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Electrification Futures Study:

Operational Analysis of U.S. Power Systems with Increased Electrification and Demand-Side Flexibility

Ella Zhou and Trieu Mai
National Renewable Energy Laboratory

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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 Bulk Power System Impacts of End-Use Electrification.* NREL/TP-6A20-73336.
5. Murphy, Caitlin, Trieu Mai, Yinong Sun, Paige Jadun, Matteo Muratori, Brent Nelson, and Ryan Jones. 2021. *Electrification Futures Study: Scenarios of Electric System Evolution and Infrastructure Development for the United States.* NREL/TP-6A20-72330.
6. Zhou, Ella and Trieu Mai. 2021. *Electrification Futures Study: Operational Analysis of U.S. Power Systems with Increased Electrification and Demand-Side Flexibility.* NREL/TP-6A20-79094. [this report]

This report, the sixth in the EFS series, presents a power system operational analysis of high electrification scenarios. The analysis includes detailed grid simulations of future 2050 power systems and electricity demand developed in earlier EFS reports, particularly the "demand-side" scenarios from Mai et al. (2018) and the "supply-side" scenarios from Murphy et al. (2021). This report also presents an analysis of the potential role and value of flexible load, using assumptions of demand-side flexibility described by Sun et al. (2020). The input data and assumptions for these studies were developed through a broad and rigorous stakeholder process during 2017-2018. They do not reflect targets on electric vehicle adoption or power sector decarbonization announced in recent years. More recent data and assumptions may yield different results, though the assumptions in the EFS high electrification and enhanced flexibility scenario are not far from the more recent estimations. For example, initiatives supported by the U.S. Department of Energy are investigating the potential of greater demand flexibility in the buildings sector (Neukomm, Nubbe, and Fares. 2019). Nevertheless, the current study provides valuable lessons on power systems operations for a highly electrified future with expansion of flexible loads. By supplementing the previously published EFS scenario analysis with more detailed modeling, this analysis helps both validate the operational feasibility of some of the scenarios modeled in the previous studies and identify new insights.

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 EFS 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. The committee members offered input throughout the study analysis period (from 2017 to 2020), 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 with affiliations listed as of 2020:

Doug Arent (committee chair)
National Renewable Energy Laboratory

Sam Baldwin
U.S. Department of Energy

Armond Cohen
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:

- Sam Baldwin, Paul Donohoo-Vallett, Sarah Garman, and Kevin Lynn (DOE)
- Imran Lalani and Cara Marcy (EPA)
- Gregory Brinkman, Wesley Cole, Brady Cowiestoll, Elaine Hale, Paige Jadun, Jeffrey Logan, Matteo Muratori, Caitlin Murphy, Gian Porro, and Laura Vimmerstedt (NREL)
- Dallas Burtraw, Kathryne Cleary, Karen Palmer, and Jhih-Shyang Shih (Resources for the Future)
- Steve Clemmer and Julie McNamara (Union of Concerned Scientists)
- Oscar Serpell (University of Pennsylvania)

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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 Analysis Team. We especially thank Paul Donohoo-Vallett (DOE) for his support and leadership throughout the EFS and for this report.

List of Acronyms and Abbreviations

AEO	Annual Energy Outlook
BA	balancing area
CAISO	California Independent System Operator
CBECS	Commercial Buildings Energy Consumption Survey
DOE	U.S. Department of Energy
DSF	demand-side flexibility
EFS	Electrification Futures Study
EIA	U.S. Energy Information Administration
ERCOT	Electric Reliability Council of Texas
FRCC	Florida Reliability Coordinating Council
GW	gigawatt
GWh	gigawatt-hour
HOGR	high oil and gas resource
HVAC	heating, ventilation, and air conditioning
ISO	independent system operator
LDV	light-duty vehicle
LNG	liquefied natural gas
LOGR	low oil and gas resource
MISO	Midcontinent Independent System Operator
MTN	Mountain Census Division
MWh	megawatt-hour
NEMS	National Energy Modeling System
NERC	North American Electric Reliability Corporation
NG-CC	natural gas-combined cycle
NG-CT	natural gas-combustion turbine
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
O&M	operation and maintenance
ORNL	Oak Ridge National Laboratory
PRM	planning reserve margin
RE	renewable energy
ReEDS	Regional Energy Deployment System model
RTO	regional transmission organization
SCE	Southern California Edison
SERC	SERC Reliability Corporation
SIC	Standard Industrial Classification
SPP	Southwest Power Pool
TEPPC	Transmission Expansion Planning Policy Committee (WECC)
TWh	terawatt-hour
VRE	variable renewable energy
W	watt
WECC	Western Electricity Coordinating Council

Executive Summary

Increased electrification of the demand sectors—residential and commercial buildings, industry, and transportation—can lead to broad and significant impacts across the energy system. Widespread electrification could transform the end-use equipment stock; alter the mix and quantity of fuel and energy consumed; require substantial growth and change in power system infrastructure; and impact the operation and flexibility needs of the power system. The Electrification Futures Study (EFS)[1] is designed to examine these potential changes and their impacts. This report—the sixth in the EFS series—uses detailed grid simulations to provide a high-resolution U.S. national-scale assessment of power system operations in future scenarios with widespread electrification.

The assessment relies on hourly unit commitment and economic dispatch modeling of a range of future power systems for the conterminous United States, as envisioned by prior EFS studies (Murphy et al. 2021). These power systems are modeled to provide sufficient electricity to serve up to 36% of 2050 final U.S. energy demand, which equates to 2050 electricity consumption that is 81% greater than that in 2018 (Mai et al. 2018; Murphy et al. 2021). The purpose of this assessment is to explore how variations in the magnitude and shape of electricity demand driven by electrification, and the extent of load participation to more-actively provide grid services, might impact the hourly operation, operational costs, and emissions of various power systems in 2050. The impacts of electrification and demand flexibility are overlayed across systems with significantly greater penetrations of variable renewable energy (VRE) than today.

Overall, we find that the high electrification scenarios envisioned in the EFS with significant VRE penetration (66% of annual national generation) can be operated to meet future increased levels of electrified demand.[2] We also find that demand-side flexibility—especially from newly electrified loads—can enhance operational efficiency by reducing VRE curtailment and increasing utilization of generators that have lower operating costs.

Figure ES-1 shows simulated generation from supply-side resources along with dispatch of flexible loads for a spring week in 2050 when nearly all generation is from VRE. During this week, the flexible loads—which are principally from system-optimal charging of electric vehicles, but also from the buildings and industrial sectors—alter electricity consumption patterns to better align with mid-day solar generation. Electric vehicles are charged during the daytime hours (negative lighter blue areas in the bottom chart), thereby helping to avoid charging during evening and nighttime hours (positive darker blue areas) when available renewable generation is low or declining. In doing so, the flexible loads can reduce VRE curtailment. The largest amount of avoided VRE curtailment from demand-side flexibility is found under the scenarios with the highest VRE share, highlighting the potential complementary relationship between VRE and demand-side flexibility. Conversely, in the absence of demand-side flexibility, electrification can exacerbate VRE curtailment due to the misalignment of some electrified loads with renewable generation patterns: high electrification scenarios have curtailment rates of 6%–9% (of available annual VRE generation) compared to 2%–3% in reference scenarios.

[1] For more information, see "Electrification Futures Study," NREL, www.nrel.gov/efs

[2] The limited amount of unserved load found in the scenarios suggests that the systems are resource adequate although additional probabilistic analysis with multiple weather years are needed to confirm the findings.

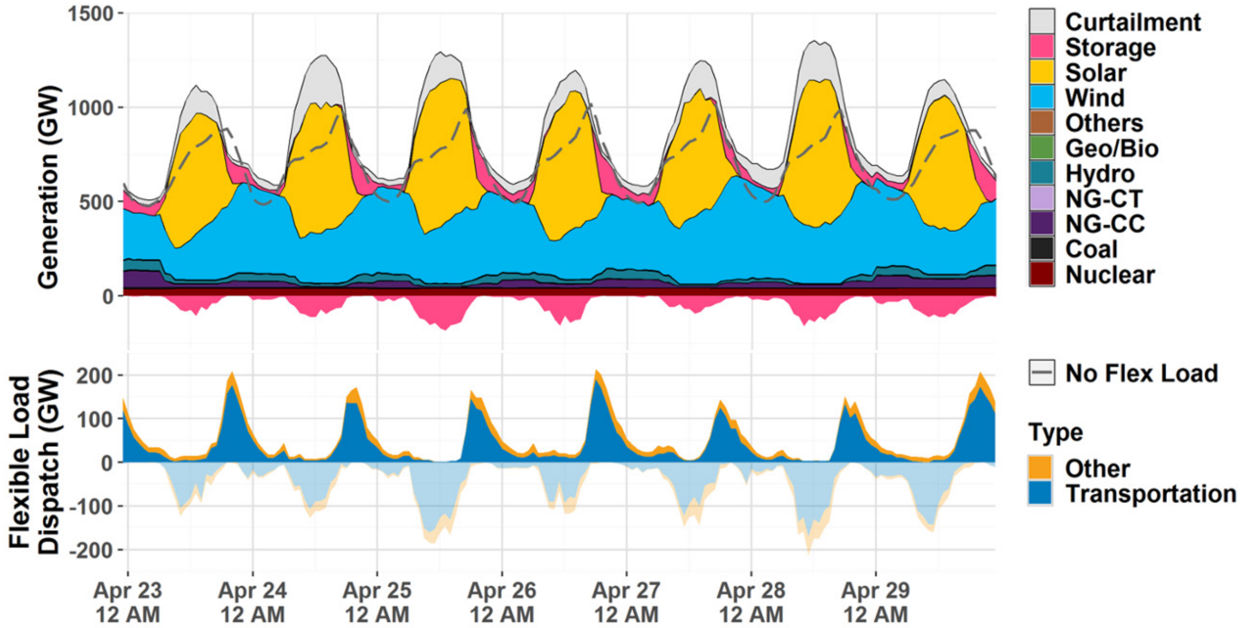

Figure ES-1. Simulated 2050 generation (top) and flexible load (bottom) dispatch during a high-renewable period in spring under a high electrification scenario. Dash line indicates the original static load without demand-side flexibility. Pink portion below the X-axis indicates storage[3] charging.

Geo/Bio = geothermal/ bioenergy; NG -CT = natural gas-combustion turbine; NG-CC = natural gas-combined cycle.

Flexible loads in high electrification systems can also reduce system production costs by providing high-value grid services during periods of system stress and by increasing the utilization of more efficient units (including VRE). In high electrification scenarios with the greatest amount of demand-side flexibility, annual production costs are estimated to be $5 billion–$10 billion (9%–10%) lower than in scenarios without flexibility. The largest savings on a percentage basis are found in scenarios with the highest VRE levels. These gross system benefits translate to an operational value of $17/MWh–$22/MWh of shifted load. These gross benefits should be compared with the costs of implementing demand-side flexibility and any associated monetary costs to end users, neither of which were in the scope of our analysis.

Finally, flexible load can enhance the ability of electrification to decarbonize the energy sector, in large part through more efficient use of VRE generation and avoiding fossil thermal generation. These effects are most pronounced under the high electrification scenario (i.e., with the greatest amount of potential flexible load) and with high VRE penetrations (i.e., through greater reduction of VRE curtailment). We found reductions in annual CO_2 emissions from enhanced demand-side flexibility of 1.6% (10.8 million tonnes CO_2/year) under reference electrification and 8.3% (44.4 million tonnes CO_2/year) when high electrification is combined with high VRE penetration, compared with corresponding scenarios without flexibility.

While there are many uncertainties regarding the extent of future electrification, the evolution of the U.S. power system, and the degree to which demand-side resources can be used to support

[3] Storage modeled in the EFS includes pumped hydro storage, compressed air energy storage, and 4-hour battery storage.

grid operations, this analysis shows the complementarity of flexible loads and renewable energy under high electrification futures—and that without demand-side flexibility, electrification can result in load profiles that could lead to greater challenges and costs. This finding highlights the value of increased integration and coordination of demand- and supply-side resources in future electric system planning and operations.

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1 Introduction

Electrification, accompanied by power sector decarbonization, is seen in the scientific community as a critical component of climate change mitigation strategies (Loftus et al. 2015; Khanna et al. 2019; Guminski, Fiedler, et al. 2019; Mahone et al. 2018; Capros et al. 2019). By shifting energy consumption away from non-electric sources and toward electricity at the final point of consumption, widespread electrification could lead to profound changes in electricity demand in several ways. First, fuel-switching from direct combustion of fossil or biomass fuels to electricity could increase the total amount of annual electricity consumption. Second, electrification could alter electricity demand profiles; for example, adoption of electric technologies could yield more pronounced daily demand peaks. Finally, electrification has the potential to dramatically lower primary energy demand due to the higher efficiency of end-use devices, especially if power is supplied by renewable energy (RE).

Alongside changes in electricity demand—driven in part by electrification—the supply side generation mix is also evolving. In particular, the recent and expected growth of variable wind and solar generation could impact electric system planning and operations, including impacts on transmission expansion and flows. At the same time, continued deployment of natural gas-fired and storage technologies and a reduction of coal-fired and nuclear capacity could increase the power system flexibility—the ability of a system to respond to changes to demand, variable renewable energy (VRE) generation, or outages and other unexpected imbalances.

The Electrification Futures Study (EFS) is a multiyear research effort that examines the implications of increasing electrification in the U.S. energy system in the context of other future supply and demand issues.[4] The study relies on a scenario analysis approach, including scenarios that envision changes to both the demand-side (Mai et al. 2018) and the supply-side (Murphy et al. 2021) of electricity. This report—the sixth in the series of EFS publications—presents an operational analysis of a set of these scenarios using detailed hourly grid simulations for the year 2050. The analysis presented in this report is designed to address the following questions:

- How do future power systems operate to serve electricity demand that includes new and changing loads from widespread electrification?
- How might flexible loads, including those from electrified end uses, be dispatched and what is the operational value of their flexibility?
- How do flexible loads operate in concert with high penetration of variable renewable energy in the highly electrified future?

In Section 2, we provide additional background context for these research questions by describing the scenarios from the prior EFS reports and findings from other relevant literature. Section 3 presents the modeling methods, key assumptions, scenarios modeled, and limitations. The analysis results are presented in Sections 4–6, with the three sections respectively focusing on the three research questions above. We conclude with a discussion of future research needs in Section 7.

[4] For more information, see "Electrification Futures Study," NREL, https://www.nrel.gov/analysis/electrification-futures.html.

