentage of flexible hours during overnight charging[b]
heavy-duty trucks	night	next	4.4	100%	55%	percentage of flexible hours during overnight charging[b]

[a] Flex duration is based on an assumption of availability of charging both at workplace and at home. Commute times are taken from the 2017 Census Bureau American Community Survey Data (see "American Community Survey," U.S. Census Bureau, https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2017/).

[b] Flex duration is based on charging time assumptions in Jadun et al. (2017).

Figures D-1 through D-4 show the resulting portion of flexible load assumed to be flexible for each subsector, and the portion of total flexible load attributed to that subsector for Reference and High Electrification under Base and Enhanced flexibility assumptions. The left panels of these figures show the "effective" portion of flexible load assumed in each subsector. This effective load percentage is based on the assumptions listed above, the customer participation rates described in Section 4.1.2, as well as the underlying subsector load profile.

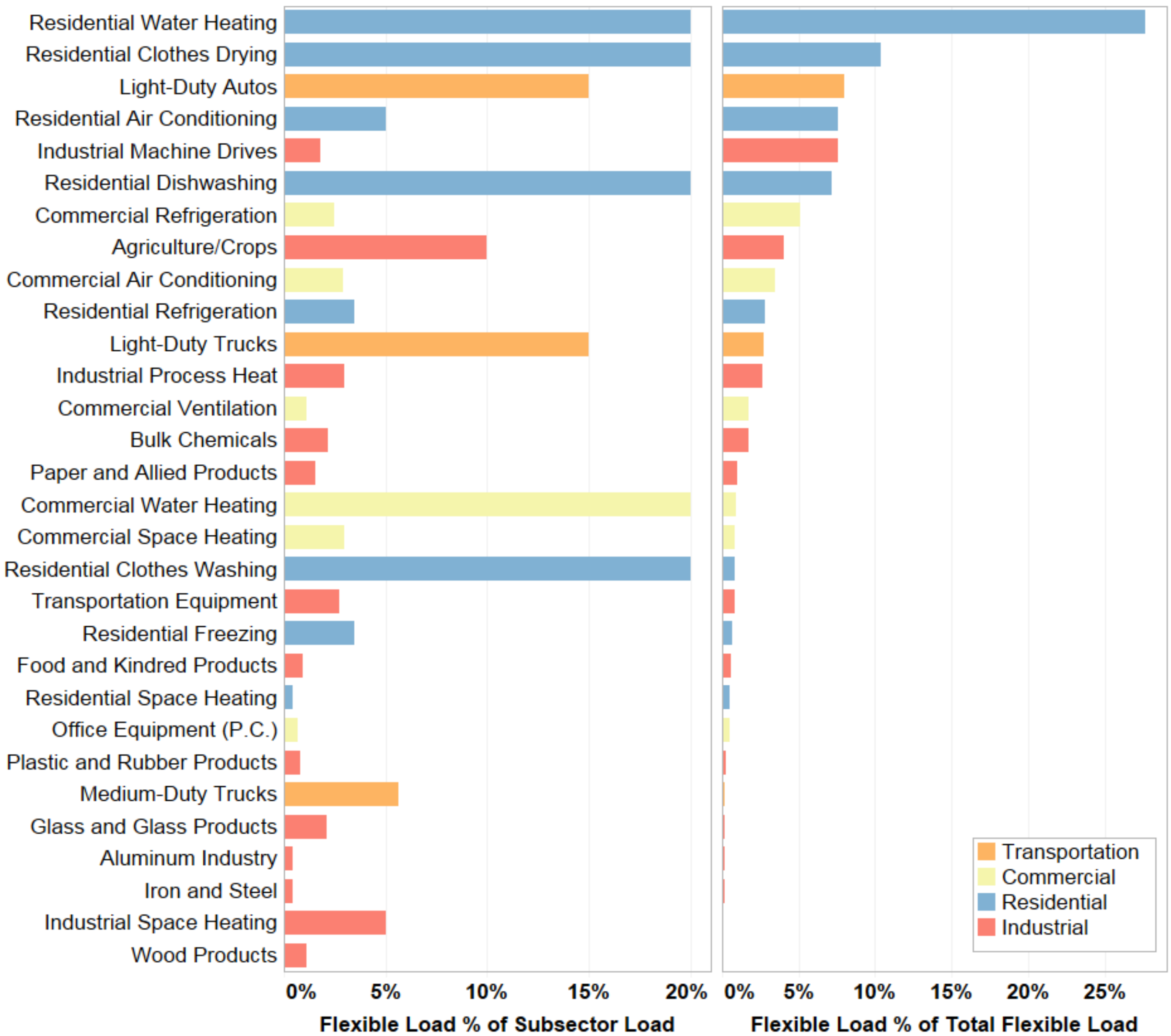

Figure D-1. Flexible load by subsector for Reference electrification and Base flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible.
The right panel shows the percentage of total flexible load attributed to the respective subsector.
Subsectors without assumed flexible load are not shown.

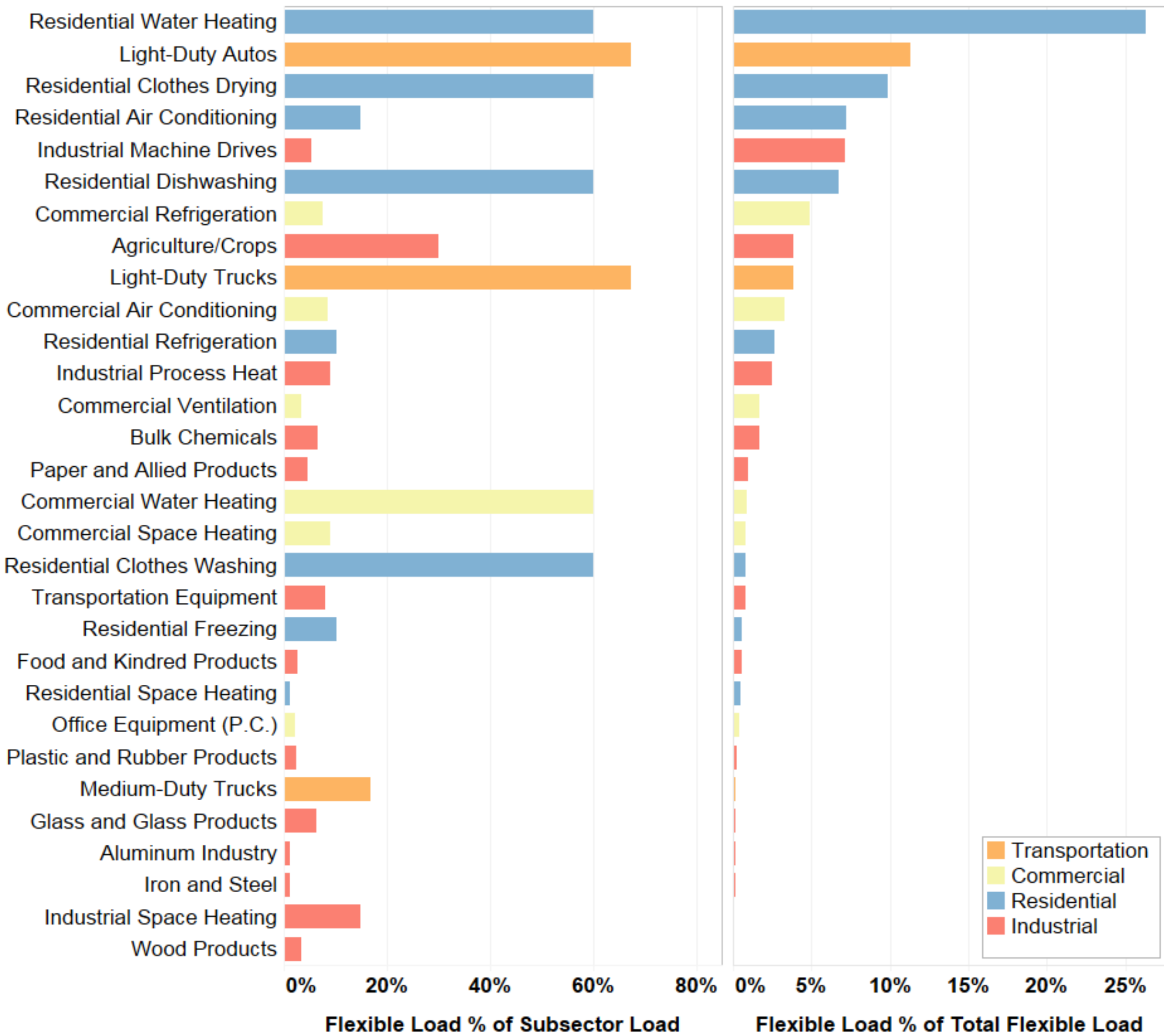

Figure D-2. Flexible load by subsector for Reference electrification and Enhanced flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible.
The right panel shows the percentage of total flexible load attributed to the respective subsector.
Subsectors without assumed flexible load are not shown.