2 Overview of the Electrification Futures Study Scenarios

The EFS applies a scenario analysis approach that includes a combination of demand-side scenarios (Mai et al. 2018) and supply-side scenarios (Murphy et al. 2021) to isolate and evaluate the impacts of electrification. The scenarios are for the conterminous United States energy system and encompass the time frame of 2018 through 2050. For the demand-side scenarios, the speed and extent of consumer adoption of end-use electric technologies across all major demand sectors—including commercial and residential buildings, transportation, and industry—are varied to develop multiple possible electrification levels. The supply-side scenarios represent different evolutionary pathways for the U.S. power system in response to the changes from electrification as well as an array of other possible changes in generation and storage technology, market, and policy conditions. Figure 1 summarizes how these two sets of scenarios are developed and how the current study of grid operations fits with these prior EFS studies. We provide additional detail, including context from relevant literature, in the remainder of this section.

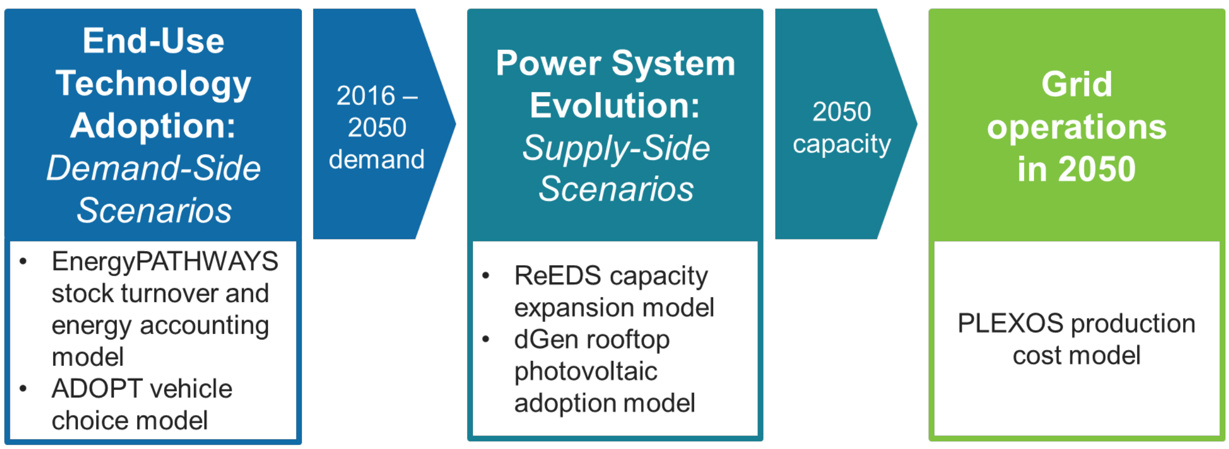

Figure 1. Electrification Futures Study structure and scenario analysis

2.1 Electrification Level: Demand-Side Scenarios

Mai et al. (2018) describe the results from the EFS demand-side analysis. The scenarios developed in that analysis include multiple levels of electrification that range from "reference" to "high" electrification to serve the same underlying demand for services. High electrification represents transformational electrification in multiple demand sectors. More specifically, it includes accelerated adoption of electric vehicles for all major on-road transportation needs, including those in the light-, medium-, and heavy-duty subsectors and for transit buses, such that electricity powers 76% of total vehicle miles traveled in 2050. High electrification also includes expanded adoption of electric heat pumps for space and water heating needs in all climate zones and electrification in other buildings subsectors. Industrial electrification is also considered in the high electrification scenarios, primarily for low temperature processes particularly where industrial electro-technologies may also offer product- and process-quality improvements.

In total, electricity is estimated to provide 36% of final energy consumption by 2050 under the high electrification scenarios, compared with 17% estimated for 2018.[5] The reference electrification scenario, which serves as a baseline for comparison, includes more-limited adoption of end-use electric technologies with adoption rates that are closely aligned with historical trends. In these scenarios, electricity's share of final energy reaches 20% in 2050.[6]

Changes in electricity demand, in terms of magnitude and timing, across electrification levels are of most relevance for the present analysis. Figure 2 shows 2050 electricity demand by sector for the reference and high electrification scenarios along with modeled estimates for 2018.[7] In the reference electrification scenarios, annual electricity demand in 2050 is about 29% higher than 2018 levels mostly due to economic and population growth with only a modest increase in electrification. In contrast, under the high electrification scenarios, 2050 electricity consumption reaches 6,700 TWh, which is 1,900 TWh (40%) greater than in the reference in 2050 and nearly 3,000 TWh (81%) greater than in 2018.

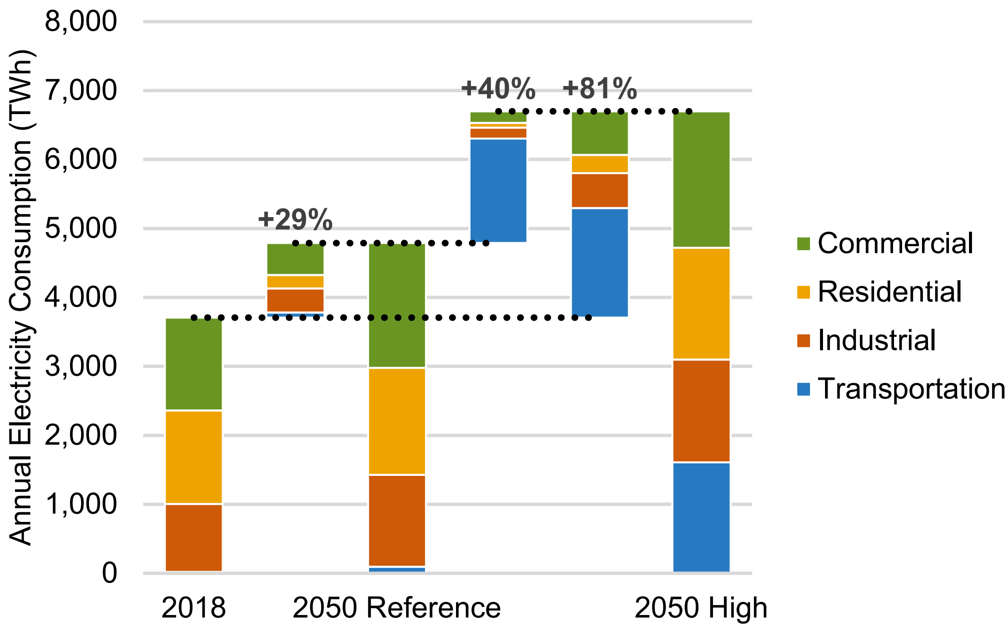

Figure 2. End-use electricity consumption under reference and high electrification scenarios

Estimates, including for 2018, are directly from the Base Case scenarios from Murphy et al. (2021), which include minor adjustments to electricity demand estimates from Mai et al. (2018).

Load growth over time under high electrification occurs in all demand sectors, but the change in annual electricity demand for transportation is greatest relative to both 2018 and the reference in

[5] This share is based on revised estimates from Murphy et al. (2021), which are slightly lower than values from Mai et al. (2018) due to differences in sectoral scope used to estimate these shares.

[6] A Medium electrification scenario, intermediate between the Reference and High (28% of final energy) scenarios, is also modeled for the earlier EFS reports but is not a focus of the present one.

[7] Scenarios with different assumptions for the efficiencies of end-use electric technology technologies (Jadun et al. 2017) result in a range of total electricity consumption for each of the Reference, Medium, and High electrification levels as presented in the prior EFS reports (Mai et al. 2018; Murphy et al. 2021). However, in the present analysis we only consider the 'Moderate' technology advancement projections.

2050. In fact, 79% of the difference in 2050 electricity demand between the high and reference electrification scenarios is from incremental electrified transportation demand. Despite the substantially greater adoption of electric heat pumps in commercial and residential buildings in the high electrification scenarios (relative to the reference scenarios), a more modest amount of incremental electricity demand is found in these sectors because of the high efficiency of heat pumps and the assumption that, in addition to replacing fossil fuel-based heaters, they also replace less-efficient electric resistance heaters (Mai et al. 2018). In these scenarios, incremental electrification in industry is assumed to be more limited than in other sectors, reflecting likely greater technical and economic challenges and the greater data limitations for this sector (Deason et al. 2018; Mai et al. 2018; Steinberg et al. 2017).

Electrification also changes the shape of electricity demand, which can impact power systems operations. In particular, buildings electrification is found to impact the timing and magnitude of peak loads particularly for regions with cold climates (Mai et al. 2018). Electric vehicle charging can also alter overall load profiles in all seasons. Hourly load shapes for the EFS scenarios, estimated using the EnergyPATHWAYS model (Mai et al. 2018) and adjusted for the ReEDS model (Sun et al. 2020), are used in the present analysis (Figure 3).

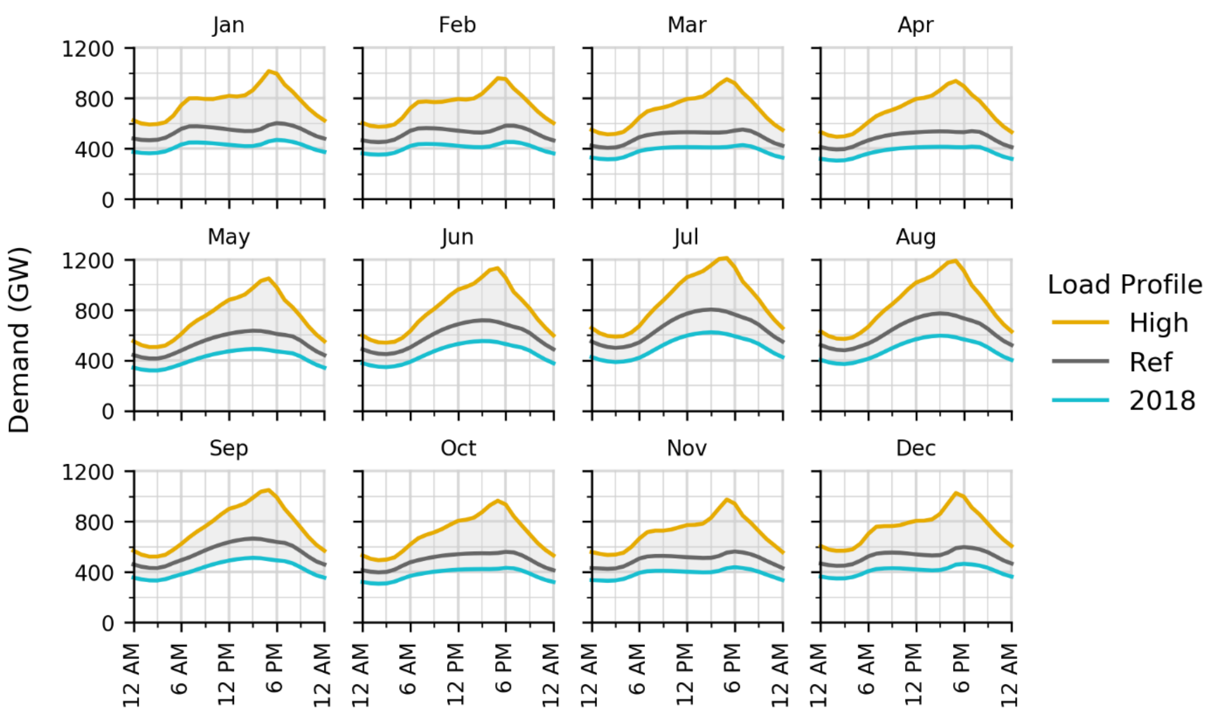

Figure 3. Month-hour electricity demand profiles for 2050 in the EFS reference and high electrification scenarios without demand-side flexibility and 2018 demand profile

Values shown represent coincident demand for the conterminous United States with hourly demand averaged for all days in each month. The values shown are for scenarios without flexibility (see Section 3).

The EFS demand-side scenarios are generated using stock and energy accounting modeling informed by consumer choice modeling, expert judgment, and data analysis.[8] These scenarios are meant to reflect "what-if" futures with different levels for electrification in the United States, where the high electrification scenarios are designed to capture transformational electrification. To provide additional context for these scenarios, we refer the reader to other projections of future electricity demand, including technical potential estimates (Deason et al. 2018; Steinberg et al. 2017; Weiss et al. 2017) that can result in much greater electrification than is estimated in the EFS high electrification scenarios.

Economic potential estimates for electrification also exist for select sectors and regions (Wilson et al. 2017; Nadel 2016). Economic potential refers to the total fuel-powered end uses for which electric alternatives have reached approximate lifecycle cost parity with fuel-powered technologies providing the same services. A variety of stock turnover models, bottom-up end-use models, and integrated systems models have been used to develop demand-side scenarios of electrification (Leighty, Ogden, and Yang 2012; Khanna et al. 2019; Brand, Cluzel, and Anable 2017). Results from economic potential or adoption scenario estimates depend on the assumptions used, which differ from those in the EFS and therefore are not directly comparable. However, the extent of electrification estimated in these studies is similar to that from the EFS scenarios. For example, the EPRI National Electrification Assessment study (EPRI 2017) employs an end-use adoption model with a range of assumptions. It finds electricity's share of 2050 final energy to range between 32% and 52% load growth between 2018 and 2050 in its highest electrification scenario. As with the EFS, load growth in EPRI (2017) is dominated by electrified transport, and it finds a similar impact of higher winter peaks from buildings electrification.

Studies of energy system decarbonization also include several scenarios with increased electrification (Williams et al. 2014; Ebrahimi, Mac Kinnon, and Brouwer 2018; Boßmann and Staffell 2015).[9] These studies generally find electrification levels that are comparable or exceed those from the EFS scenarios. In other words, these studies identify electrification as one of the primary means to reduce economy-wide greenhouse gas emissions.

2.2 Power Sector Evolution: Supply-Side Scenarios

Murphy et al. (2021) introduce the EFS supply-side scenarios, which include 29 scenarios representing changes in the U.S. power sector through 2050. These supply-side scenarios span variations in multiple dimensions including, most prominently, the electrification level, end-use electric technology advancement, renewable technology costs and performance, natural gas prices, and a variety of system constraints. The modeling analysis by Murphy et al. (2021) covers capacity and generation mix changes to the U.S. electricity system and several broader energy sector-wide impacts, including system costs, air emission, and energy consumption.

One of the trends from the EFS supply-side scenarios is that nearly all future increases in electricity demand, including those from new electrification-driven loads, are met by a

[8] The Reference scenario is largely based on the AEO2017 Reference case. For all scenarios, the EnergyPATHWAYS energy accounting and stock rollover model is used to generate these estimates. See Mai et al. (2018) for details.
[9] The highest electrification scenarios from EPRI (2017) considers an increase in carbon price.

combination of natural gas-fired and renewable energy technologies (Murphy et al. 2021). For example, across all scenarios with high electrification, the combined share of total generation from natural gas and renewable energy ranges from 82% to 90% in 2050, compared with 56% in 2019. This comparison understates the absolute amount of generation from these sources, given the much greater overall electricity generation and consumption estimated for 2050 with increasing levels of electrification (see Figure 3, page 4).

While growth in the combined share and amount of natural gas and renewable energy generation is found in all the EFS supply-side scenarios, Murphy et al. (2021) also found considerable trade-offs and competition between natural gas-fired and renewable energy sources. For example, scenarios with the largest growth in gas generation had more limited amounts of renewable energy deployment and vice versa. Another trend identified from prior EFS analysis is that most of the growth in renewable energy is from variable wind and solar technologies: across all high electrification scenarios, annual penetration of VRE generation ranged from 24% to 79% in 2050, compared with about 9.8% in 2019.[10]

Section 3 presents the capacity mixes, based on the EFS supply-side scenarios, used for the present analysis. These changes to electricity supply, along with changes in the magnitude and timing of electricity demand envisioned, raise questions about the operational feasibility of such scenarios and the possible technical and economic challenges—such as VRE curtailment, provision of operating reserves, and transmission congestion—of serving demand and other grid services for all hours.[11] Furthermore, the EFS scenarios were developed using a long-term capacity expansion model, the Regional Energy Deployment System (ReEDS) model (Cohen et al. 2019; Sun et al. 2020), and its associated simplifications, including a reduced-form representation of generation dispatch. The present analysis, which uses hourly unit commitment and economic dispatch modeling, is designed in part to verify whether the lower-fidelity modeling from the prior EFS analysis sufficiently captured the grid operations of the scenarios. Section 3 describes the model linkages in detail.

As with the EFS demand-side scenarios, an examination of the literature can help provide additional context for the supply-side scenarios. Scenarios with increased electrification in EPRI (2017), for instance, also find that increases in natural gas generation to meet electrification-driven load growth. The growth in generation from renewable energy technologies, especially VRE technologies, is another commonality of the EFS scenarios and those in recent studies (Luderer et al. 2014; Hansen, Mathiesen, and Skov 2019; Dennis, Colburn, and Lazar 2016; Berrill et al. 2016). The estimated growth in renewable energy is most pronounced in scenarios with an explicit or implicit price on carbon emissions.

The EFS scenarios, as well as other recent scenario studies (Dupont et al. 2014; Baruah et al. 2014; Quiggin and Buswell 2016; Richardson and Harvey 2015) envision increasing power system flexibility, including through the expansion of flexible loads. Given the complexities with

[10] Unless otherwise noted, penetration is presented on a post-curtailment annual energy basis and as a fraction of total generation.
[11] Many of the scenarios also include substantial retirements of coal and nuclear capacity, transmission expansion, and increases in energy storage capacity.

demand-side flexibility and its model implementation, we provide an overview in the next section of how it was considered in prior EFS reports and in the broader literature.

2.3 Demand-Side Flexibility

Demand-side flexibility (DSF) refers broadly to any programs or capabilities in the electricity demand sectors (buildings, transportation, and industry) that enable or encourage end-users to alter their consumption with the aim of improving the efficiency and/or reliability of the power system. DSF is varied and complex in terms of the type of programs and the different grid services that it may provide. Existing DSF programs adopted in the United States include (1) time-based pricing programs (e.g., time-of-use pricing, real-time pricing, critical peak pricing programs); (2) incentive-based programs (e.g., direct load control, interruptible/curtailable service, demand bidding/buy back, and emergency demand response programs); and (3) direct participation in restructured power markets, including capacity and ancillary service markets (Aalami, Moghaddam, and Yousefi 2010; FERC 2018). A variety of names and terms, such as demand response and demand-side management, are used to refer to these programs. Overall, there is growing interest and potentially adoption of DSF and distributed energy resources especially in light of recent regulatory changes pertaining to electricity markets. Specifically, in September 2020, the Federal Energy Regulatory Commission (FERC) issued Order No. 2222 (FERC 2020), which opens up the U.S. organized whole power markets to distributed energy resources through aggregators.

DSF can also be categorized by the behavior of the end-use equipment owners (Alstone et al. 2017). One category is load shifting, which occurs when energy consumption moves from periods of high demand (and prices) to periods of low demand. Load shedding (also referred to as peak shaving) is when consumption is curtailed during times of system stress, but that curtailed energy is not necessarily made up during other periods. DSF can also include short-term dynamic adjustments, possibly including power injections from the customer side, to manage disturbances in the seconds-to-hour timescale (Alstone et al. 2017). On longer timescales, power-to-heat and power-to-hydrogen are also seen as a type of flexible load to provide energy system flexibility and facilitate renewable energy integration (Qadrdan et al. 2017; Lewandowska-Bernat and Desideri 2018; Lund et al. 2015; D. Wang et al. 2018).

In addition to the complexities associated with the multiple types of DSF, analyzing the future extent and impact of DSF is challenging because of the interplay of electricity demand, regulatory and market design, pricing and business models, consumer behavior, and grid and communications infrastructure (Jones et al. 2018; Patteeuw, Henze, and Helsen 2016). The EFS does not comprehensively model all these factors, and it considers the total flexible load potential as exogenous in its scenarios. In the remainder of this section, we summarize the treatment of DSF in prior EFS analysis and review other recent studies.

DSF was considered in the EFS supply-side scenarios (Murphy et al. 2021) as aggregated flexible load that could be optimally dispatched (from a system perspective), but constrained by amount, timing, direction, and duration for each demand subsector (e.g., water heating, vehicle charging).[12] As modeled, this flexible load can shift energy between dispatch periods, which can reduce operating costs, help avoid peaking capacity needs, and lower operating reserve

[12] See Sun et al. (2020) for assumptions and modeling details.

requirements. Other types of DSF, such as load shedding, were not modeled. Three different levels of DSF, based on exogenously assumed participation rates, were considered: Current, Base, and Enhanced. Current DSF holds customer participation constant from 2018 to 2050. Base flexibility assumes 20% customer participation rates in 2050 for all sectors, which is based on successful programs surveyed in the 2016 EIA 861 data (EIA 2018). Enhanced DSF represents an expansion of light-duty vehicle participation to over 90% of demand response events.[13] Murphy et al. (2021) and Sun et al. (2020) provide details for these assumptions. Our present analysis is based on many of the same assumptions from Sun et al. (2020) but applied at higher sectoral resolution. Our method, inputs, and assumptions are described in Section 3.

The EFS analysis—both prior reports and the present analysis—do not attempt to predict the amount of future DSF; instead, they are designed to assess how DSF might affect the evolution and operation of the future power system. The analysis does not consider the cost of DSF; that is, we assume the implementation and operational costs of DSF to be zero – same as that of battery storage and VRE. In doing so, our analysis estimates the gross benefits of DSF to the grid only rather than providing a full cost-benefit analysis. For example, the prior EFS analysis finds that the total (operational and long-run) value of flexible load is $16 MWh–$19/MWh under high electrification but does not assess whether the costs to implement the flexibility is lower than these estimated system benefits.

DSF can offer a range of benefits to the system. The prior EFS analysis (Murphy et al. 2021) finds that the primary benefit of DSF is to avoid or defer the need for capacity investments, particularly for peaking needs, but also for other generation and transmission investments. For example, with high electrification, Murphy et al. (2021) find that having enhanced flexibility would avoid 100 gigawatts (GW) of installed capacity by 2050 compared to having base-level flexibility. Other studies have also found that avoiding capacity is a major benefit of flexible load (Hale, Stoll, and Mai 2016; Nolan, Neu, and O'Malley 2017; Gils 2016; Smith and Brown 2015).

In addition to avoiding capacity, there is also operational value from DSF. Multiple studies conclude that DSF, such as load shifting of heat pumps and smart electric vehicle charging, can reduce renewable curtailment (Gottwalt et al. 2017; Mileva et al. 2016; Teng, Aunedi, and Strbac 2016). For example, modeling of the 2025 Belgian power system operation shows that by shifting 2% of total demand, the system can avoid up to 41% of renewable curtailment (Dupont et al. 2014). More generally, studies have found multiple sources of potential value from DSF, including providing operating reserves (Stoll, Buechler, and Hale 2017; Roos and Bolkesjø 2018; Ma and Cheung 2016; Katz, Balyk, and Hevia-Koch 2016), lowering production costs and electricity prices (Tveten, Bolkesjø, and Ilieva 2016; Märkle-Huß, Feuerriegel, and Neumann 2018), and reducing the need for storage (Li and Pye 2018). While flexibility can be sourced from a range of demand-side sources, some studies have focused on the values from new electrified loads, particularly flexible electric vehicle charging (Pavic et al. 2014; Pavić, Capuder, and Kuzle 2015; Schuller, Flath, and Gottwalt 2015).

[13] Typically, the system operator's request to the flexible demand to reduce demand for a specific time period on a specific day is referred to as a demand response event. This assumption is based on a PG&E and BMW study (Kaluza, Almeida, and Mullen 2017).

3 Methods

The PLEXOS model is used for the grid simulations for the analysis presented in this report. PLEXOS is a commercial production cost model developed by Energy Exemplar. It has been used to study renewable grid integration with various geographic scope (Brouwer et al. 2016; Lew et al. 2013; Bloom et al. 2016; Palchak et al. 2017) and to examine the impacts of energy storage and demand response (Cleary et al. 2015; Hummon et al. 2013; Denholm et al. 2015; Frew et al. 2019). For this analysis, we use PLEXOS to develop hourly grid simulations for power systems scenarios in 2050 to investigate the operational impacts of electrification, DSF, and VRE integration.

In this section, we describe the PLEXOS production cost model configurations, data inputs, and assumptions used. We present the data linkage process from the ReEDS capacity expansion modeling as well as the specific EFS supply-side scenarios examined. And we describe the DSF units developed for the grid simulations. Finally, we discuss limitations with our approach.

3.1 Modeling Overview

We use PLEXOS to investigate whether hourly electricity demand and operating reserves can be met,[14] as well as trends in electricity prices, regional power exchange, renewable curtailment, and other operational results. For our analysis, PLEXOS is configured with mixed integer programming unit commitment modeling and co-optimization of energy and ancillary services for the conterminous U.S. power system.

The primary inputs to PLEXOS include the hourly electricity demand, generation and transmission capacity, generator characteristics including operational costs, and fuel prices. These inputs are scenario-specific and, in this analysis, are taken directly from the EFS supply-side scenarios where available (see Section 3.3). The workflow of converting each ReEDS scenario result into a unique PLEXOS model is illustrated in Figure 4 (page 10).

This workflow includes programmatically recreating the 2050 capacity from several ReEDS scenarios into PLEXOS. In this step of the workflow, information about hourly load by demand subsector, generation capacity by type, and fuel prices for each of the 134 model balancing areas (BAs) in ReEDS and the transmission capacity between model BAs are replicated in the corresponding zonal PLEXOS model. Because our model is zonal, the lines between the 134 zones do not simulate actual transmission lines, but rather the interfaces between the zones. For this reason, we do not use individual transmission line properties (e.g., resistance and transmission loss) to constrain them. Instead, we model simple pipe-flow interface constraints between zones.

[14] NERC's definition of reliability includes the concept of adequacy. The bulk-power system will achieve an adequate level of reliability when it "1) is controlled to stay within acceptable limits during normal conditions; 2) performs acceptably after credible Contingencies; 3) limits the impact and scope of instability and cascading outages when they occur; 4) System's Facilities are protected from unacceptable damage by operating them within Facility Ratings; 5) System's integrity can be restored promptly if it is lost; and 6) has the ability to supply the aggregated electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components" (NERC 2007). Rather than a full reliability analysis, our study focuses on the last feature of reliable operation.

Beyond location and type, the process transfers other characteristics of the generation fleet from ReEDS, such as build year, category, cooling type, and heat rate.[15] This process has been used in prior modeling analyses (Frew et al. 2019; Cole et al. 2018; Gagnon et al. 2018), but key elements and EFS-specific changes are highlighted in Figure 4.

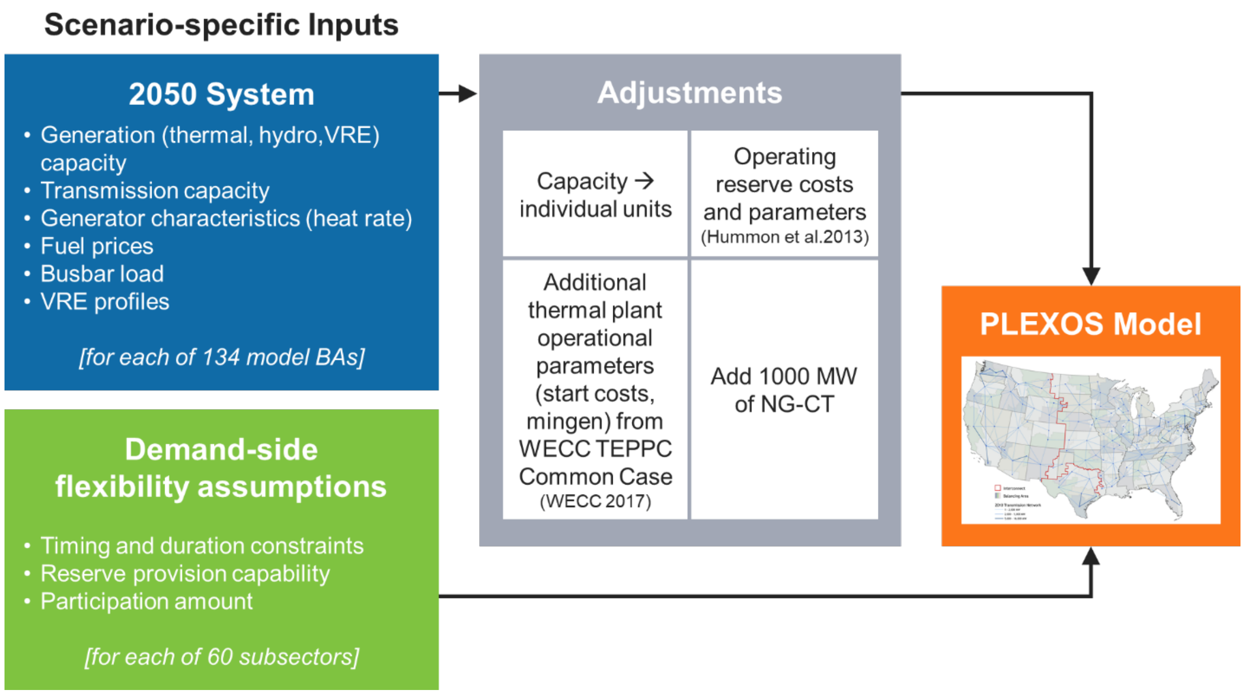

Figure 4. Illustration of ReEDS-to-PLEXOS workflow

BAs = balancing areas, NG-CT = natural gas-combustion turbine

The workflow includes additional adjustments in data and model representation to better fit the PLEXOS unit commitment and economic dispatch framework. For example, mapping the ReEDS scenarios—which are derived from a linear program with capacity amounts rather than discrete units—to PLEXOS requires translating the installed capacities from the former to individual units in the latter. We preserve the vintage, regions, and heat rate bin information from ReEDS (Cohen et al. 2019) and decompose the capacity builds into reasonable-size units.[16] In the translation to every PLEXOS model, another change to the generator capacity from ReEDS is the addition of 1,000 MW (two 500-MW units) of natural gas combustion turbine capacity located in the model BA that includes Chicago.[17]

[15] Other specific parameters taken from ReEDS include emissions, outage rates, storage efficiencies, and hydropower seasonal energy limits.