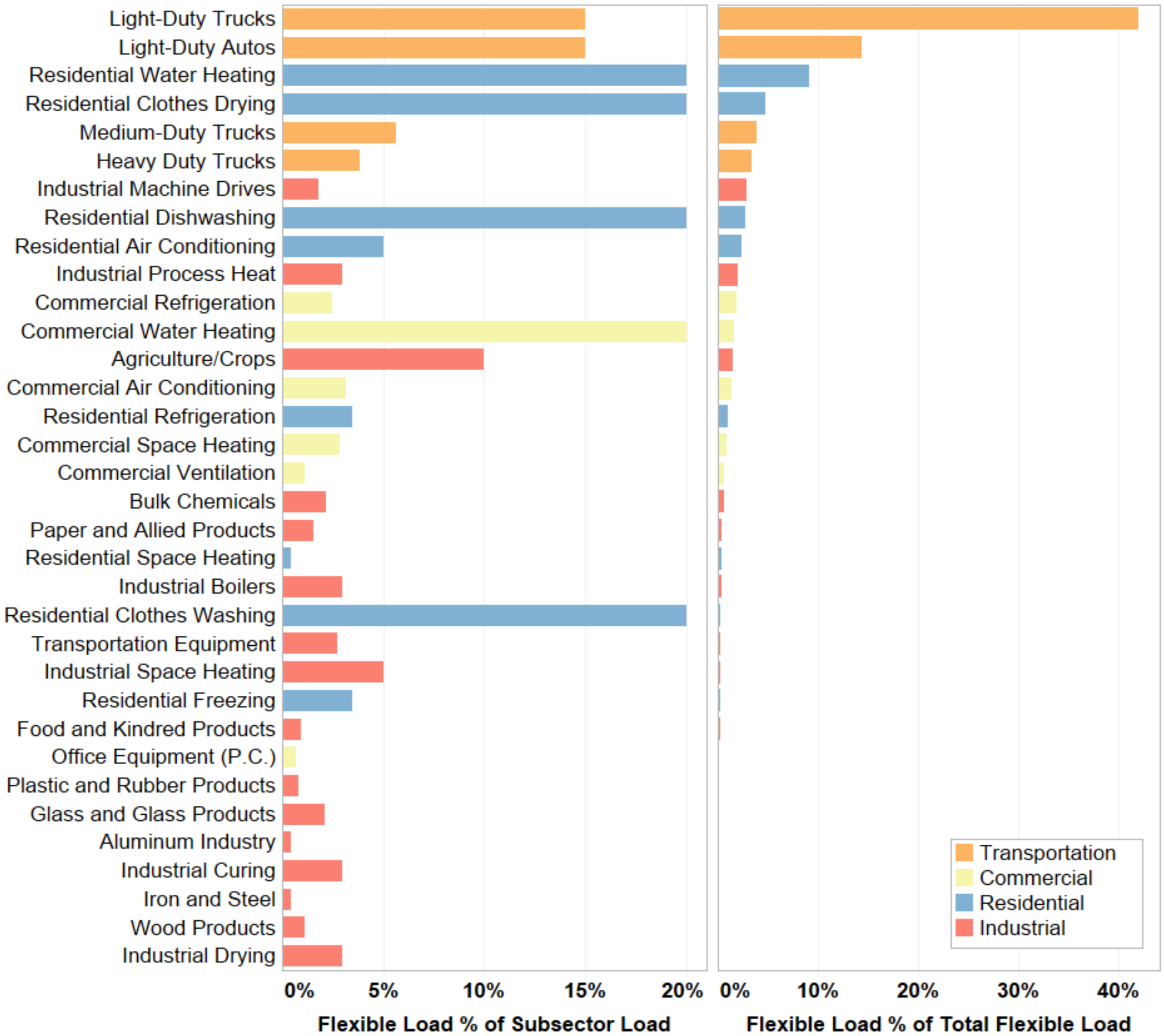

Figure D-3. Flexible load by subsector for High electrification and Base flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible.
The right panel shows the percentage of total flexible load attributed to the respective subsector.
Subsectors without assumed flexible load are not shown.