[16] In particular, we decompose units that are larger than the biggest unit of that generator category from the WECC Transmission Expansion Planning Policy Committee's WECC Common Case database into smaller units that are about the average-size unit of that category.

[17] This addition was determined through multiple test simulations that found ReEDS was slightly underestimating installed capacity needs for the BA (i.e., the BA did not have adequate generation and transmission resources to meet its local peak demand). One reason for this underestimation is that this model BA is associated with the PJM model planning reserve region but is geographically disconnected from the rest of the PJM region. Because the

Primary operational parameters are based directly on ReEDS data, but parameters from other sources are added where unavailable from ReEDS. These include start costs, ramp rates, and minimum stable generation levels. For these parameters, we assume values based on the corresponding generation category from the Western Electricity Coordinating Council (WECC) Common Case database (WECC 2017). Since technology-specific parameters are used, the substitution of the western data for the absence of unit-specific data in other parts of the country is unlikely to dramatically affect our key results. Utility-scale wind and solar plants use hourly time series produced by NREL's Renewable Energy Potential (reV) model, which uses data from the Wind Integration National Dataset (WIND) Toolkit and the National Solar Radiation Database (NSRDB) (Maclaurin et al. 2019). For distributed solar PV, we use hourly profiles produced by NREL's Distributed Generation Market Demand (dGen) model (Sigrin et al. 2015). All of the VRE profiles are consistent with the corresponding ReEDS scenario inputs, and all VRE and load profiles are based on synchronized 2012 weather (Sun et al. 2020).

We model three different types of operating reserves: regulating reserves, contingency reserves, and flexibility reserves (Table 1). Reserve requirements are based on total load in the case of regulating and contingency reserves, but flexibility reserve requirements are partly based on the amount of VRE in the system. We only model "up" reserves to save computation time as "down" reserves are typically easier to procure.[18] Operating reserves are kept for a variety of reasons related to balancing active power generation and load (Ibanez, Krad, and Ela 2014). Contingency and flexibility reserves are used to correct an imbalance and restore frequency to its normal bandwidth within about 10 minutes and about 30 minutes respectively. The former is often used to manage unforeseen generation and transmission outages, while the latter is an emerging reserve product used to manage net load ramps and VRE forecasting errors (Denholm et al. 2019). They can be provided by spinning and fast-start non-spinning generation units or by electricity consumers that can change their consumption within the required time frame. Regulating reserve requires a response time of several seconds to minutes to correct the current imbalance and mitigate frequency deviations both during normal operation and in case of contingencies (Zhou, Levin, and Conzelmann 2016; Denholm et al. 2020).[19] We assume an operating cost for conventional units providing frequency regulation service to represent the wear and tear costs and heat rate degradation on these units that is consistent with Hummon et al. (2013) (Appendix).

capacity addition is applied equivalently in all scenarios, this should not significantly affect a comparison between scenarios, especially since the scope of the analysis here is of grid operations only and not investment decisions. Furthermore, the addition represents a change of less than 0.1% of 2050 U.S. capacity in all scenarios.

[18] In many cases, the system can easily decrease generation with little cost and therefore "down" reserve requirements are often not binding. However, the inclusion of down reserves may increase renewable curtailment.

[19] As a security-constrained unit commitment model, PLEXOS ensure that the adequate operating reserve capacity is available for each time interval but does not simulate "events" for when those reserves are used. Furthermore, the model does not represent other essential reliability services beyond the operating reserves listed. These include primary frequency response. One implication is that load resources for frequency response are not modeled but could be an important grid service that demand-side options could provide (Denholm et al. 2020).

Table 1. Ancillary Service Assumptions

Ancillary Service Product	Time Frame (seconds)	Hourly Requirement Based On	Provision Can Come From
Flexibility	1,200	2% of VRE hourly generation capacity	Coal, NG-CC, NG-CT, Biomass, Hydro, Storage, Wind, Solar, Geothermal
Contingency	600	3% of Load	
Regulation	300	1% of Load	Same as above without NG-CT

NG-CC = natural gas-combined cycle; NG-CT = natural gas-combustion turbine

While several assumptions are needed in the translation from the ReEDS capacity expansion model to the PLEXOS production cost model, the end result of this is a model representation of 2050 power systems for the conterminous United States with unit-level representation, zonal transmission interfaces, and a suite of realistic operating reserves and system parameters. Such a model representation enables a detailed assessment of hourly operations under various electrification scenarios.[20]

3.2 Implementation of Demand-Side Flexibility in PLEXOS

For demand-side flexibility modeling, we use the hourly flexible load availability profiles developed in previous EFS studies as inputs (Murphy et al. 2021; Sun et al. 2020). It is important to note that the DSF model representation is applied directly in PLEXOS so that DSF is endogenously dispatched in the model based on constraints and hourly considerations for multiple subsectors individually. In other words, although the ReEDS analysis in the prior EFS studies aggregates all the flexible loads and their shifting behaviors into one time series for the capacity expansion model, we model each major subsector with flexible end use as a unique DSF unit in each of the 134 model zones in PLEXOS. Based on their shifting behavior, we distinguish 13 types (Table 2, page 15) of DSF from the commercial, industrial, residential, and transportation sectors and an "other" DSF category that captures all the other uncategorized flexible end uses across the four main sectors. Because each DSF unit in each balancing area could be seen as an aggregator of many DSF customers within that category, these DSF units are dispatched linearly, and not subject to the mixed integer decisions that bound the on-and-off status for other generator types modeled in this analysis.

As mentioned above, we only consider flexible end uses for energy shifting, not shed-able demands. This means the timing of end-use electricity consumption can be varied but the total annual amount is uniform across scenarios with the same electrification level. As such, it is not an emergency resource that is meant to be only used once or twice a year, but rather a source of system flexibility that has different levels of availability throughout the year.

The total load the modeled system needs to meet is a combination of the flexible and inflexible (i.e. static) loads (Figure 5). For every scenario, generation and net imports need to meet the sum

[20] The present analysis does not include load or VRE forecast error analysis with subhourly modeling; in other words, we do not run separate day-ahead and real-time simulations

of these two load components for each BA and each hour,[21] but when there are DSF units, the model can use them to shift all or some of the flexible load to another hour.

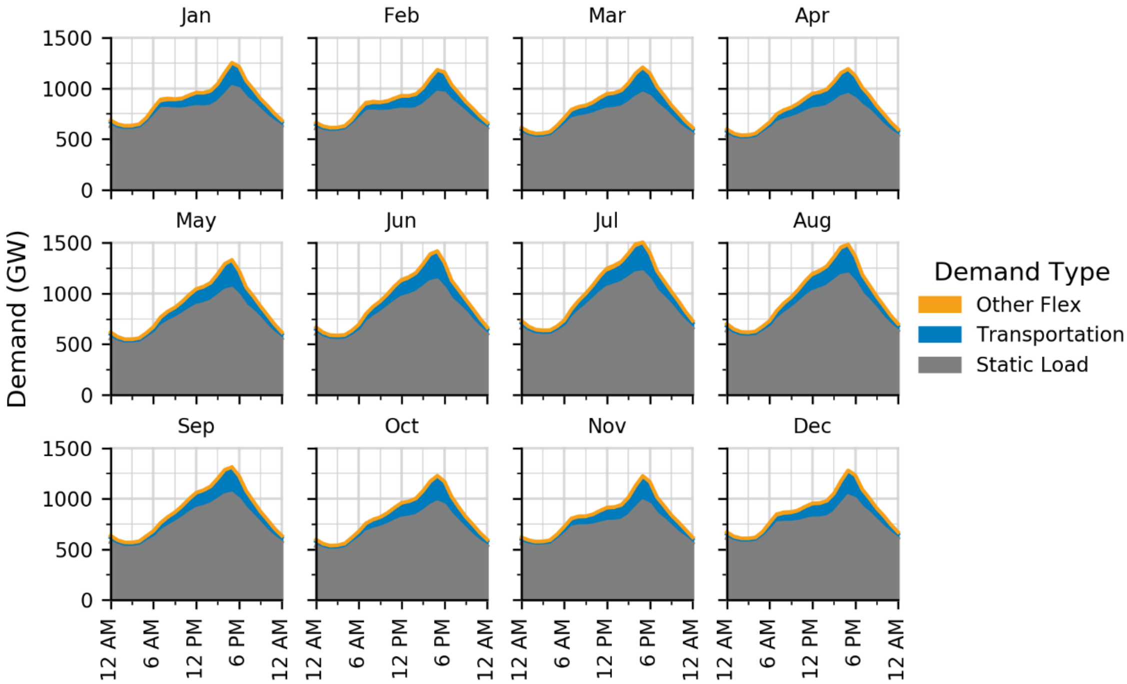

Figure 5. Flexible and inflexible load in 2050 under high electrification with high DSF

The hours in the x-axis correspond to the local time of each balancing area. The figure shows the general flexible and inflexible demand trends throughout the day without time-shifting cross time zones. Other Flex = all non-transportation flexible demand.

Our PLEXOS implementation of DSF is conceptually similar to that of battery storage (Hale, Stoll, and Novacheck 2018). Battery storage is modeled with a max capacity limit, a round-trip-efficiency, a state of charge between empty and full, and zero variable operation and maintenance cost (these assumptions are consistent with ReEDS input). Similarly, a DSF unit is modeled with a max capacity limit which is equal to the annual max flexible load, a 100% round trip efficiency, and without any operating costs. DSF does not have a state of charge, but it has a similar boundary of where its energy level could be. Unlike a battery storage which can stay at a certain state of charge for a long time, a DSF unit has the additional requirement that the end-use service must be performed on a given day or week, so DSF units have some additional constraints that do not apply to battery storage. All else equal, the least-cost dispatch framework of PLEXOS will first deploy the zero-marginal cost resources, such as DSF, battery storage, and VRE subject to their own hourly availability or other constraints.[22] The modeled DSF operation

[21] We assume failure to meet the load will result in a high penalty well above the cost of any generation or reserve. If the generation costs (and costs of other penalties added together) exceed the unserved load penalty, the system will drop load.

[22] Because of the diversity of technologies that could potentially provide demand-side flexibility and the wide range of existing and new business models under which they may operate, currently there is no robust estimate of DSF operational costs for the United States. An initial study from FERC constructed a framework to evaluate the cost and benefits of demand response programs (Woolf et al. 2013). If operating costs for DSF were included, the model

most directly reflects a centralized system operator perspective; however, we recognize other mechanisms (e.g., real-time pricing and incentive programs) could yield similar behavior.

We constrain the DSF units in our model in four main ways, according to how the flexible load shifting could happen:

1. Energy Balance Constraint: Because DSF does not generate electricity but rather shifts energy to a different period of consumption, we require each DSF unit to maintain the energy balance on a daily or a weekly basis. Daily energy balance is assumed for most end uses, particularly for end uses in the building sectors, such as home appliances, heating and cooling. Light-duty vehicles (LDVs), because of their large battery packs relative to the small amount of energy used in a typical day, are allowed to balance weekly, which means they do not need to be charged every day.

2. Demand Increase Capacity Constraint: This is the physical electrical capacity of the end-use unit to increase its consumption. For example, if actual air conditioning load in a region is 10 MW at a given hour, but it can technically increase to 15 MW if all air conditioning units in the region are operating at full capacity, then the 5-MW headroom is the demand increase capacity of the air conditioning load in the region. Because we do not have the data available for the maximum technical electricity power consumption for each end use, we simply assume the demand increase capacity equals the difference between the annual maximum observed flexible load for that subsector in that region and the flexible load at the given hour. Demand increase capacity is calculated as:

$$DIC_i = Max(E) - E_i$$

where DIC_i is the demand increase capacity of the DSF unit at hour i, $Max(E)$ is the maximum of flexible energy taken over the whole year; E_i is the flexible energy at hour i.

3. Duration Constraint: The duration constraint controls the duration and depth of the DSF unit operation. For example, suppose a DSF unit can shift 4 MWh of energy each hour for a max shifting duration of three hours per day, it can operate in several ways. If it shifts 12 MWh all at once, the DR event cannot last more than an hour, but if it only shifts 4 MWh per hour, the DR event can last three hours. It is represented by the inequality:

$$\sum_{i \in D_i} \frac{G_i}{E_i} \leq \mathrm{T}$$

where D_i is the set of all time indicies that fall on the same balancing period (day or week) as hour i, G_i is the amount of demand that is being shifted away from hour i (and will be met at a different hour), E_i is the amount of flexible energy available in hour i, and T is the number of hours that the resource may be shifted per balancing frequency (day or week). Multi-hour

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dispatch decisions for DSF and other system assets could differ from those reported here. As a result, the estimated economic value of DSF would differ from the values reported in the following sections. However, if these costs are small, then the differences from our modeled dispatch and estimated gross benefits would also likely be modest.

shifting does not need to occur consecutively within a balancing period. Specifically, we allow light-duty vehicles to be balanced weekly due to its relatively limited energy usage per day.

4. Timing Constraint: We impose a timing constraint for end uses that are unplugged from the outlets for certain periods and therefore unable to provide flexibility. This constraint is only imposed in the transportation sector. Specifically, we assume the medium-duty and heavy-duty vehicles can only be charged between 9 p.m. and 8 a.m. local time, because we assume the trucks electrified in the EFS operate during the day. In contrast, we assume that by 2050, both home charging and workplace charging would be more available, so we do not restrict the charging time for light-duty vehicles.

The parameters for all DSF units in the core scenarios are summarized in Table 2. Assumptions related to each subsector's availability (such as flexibility potential and participation rate) are documented in Section 4.1.2 of Sun et al. (2020).

Table 2. Balancing Frequency and Duration Assumptions for Flexible Loads

Sector	Subsector	Pump Capacity	Balancing Frequency	Duration Constraint
commercial	water heating	$Max(E) - E_i$	1d	4h
	air conditioning		1d	1h
	space heating		1d	1h
industrial	machine drives		1d	1h
	process heat		1d	1h
residential	water heating		1d	8h
	clothes washing and drying		1d	8h
	dishwashing		1d	8h
	air conditioning		1d	1h
	space heating		1d	1h
transportation	light-duty vehicles		1w	8h
	medium-duty vehicles	$Max(E) - E_i$ for plugged-in hours; 0 for unplugged hours (8 a.m. to 9 p.m.)	1d	7h
	heavy-duty vehicles		1d	4h
all sectors	other[a]	$Max(E) - E_i$	1d	1h

h = hour; d = day, w = week
[a] full list of subsectors aggregated into the other category is available in Sun et al. (2020).

In addition to the constrained energy-shifting described above, we allow DSF units to provide contingency and flexibility reserves. We do not allow demand-side resources to provide regulation reserves[23]. We also do not model vehicle-to-grid (V2G) technologies, which may provide energy, contingency, flexibility, and regulation reserves. Allowing V2G could change the value of DSF and affect grid service prices. For simplicity, we assume a DSF unit's capacity to provide reserves is the same as its capacity to provide energy at the given hour. That is, if a DSF unit is available, it can reduce its flexible consumption to provide both energy and reserves.[24]

The subsector-specific characteristics and constraints to DSF (i.e., energy balance period, pump capacity, duration, and reserve provision capability) are assumed to be the same in all the core scenarios (Table 3). However, the amount of DSF availability is scenario-dependent, as it involves assumptions on end-use participation in DSF as well as inherent differences in the amount and timing of electricity consumption (by subsector) driven by electrification. These scenario differences are described in the following section.

3.3 Scenarios

The core set of scenarios in the present analysis include variations along three dimensions: electrification level, VRE penetration, and DSF amount (Table 3). Results from the No DSF scenarios will be discussed in Section 4. The role of demand-side flexibility will be explored in Section 5 with a focus on Ref-NoFlex vs. Ref-HiFlex and High-NoFlex vs. High-LoFlex vs. High-HiFlex scenarios. Then in Section 6, we compare the three Low RE Costs scenarios with the three Mid RE Costs scenarios to see how VRE penetration may change the conclusions from the previous two sections.

[23] Regulation reserve is held to provide continuous, fast (second-to-second and minute-to-minute), and frequent correction of the supply and demand, typically done by system operators sending out a 4-second-interval automatic generation control signal to units that have the ability to rapidly adjust their output. While it is technically possible for DSF to provide regulation, it is the most technically-demanding reserve of the three we modeled. If we allow DSF to provide regulation, we are likely going to see slightly higher values for DSF because regulation typically has higher value than the other two reserves.

[24] This model representation may double-count DSF in some hours, as it allows the same DSF to provide both energy and reserve services at the same time. This is consistent with previous DSF studies (e.g., Stoll, Buechler, and Hale 2017) and is employed for computational tractability. It results in slightly over-valuation of DSF. Future work is needed to examine the impact of different model representations.

Table 3. Core Scenarios

Electrification Level	Renewable Energy Cost Assumption	Demand-Side Flexibility	Scenario Name
Reference	Mid RE[a] Costs	No	Ref-NoFlex
		Enhanced	Ref-HiFlex
High	Mid RE Costs	No	High-NoFlex
		Base	High-LoFlex
		Enhanced	High-HiFlex
	Low RE Costs	No	High-HiRE-NoFlex
		Base	High-HiRE-LoFlex
		Enhanced	High-HiRE-HiFlex

[a] RE = renewable energy

The core scenarios are based largely on the prior EFS supply-side scenarios (Murphy et al. 2021)[25] except for the difference in treatment of DSF. In the present analysis, scenarios with the same electrification and RE cost assumptions have the same generation and transmission builds, because we base our capacity mixes on ReEDS-generated scenarios *with no DSF* assumed (Figure 6). In other words, whereas Murphy et al. (2021) examine how DSF might affect the capacity mix, in this analysis, we study its operational impacts by incrementally adding DSF after the overall capacity mix has already been determined. In the Ref-, High-, and High-HiRE-scenarios, VRE accounts for 52%, 50%, and 59% of the total capacity, natural gas accounts for 34%, 39%, and 23% of the capacity, and storage accounts for 2%, 2%, and 14%.

Two of the DSF levels modeled in our scenarios, LoFlex and HiFlex, are designed to be consistent with the Base and Enhanced flexibility, respectively, from the prior EFS analysis in terms of total amount (Murphy et al. 2021, Sun et al. 2020).

Table 4 (page 18) shows the amount of flexible loads assumed in the core scenarios by sector and as a percentage of total load.

[25] More specifically, the 2050 power systems and other parameters from the ReEDS analysis are used to generate corresponding PLEXOS models using the process described in Section 3.1.

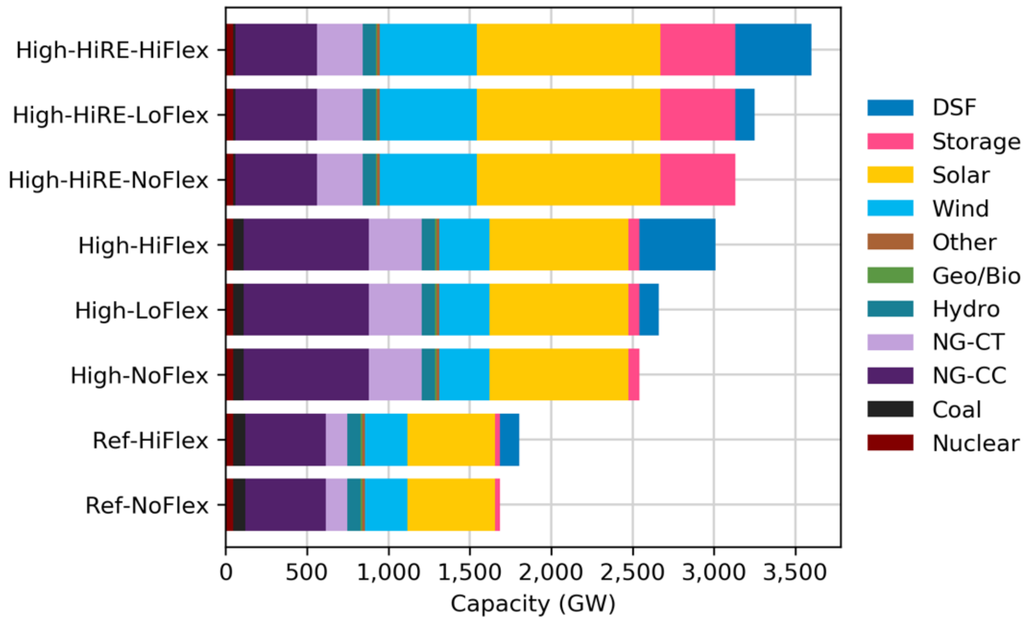

Figure 6. Simulated 2050 installed generation capacity in the core scenarios[26]

The amount of DSF here represents the maximum shiftable capacity of all DSF units. DSF = demand-side flexibility; Geo/Bio = geothermal/ bioenergy; NG -CT = natural gas-combustion turbine; NG-CC = natural gas-combined cycle.

Table 4. Flexible Load in 2050[a]

Scenario	Transportation Sector	Residential Sector	Commercial Sector	Industrial Sector	All Sectors
Ref-NoFlex High-NoFlex High-HiRE-NoFlex	0	0	0	0	0
Ref-HiFlex	55 TWh (58%)	195 TWh (13%)	42 TWh (2%)	65 TWh (5%)	357 TWh (7%)
High-LoFlex High-HiRE-LoFlex	191 TWh (12%)	62 TWh (4%)	20 TWh (1%)	27 TWh (2%)	299 TWh (4%)
High-HiFlex High-HiRE-HiFlex	825 TWh (51%)	187 TWh (12%)	60 TWh (3%)	80 TWh (5%)	1,151 TWh (17%)

[a] Values show absolute annual available amount of flexible load (in terawatt-hours) and percentage of flexible load relative to total annual load by sector. Load from all sectors may not equal the sum of the individual sectors because of rounding.

[26] Storage modeled in EFS includes pumped hydro storage, compressed air energy storage, and 4-hour battery storage.

3.4 Scope and Modeling Limitations

The present analysis applies detailed grid simulations to examine power systems operations under various electrification scenarios. In doing so, the analysis supplements prior EFS analyses and builds on the broader collection of studies that examine power systems operations with changes to load shapes, increases in VRE penetration, and greater interactions between electricity supply and demand. Despite this higher-resolution modeling, several remaining scope and modeling limitations are important to acknowledge to properly interpret our findings.

Operations Only: The present analysis includes simulations of 2050 power system operations only, and it does not examine investment decisions or other long-run impacts. The capacity mixes used for the present analysis are based on capacity expansion results described in prior EFS reports (Murphy et al. 2021, Sun et al. 2020). These reports also document the limitations of ReEDS and the related analysis. Therefore, all modeled findings reported here relate to operational impacts only; for example, the economic value of DSF represents the production cost value of DSF and excludes its potential value in avoided capacity.

Spatial Resolution and Transmission Modeling: As with the broader EFS, the geographic scope of the present analysis is the conterminous United States.[27] As described in Section 3.1, the modeled network for this geographic extent comprises 134 model BAs. Transmission is represented as a pipe-flow where capacity limits constrain the power exchanges between BAs as opposed to more-realistic transmission representations, such as DC or AC power flow modeling.[28]As a result, we might underestimate the extent of transmission congestion within and between zones.

Within each model BA, individual generator units are represented, but simplifications are used in the representation of these units. For example, each unit uses a single heat rate, rather than unit-specific heat rate curves.[29] Furthermore, generators are decomposed using average unit sizes and, therefore, a set of generators in a region have more uniform sizes than would be expected. In general, our model representation omits certain unit-specific detail.[30] Additional nodal modeling with more granular generator unit and high-resolution transmission modeling would enable a more robust examination than was conducted for the present analysis.

Representation of Demand-Side Flexibility: The future amount of and constraints to flexible loads are highly uncertain because of the complex behavioral and technical factors involved.[31] Sun et al. (2020) discuss these factors and limitations in representing DSF in the EFS, and these also apply here. In particular, the amount of DSF is assumed exogenously in each scenario and

[27] Electrification could lead to transmission expansion as well as increased coordination and power transfers between the United States and neighboring countries, but we do not include such possibilities in this analysis.

[28] Transmission and distribution losses are considered when ReEDS optimizes the capacity build, but the zonal load reflects bus-bar load in the present analysis. We do not model transmission losses in this analysis.

[29] Within a region, the units of each generator category (e.g., natural gas-combined cycle [NG-CC]) can have different heat rates based on the heat rate bins used in ReEDS (Cohen et al. 2019).

[30] Hydropower is an example of how a coarser treatment is applied. Specifically, we use time-slice energy limits from ReEDS, without using detailed unit-level weekly or daily energy limits or differentiating the varied types of hydropower technologies and operations.

[31] Transportation electrical load profiles and flexibility behaviors are particularly uncertain, as vehicle demands are still evolving and depend on future developments to charging infrastructure, city planning, and many other factors (Zhang et al. 2020; Marra et al. 2012; S. Wang et al. 2020; Majidpour et al. 2016).

the cost for implementing and operating DSF are not included. Because our analysis excludes such costs, our results should be interpreted as a gross operational valuation of DSF only and not a cost-benefit analysis of flexible loads. Furthermore, we made several assumptions regarding various operational aspects of future DSF (Section 3.2). For example, we assume 100% round trip efficiency for all DSF even though pre-cooling or postponing air conditioning may have higher or lower efficiency that is typically temperature-dependent and can lead to changes in electricity demand. It is possible for DSF to provide energy and either of the flexibility or contingency reserves simultaneously in our study, leading to a slight overestimation of DSF values; while not allowing DSF to provide regulation reserve results in an underestimation. These model choices are admittedly imperfect, but model decisions are needed given uncertainties in future DSF aggregation technologies and business models. We also acknowledge that many regulatory and market factors can impact the operation and value of DSF (Eid et al. 2015; Paterakis, Erdinç, and Catalão 2017), but are outside of the scope of this analysis. We do not claim to have accurately represented all the subsector DSF behaviors, but our analysis can demonstrate the operational value of DSF in aggregate and how this value might change under different conditions (e.g., with greater electrification or VRE penetration).

Load Profiles: In addition to uncertainties and hard-to-predict behavior of flexible loads, there is a similarly great deal of unknowns with respect to future (static and dynamic) loads. These unknowns can stem from broad demographic or structural shifts in the economy, technology innovation, changes to weather patterns, and behavioral patterns. Newly electrified loads may be subject to these and additional uncertain factors (e.g., infrastructure availability for electric vehicle charging). Our analysis relies on a single base load profile for each scenario based on the EnergyPATHWAYS modeling using a single weather year — 2012 (Mai et al. 2018). Further research is needed to understand how our findings might vary with several sensitivities to these assumptions. For example, the base profiles for light-duty electric vehicle charging relied on a "home-dominant" charging regime[32] and future analysis of work-dominant charging, autonomous vehicles, or significant ride-sharing could lead to different findings on the availability and dispatch of DSF. Multiple weather years can also be evaluated, which might enable a more robust evaluation of the impacts of extreme weather events on the operations of power systems with widespread electrification.

While acknowledging these limitations, the present analysis is, at the time of writing, the first to examine hourly systems operations, including with endogenous DSF, under high electrification grids for the entire conterminous U.S. system using models with detailed geographical and temporal resolution, and mixed integer programming (for security constrained unit commitment and economic dispatch modeling). The following sections present the results from these grid simulations.

[32] The operation assumptions (Section 3.2) of demand-side flexibility are slightly different from the ReEDS analysis. In the case of light-duty vehicles, both home-charging and workplace-charging are allowed in the current analysis.

4 Results: Operation an Electrified System without Demand-side Flexibility

We first examine the hourly operation of the EFS scenarios *without* demand-side flexibility, including resource adequacy, inter-regional transmission, and VRE curtailment. As described in Section 3, these NoFlex scenarios rely directly on the capacity mix generated from the ReEDS model (Murphy et al. 2021); therefore, the operational feasibility metrics (such as unserved energy) indicate whether the optimal portfolio from ReEDS is resource-adequate.[33] By examining scenarios with reference and high electrification levels we can test whether electrification—and its impacts on annual energy demand, hourly demand, operating reserve requirements, and the capacity mix—impacts the ability to serve load or operating reserves. Subsequent sections examine the fuller set of scenarios to explore the role of flexible load and the impact of VRE in detail.