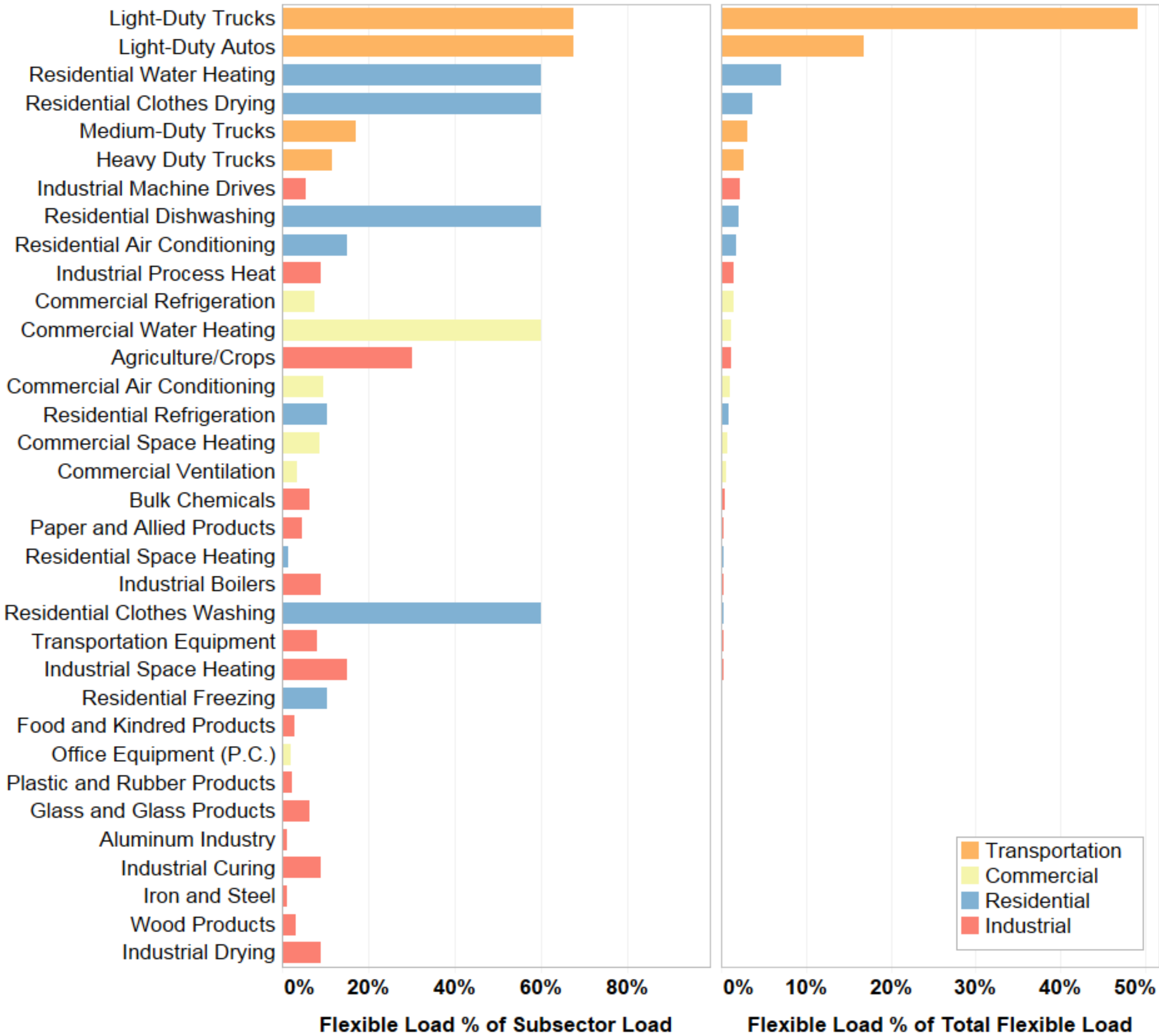

Figure D-4. Flexible load by subsector for High electrification and Enhanced flexibility in 2050 as a percentage of the total subsector load (left) and total flexible load across all subsectors (right)

The left panel shows the percentage of load in each subsector that is assumed to be flexible. The right panel shows the percentage of total flexible load attributed to the respective subsector. Subsectors without assumed flexible load are not shown.

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15013 Denver West Parkway
Golden, CO 80401
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