4.1 Generation and Resource Adequacy

Figure 7 shows annual electricity generation for all three NoFlex scenarios based on the ReEDS-built systems in Murphy et al. (2021). Natural gas generation accounts for 34%, 42%, and 25% of total annual generation in Ref-NoFlex, High-NoFlex, and High-HiRE-NoFlex, respectively. Ref-NoFlex and High-NoFlex use mid-case technology cost assumptions and have 42%–43% VRE penetration, while High-HiRE-NoFlex, which relies on lower renewable energy and storage cost assumptions to generate the capacity mix, reaches post-curtailment VRE penetration of 66%. In all scenarios, VRE generation is approximately evenly split between wind and solar generation. Murphy et al. (2021) present details on the factors driving generation mix differences between scenarios.

[33] As noted in Section 3.1, ReEDS underestimated the need for capacity in a single model BA that includes the Chicago metropolitan area.

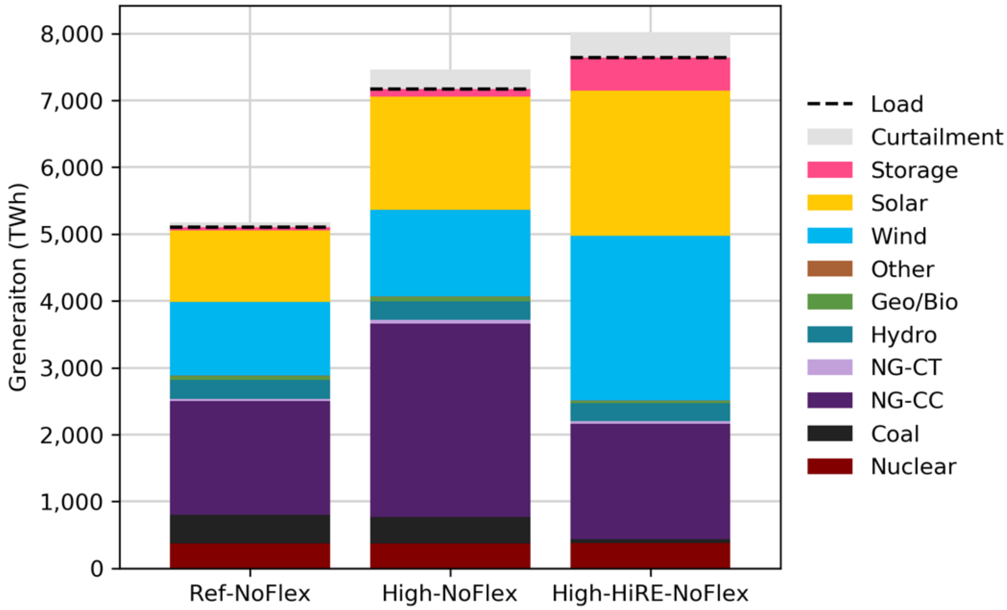

Figure 7. Simulated 2050 annual generation for NoFlex scenarios[34]

Geo/Bio = geothermal/ bioenergy; NG -CT = natural gas-combustion turbine; NG-CC = natural gas-combined cycle.

In all regions, High-HiRE-NoFlex has a greater share of VRE than Ref-NoFlex and High-NoFlex (Figure 8). In High-HiRE-NoFlex, VRE penetration exceeds 50% in nearly all regions, including 78% by 2050 in the Southwest Power Pool region.

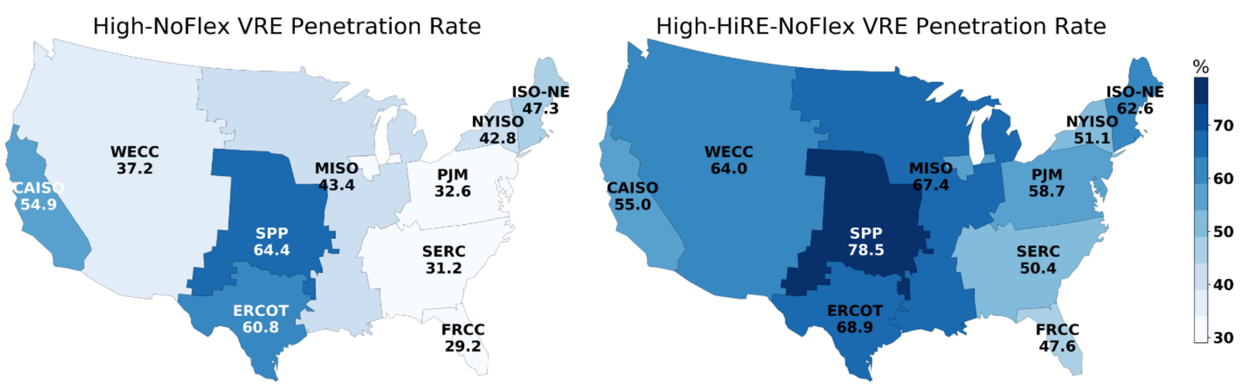

Figure 8. Annual VRE penetration by region under High-NoFlex VRE scenario (left) and High-HiRE-NoFlex VRE scenario (right)

WECC refers to the non-CAISO WECC region. Similarly, SERC excludes FRCC.

The PLEXOS simulations indicate that the system serves more than 99.99% of the load and 99.96% of the operating reserves for the three NoFlex scenarios, which complies with NERC's reliability standards related to resource adequacy and operating reserves (NERC 2011, 2017). Figure 9 shows the system dispatch under Ref-NoFlex, High-NoFlex, and High-HiRE-NoFlex during days with potential high system stress—the highest total load, highest net load, and

[34] Storage modeled in EFS includes pumped hydro storage, compressed air energy storage, and 4-hour battery storage.

highest net load ramping—and that load can be served during these challenging days. In these scenarios where DSF is not available, storage is instrumental in charging when it is low-cost (shown as the pink area below x-axis) and discharging during times of system need (as the pink area above x-axis). For example, in the High-HiRE-NoFlex operations, storage consumes excess generation during the day and discharges during the evening ramp hours. When storage capacity is insufficient, peaking units, such as NG-CTs, are used during these ramping periods; this is particularly prevalent in High-NoFlex. Electrification and VRE also change other operational behavior, such as thermal plant commitment and dispatch patterns, transmission flows, and renewable curtailment as we describe in latter sections.

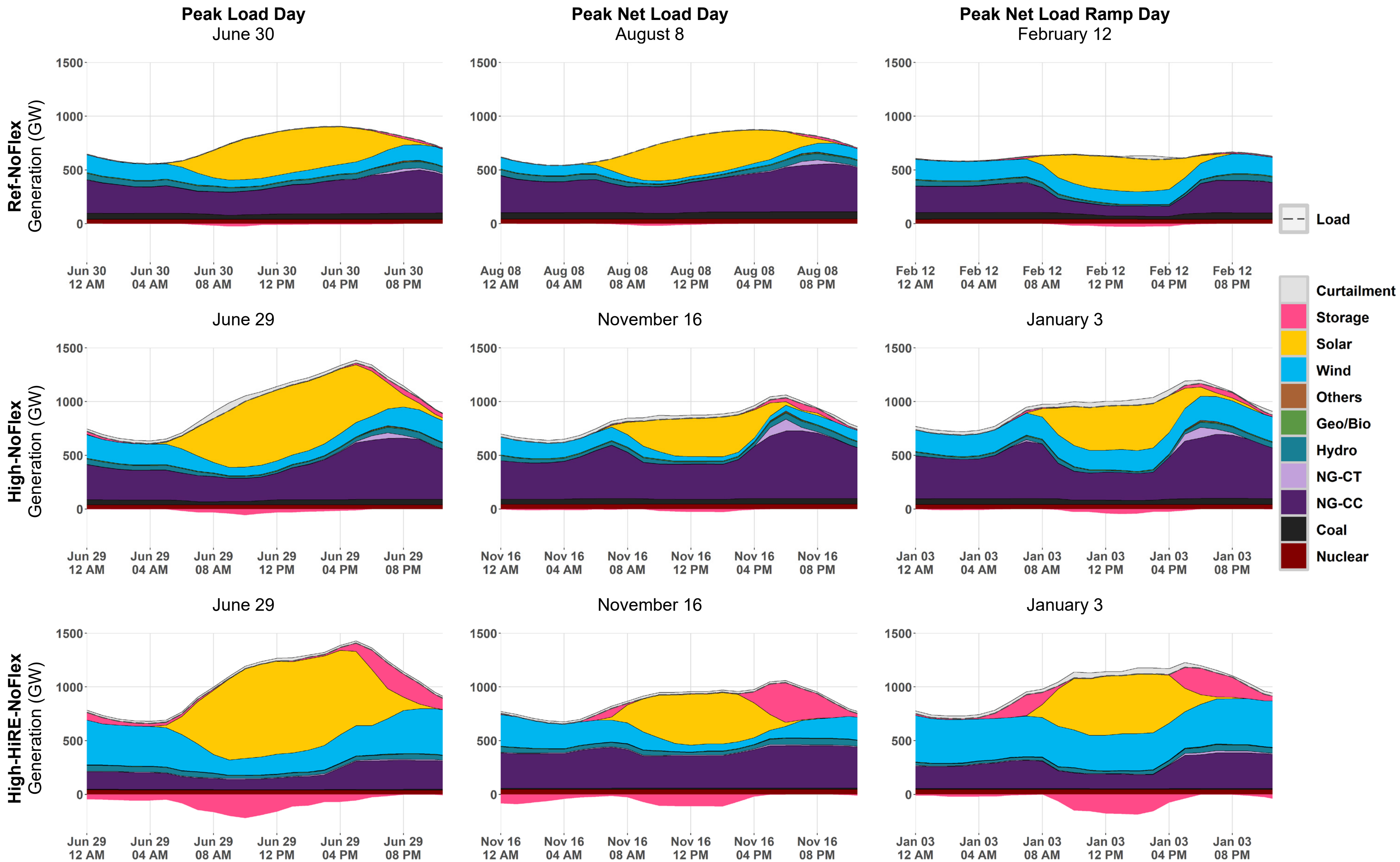

Figure 9. Daily system dispatch during potential high system stress days in 2050 in the NoFlex scenarios

The production cost modeling converts all time zones into EST. All dispatch and other operational figures are shown in EST unless otherwise noted. Pink area below the x-axis indicates storage charging.

In addition to supporting energy balancing, storage also plays a crucial role in providing operating reserves in the absence of DSF. Meeting the operating reserve requirements dictates having sufficient headroom and ramping capability in the timescales of the different reserve products. Figure 10 shows the operating reserve provision by technology for the three NoFlex scenarios. In these scenarios, storage, hydropower, and natural gas technologies are the main contributors to contingency and flexibility reserves. Nearly all regulation reserves are provided by storage for all three scenarios. Comparing High-NoFlex with Ref-NoFlex, we see that electrification-driven increases to contingency reserves are primarily met by natural gas and storage technologies. However, in High-HiRE-NoFlex, where storage deployment is significantly greater (Figure 6, page 18) than in the other scenarios, reserves of all types are primarily satisfied by storage. Figure 10 also shows how wind, solar, and hydro technologies provide moderate amount of reserves.

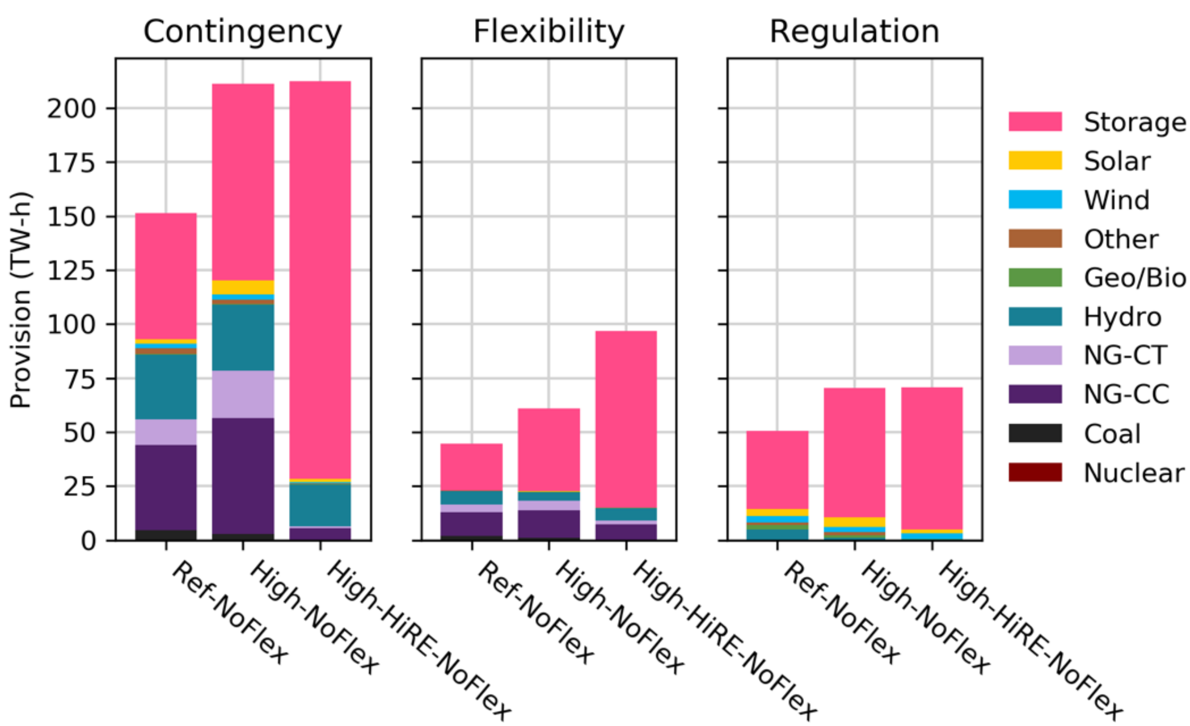

Figure 10. Operating reserve provision by technology type in the NoFlex scenarios

4.2 Transmission Impacts

As discussed in the previous section, without DSF, storage provides crucial grid flexibility for load balancing and operating reserves in all three scenarios, including those with high electrification and high shares of renewable energy. In this section, we describe how the system also relies on power transmission between zones for balancing.

Figure 11 shows the amount of annual energy exchange between 10 regions that are closely aligned with existing independent system operator (ISO)/regional transmission organization (RTO) regions or North American Electric Reliability Corporation (NERC) reliability regions. In general, there are only minor differences in the geographic pattern of energy flows between the three NoFlex scenarios. In all three scenarios, the Midcontinent Independent System Operator (MISO) and non-CAISO (California Independent System Operator) WECC regions are major exporters whereas regions in the southeastern United States (SERC Reliability Corporation [SERC] and Florida Reliability Coordinating Council [FRCC]) and CAISO are importers. In terms of magnitude, imports and exports are very similar between the Ref-NoFlex and High-NoFlex scenarios,[35] which means electrification by itself does not appear to have a significant impact on inter-regional transmission flows as local generation resources are relied upon to meet incremental demand from electrification (Murphy et al. 2021). On the other hand, under High-HiRE-NoFlex, the amounts of both import and export are greater in most regions. The increase in energy exchange is particularly prominent in the MISO region and the non-CAISO WECC region, which corresponds to the high VRE penetration in the regions shown in Figure 8 (page 22).

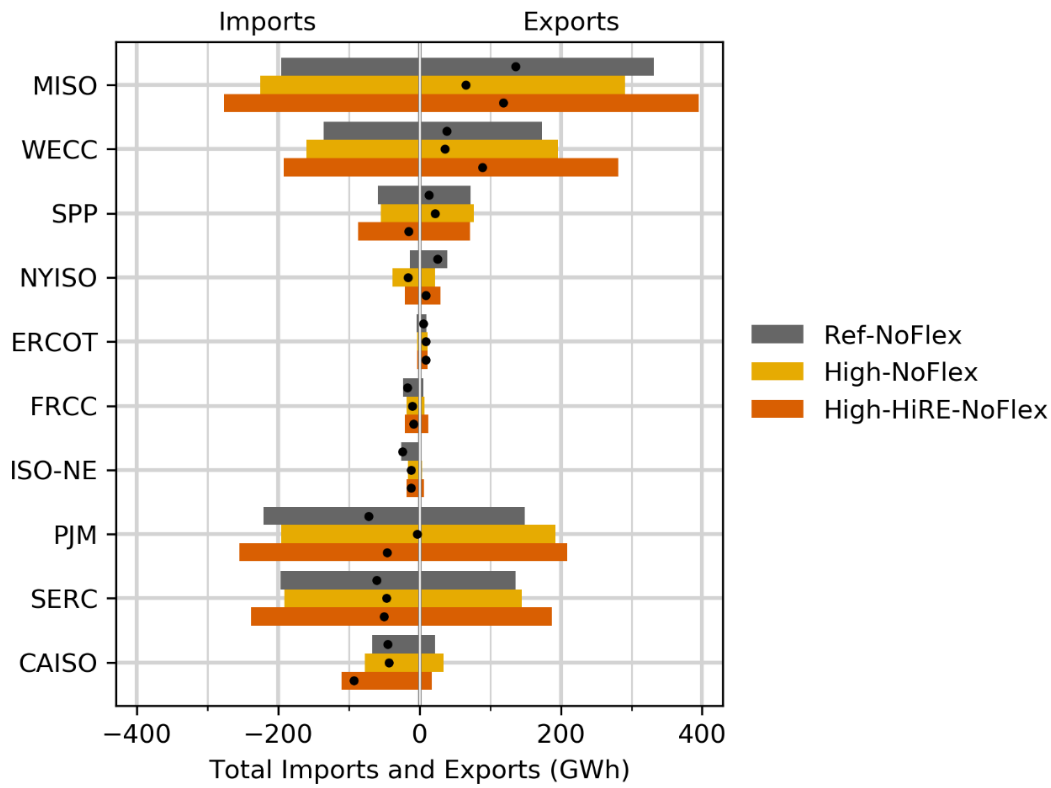

Figure 11. Total import and export by region in the No-Flex scenarios

Black dots indicate the net annual import/export value. WECC refers to the non-CAISO WECC region and SERC excludes FRCC.

[35] Total transmission capacity in High-NoFlex and High-HiRE-NoFlex are 3% and 16% greater, respectively, than that in Ref-NoFlex.

Without transmission expansion or changes to operating practices, higher penetration of VRE can push transmission lines to their power transfer limits and cause issues such as network congestion and voltage stability (Yao et al. 2005). Our results show that high electrification and high VRE penetration leads to higher average utilization of the transfer capability between interfaces (Figure 12), which highlights the importance of inter-regional coordination and transmission in low carbon grids (Brown and Botterud 2020). We also show that interfaces with smaller capacities tend to be more congested or have higher utilization rates (shown as the smaller circles at the top of the utilization rate spectrum in Figure 12). The results show a slight increase in transmission utilization and congestion frequency with electrification, but more pronounced transmission impacts when electrification is combined with increased VRE (Figure 13). The transmission results indicate that the transmission expansion (including long-distance transmission and spur-line development) envisioned in Murphy et al. (2021) is important for operating a power system with high electrification and high renewable energy penetration.

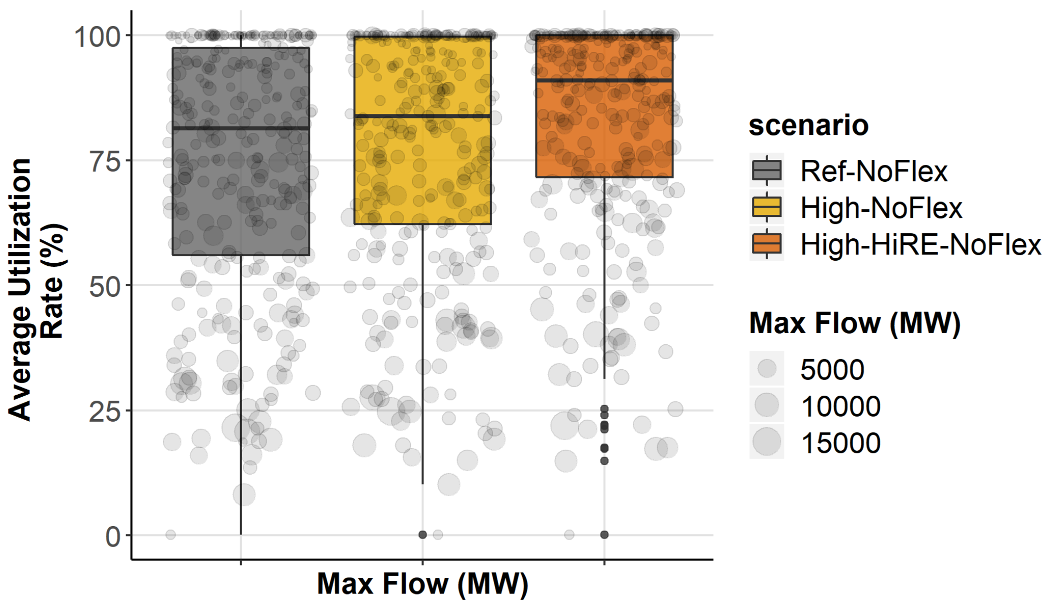

Figure 12. Average interface transfer capability utilization rate distribution in the NoFlex scenarios

Each grey bubble represents a zonal interface.

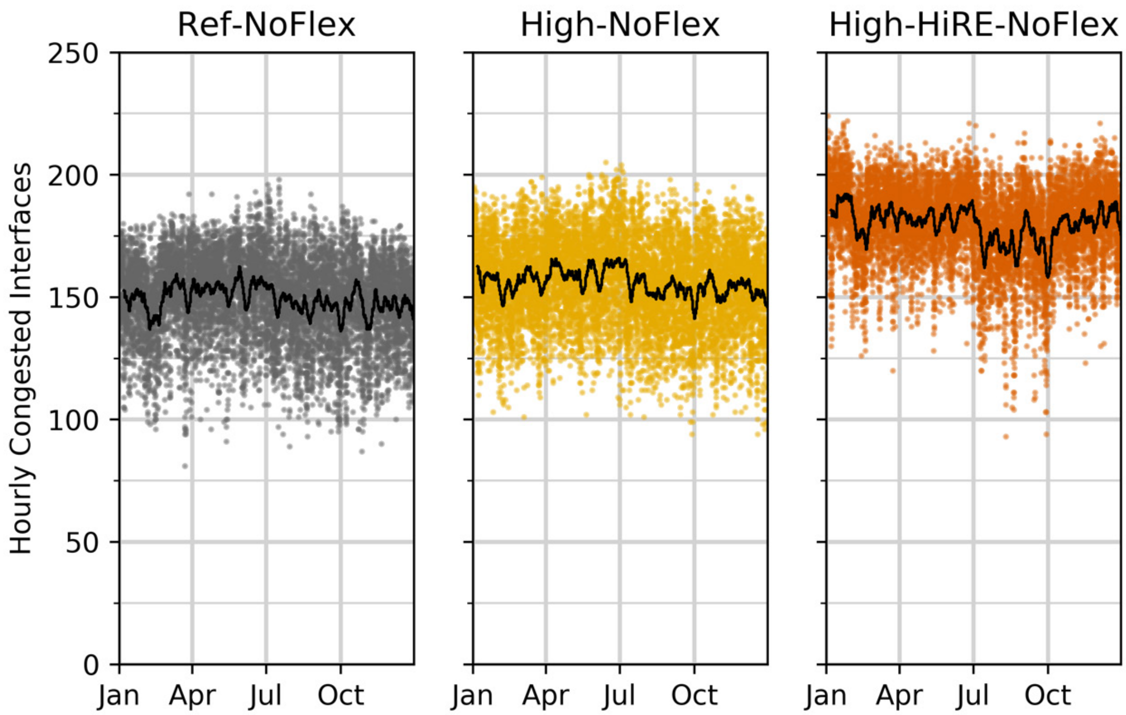

Figure 13. Number of congested interfaces at each hour throughout the year in the NoFlex scenarios

There are 471 zonal interfaces modeled.

Transmission congestion can lead to curtailed energy, which has also been observed in previous electrification studies (Guminski, Böing, et al. 2019). Other system inflexibilities, such as minimum plant loading and minimum on/off periods, can also lead to curtailed VRE.

4.3 Renewable Curtailment

High VRE penetration in the high electrification scenarios (in the absence of demand-side flexibility) can result in higher rates of renewable curtailment. Total curtailment is estimated to be 3% of annual available VRE in Ref-NoFlex and 8%–9% in High-NoFlex and High-HiRE-NoFlex (Table 5). The amount of VRE in all three scenarios is significantly greater than that in 2019 when VRE comprised about 10% of total generation. VRE penetrations in 2050 are estimated to be similar under Ref-NoFlex and High-NoFlex (42%–43%), but the curtailment rate is about three times greater under the high electrification case. This is because simulated electrified loads across the demand subsectors have different usage patterns that may not coincide with the renewable profiles—especially without demand-side flexibility. This phenomenon has also been noted other studies (e.g., Ebrahimi, Mac Kinnon, and Brouwer 2018).

Table 5. Simulated 2050 Post-Curtailment Renewable Penetration and Curtailment Outcomes

Scenario	Ref-NoFlex	High-NoFlex	High-HiRE-NoFlex
VRE Generation (TWh)	2,172	2,987	4,641
VRE Penetration	43%	42%	66%
RE Penetration	50%	47%	70%
VRE Curtailment (TWh)	74	298	377
VRE Curtailment Rate[a]	3%	9%	8%

[a] Curtailment rate is the fraction of annual available VRE generation that is unused.

Absolute curtailment in High-HiRE-NoFlex is greater than that of High-NoFlex, as is expected due to the greater VRE in the former. Yet High-HiRE-NoFlex has a lower national average curtailment *rate*. The reasons behind this are the significantly greater amount of energy storage capacity in this scenario (462 GW versus 69 GW in High-NoFlex and 30 GW in Ref-NoFlex) and the greatly expanded transmission capacity (13% increase) in High-HiRE-NoFlex compared with High-NoFlex. Much of the storage is deployed in the east as well as CAISO, but even though storage can lower curtailment, its operation is accompanied by storage loss, which we assume to be 15%.

Though curtailment can negatively impact the economics for VRE technologies, our simulations show curtailment can be a part of the optimal dispatch and help meet grid service needs, particularly in high electrification systems (O'Shaughnessy, Cruce, and Xu 2020). Another mechanism to reduce curtailment is through DSF as we discuss in the following sections.

5 Results: Increasing Efficiency of High Electrification Systems with Demand-Side Flexibility

In Section 4, we examine the hourly operation of the EFS scenarios in the absence of demand-side flexibility. Many studies have postulated that electrification could help enable the expansion of demand-side participation in power system planning and operations (see Section 2.3). In this section, we examine how flexible loads can change systems operations in the reference and high electrification scenarios with moderate levels (42%–43%) of VRE. In particular, we describe the behavior of the flexible loads as well as the operational economic value of this flexibility with various levels of electrification. In Section 6, we examine how these could change with higher VRE penetrations.

In comparing (1) Ref-HiFlex with Ref-NoFlex and (2) the High-Lo/HiFlex scenarios with High-NoFlex, the analysis indicates DSF can produce a range of system benefits that includes reduced operational costs, price volatility, and renewable curtailments. DSF helps the system achieve these operational benefits by providing two types of services: energy shifting and operating reserves.

5.1 Energy Shifting

Demand-side flexibility reduces power system operating costs primarily by increasing demand during low-price periods and decreasing demand during high-price periods. In other words, load shifting helps increase utilization of generators with low operating costs and avoids the utilization of higher-cost ones. Figure 14 shows the diurnal patterns of DSF energy service provision (in darker shades, above the x-axis) and energy recovery (in lighter shades, below the x-axis) by season; the top panel shows the hourly mean energy provision and recovery in absolute amounts, while the bottom panel shows hourly deployment of flexible loads by sector as a percentage of its average daily availability. The energy service provision means demand reduction (i.e., where the energy consumption is *shifted from*), which from hereon we refer to as "energy" because this study is from the grid operation perspective. Energy recovery corresponds to when energy consumption is *shifted to* (we refer to as "energy consumption"). Because we assume the DSF has an efficiency of 100% in this analysis, there is no energy loss in the shifting process, so the total energy service provision equals the energy recovery.[36]

[36] Mismatches between the two are allowed, but with a cost penalty, in our modeling for computational tractability reasons. Such violations do occur in our grid simulations but are modest on an annual basis. For example, in the High-HiFlex scenario, violations accounted for less than 1% of the shifted load. In addition, light-duty vehicles are balanced weekly, so it is possible that the few remainder days in our monthly simulation have unequal energy consumption and recovery in the light-duty vehicle fleet.

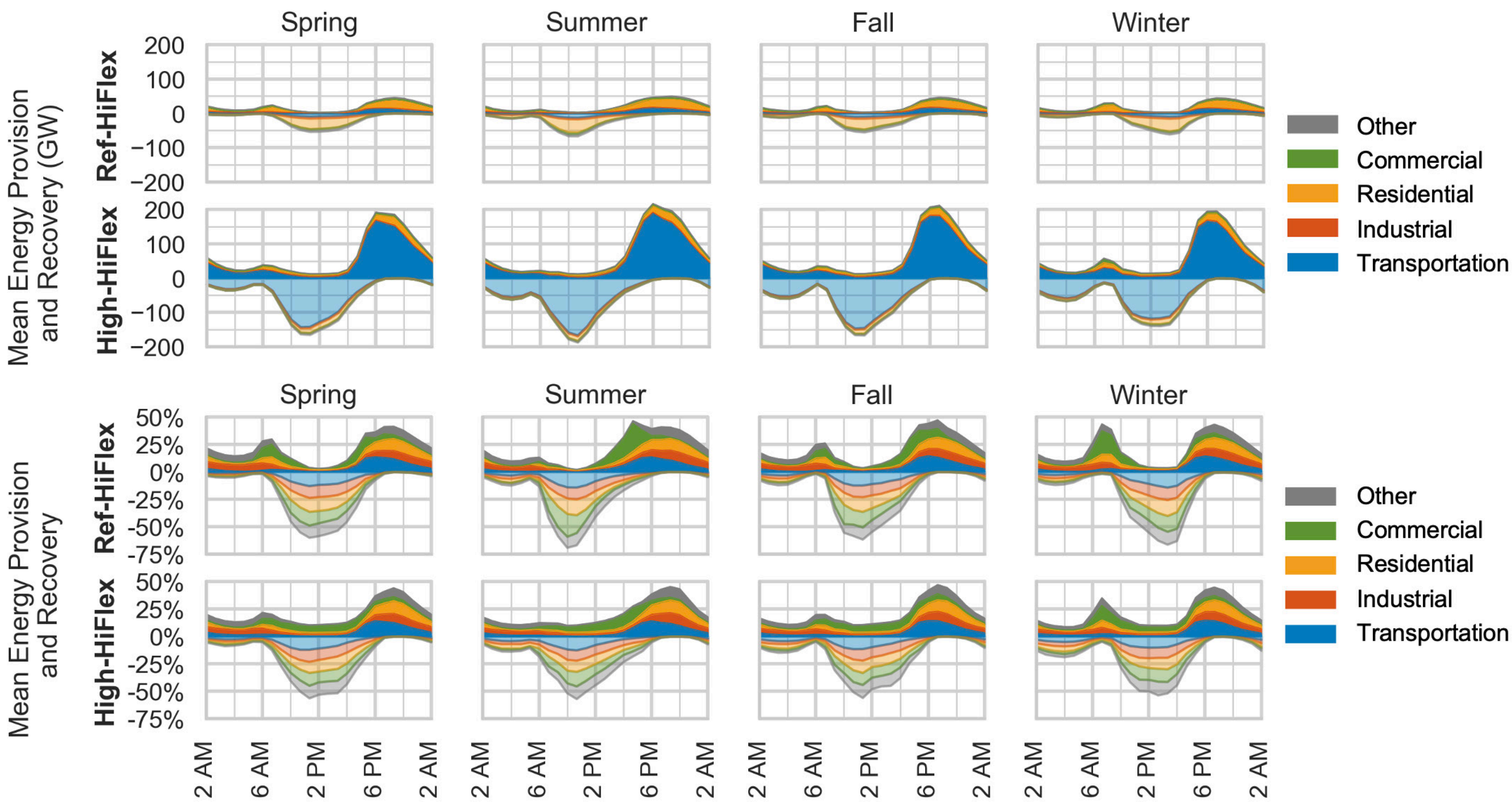

Figure 14. DSF dispatch by sector during each hour of the day in absolute (top) mean daily provision and as a percentage (bottom) of daily provision by sector in Ref-HiFlex and High-HiFlex scenarios

Positive values indicate mean energy provision (i.e., when flexible loads are not consuming energy) and negative values represent energy recovery (i.e., when flexible loads are consuming energy). The “Other” category refers to the aggregation of miscellaneous loads from all sectors (see Section 3.2).

We analyze the DSF operation across scenarios, by examining the seasonal and diurnal patterns of DSF operation and by looking into any differences in DSF behavior across demand sectors (e.g., transportation versus buildings). The analysis is organized from longer time scale to shorter time scale, from national to subnational (in Text Box 1).

In national aggregate, DSF operation patterns are generally similar under reference and high electrification scenarios: DSF tends to shift energy consumption from the morning and evening hours to the mid-day period. This load shifting pattern enables the system to utilize the solar generation during the day, as Ref-HiFlex and High-HiFlex have similar amounts of solar (21%–24%).

But a comparison of Ref-HiFlex and High-HiFlex reveals differences exist between the various DSF sectors due to electrification. As we expect, most of the flexible load comes from the residential sector under reference electrification, whereas the transportation sector is the main source of DSF under high electrification. This represents a shift in the absolute amount of flexibility as well as a relative shift between sectors and the sectoral shift in the optimized dispatch outpaces the scale of the input assumptions. For example, about 200 GW of demand is shifted away from the evening period under High-HiFlex versus 50 GW under Ref-HiFlex– that is, the utilization of flexible loads increased by 4 times when the availability of flexible loads only increased by 3.2 times in High-HiFlex over Ref-HiFlex. This indicates that the timing of optimized vehicle charging can potentially provide higher value shifting. In other words, the operational behavior of this electrification-associated flexibility aligns well with the system needs based on our assumptions for demand flexibility (Section 3.2). Additional study is needed on behavioral and other difficult-to-model aspects of flexible loads.

In terms of seasonal patterns, we observe that the maximum daily energy provision from the DSF is similar across seasons for each scenario, suggesting that the system can benefit[37] from flexibility throughout the year. The magnitude of energy recovery follows the sun's pattern and moves later in the day as the seasons go from spring to winter. In the spring, unlike any other season, nearly all of the demand increase (energy recovery) occurs during daytime hours when PV provides low marginal cost generation (Mills and Wiser 2015). In the winter, the DSF units have two energy-provision peaks that correspond to the twin peaks in winter net load demand due to patterns in heating and lighting demands, while the DSF energy provision in the summer is relatively flat until evening.

Flexible loads can help facilitate supply-demand balance. As seen in Figure 15, DSF effectively reduce the net load ramps. This is achieved by providing flexibility during the more-stressful periods such as the morning and evening ramps. For example, Figure 16 shows the system net load ramps in High-NoFlex, High-HiFlex scenarios, and their differences. In the figure, the warm (red) tones indicate up ramps and the cooler (blue) tones indicate down ramps; the darker the shade, the steeper the ramps. The first two panels of Figure 16 show that the steepest ramps occur in the non-summer months: the up ramps around 4 p.m. and the down ramps around 8–9 a.m. and after 8 p.m. In the summer, the ramps are more diffused; the down ramps in the mornings occur earlier and the up ramps in the evenings occur later. Overall, in the third panel

[37] We note that we assume DSF operation incurs zero cost. The amount and timing of load shifting would be impacted if we add operational costs to DSF.

(High-HiFlex minus High-NoFlex) the blue shades in the mornings and throughout summer mid-day indicate that DSF reduces up ramps during this period, and the red shades in the afternoon hours throughout the year indicate DSF reduces evening down ramps.

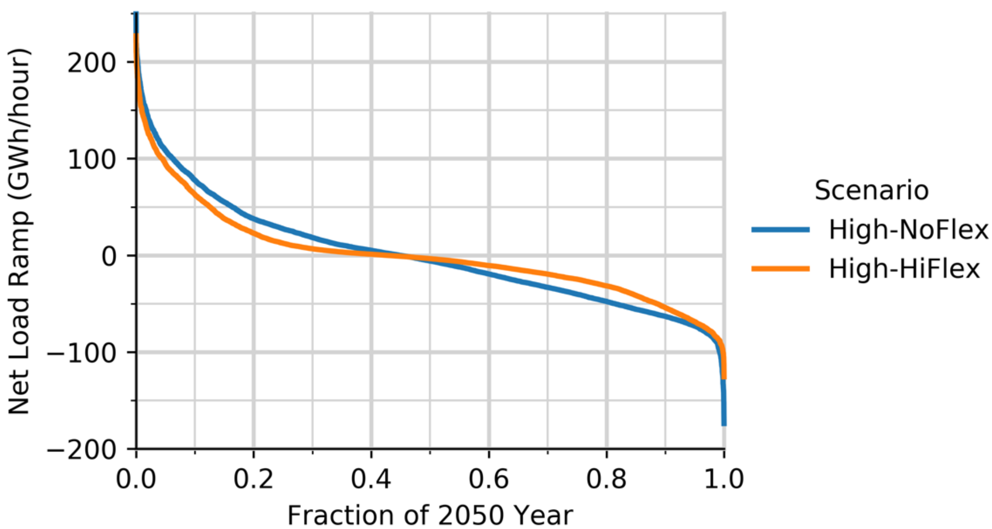

Figure 15. System net load ramp duration curve

Up ramps are illustrated above y=0 line, and down ramps are illustrated below y=0 line.

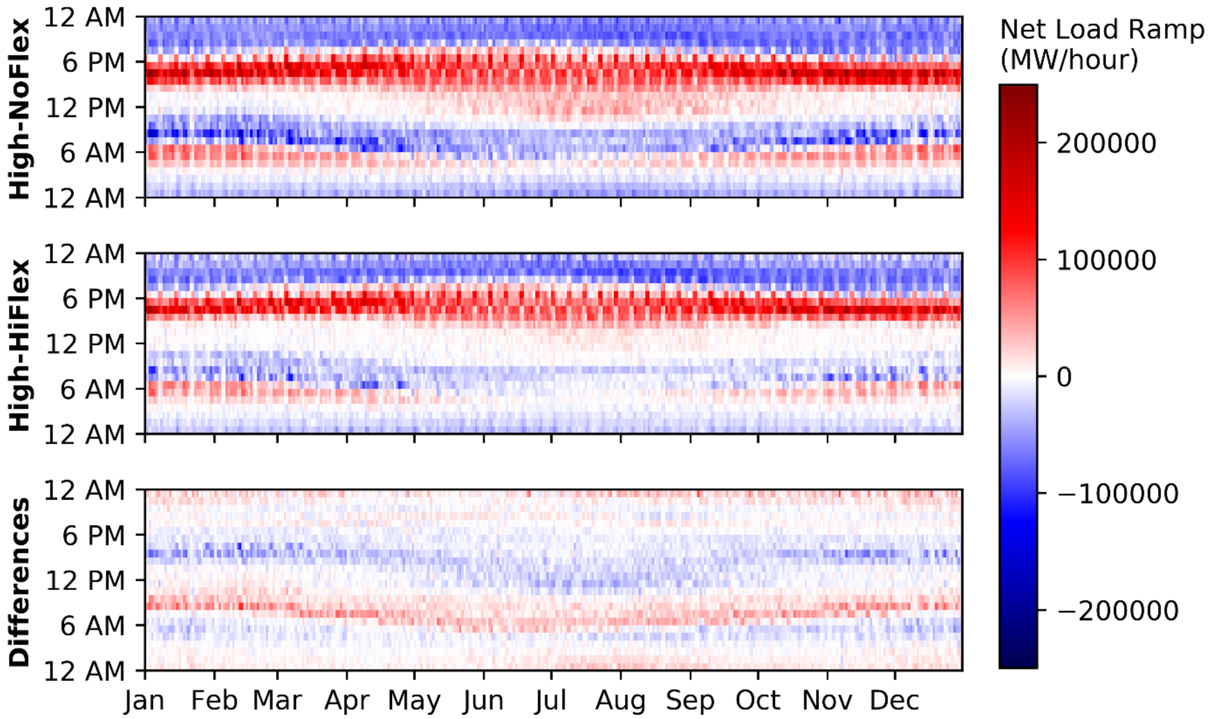

Figure 16. System net load ramp of High-NoFlex, High-HiFlex, and their difference (HiFlex minus NoFlex) by day of the year and time of day

Finally, the sectoral differences in flexible load availability also transfer to how DSF units operates within a day. For example, the commercial sector provides energy shifting throughout the day but not during the night (shown as green stack in Figure 14, page 31). The flexibility in the residential sector on the other hand, provides most of its flexibility by shifting energy use from the nighttime period to the daytime period (shown as yellow stack in Figure 14). This suggests flexibility in different end uses may play different roles in providing the flexibility to the future power system.

Text Box 1. Regional Variance in DSF Energy Shifting

Even though the national average shows very similar patterns for DSF operation through all four seasons, a closer look into the regions reveal some regional and seasonal nuances. DSF operation is shaped by the unique generation mix and net load characteristics of each region. In Figure 17, we show a few snap shots of seasonal DSF operation for six regions: for the non-CAISO WECC and NYISO regions, we show the DSF winter dispatch; for CAISO, PJM, ERCOT, and SPP, we show the DSF summer dispatch. As we discussed in Section 2, electrification has the potential to drive some regions in the Northeast and Northwest into winter peaking. In the figure, we identify the top 100 peak hours for each balancing area and color-code them with pink if more of these 100 peak hours fall into the summer months, with blue if more of the 100 hours fall into winter months. It shows that some places in Montana and Washington (light blue) are mainly winter peaking, and places in Nevada and New York shown in purple are dual-peaking (with peak hours in both summer and winter). We compare the DSF operation in these regions from east to west. All DSF figures are in the same scales showing the diurnal pattern of hourly mean energy provision (above the x-axis) and recovery (below the y-axis) in gigawatt. Note all hours shown are in Eastern Time Zone.

First, NYISO and PJM have very similar seasonal DSF operation patterns because they are both dual-peaking systems and have similar generation mixes (with natural gas accounting for around 43%–52% of the total generation). We show the winter DSF for NYISO and summer DSF for PJM to avoid repetition. In the winter, the simulation shows these regions have substantial DSF energy consumption during the overnight hours to provide energy service during morning ramp-up periods. In the summer, these regions show energy consumption at smaller amounts overnight and at larger amount starting from early morning corresponding to the ramp up in solar generation. The majority of the DSF energy service is provided during the evening hours.

Then we compare the summer DSF operation between ERCOT and SPP; both are summer-peaking systems with higher wind penetration in the generation mix than NYISO and PJM. Between them, SPP has higher wind penetration (44%) than ERCOT (34%) and lower solar penetration (18%) than ERCOT (25%). This strongly affects their DSF dispatch: ERCOT’s DSF energy consumption has a much sharper morning peak while SPP’s DSF has more energy consumption from midnight through afternoon corresponding to the variability in the wind generation.

Finally, we show the winter DSF in non-CAISO WECC and the summer DSF in CAISO. The non-CAISO WECC is a much bigger region with diverse generation sources and with balancing areas that are summer-peaking, winter-peaking, and dual-peaking. CAISO on the other hand is a summer peaking system with 44% solar generation in our simulation. As a result, CAISO is the only region in the country that shows no DSF consumption at all in the summer nights. The DSF in the non-CAISO WECC region provides substantial energy service throughout the average winter day (relative to NYISO) in addition to the morning and evening ramp periods. It consumes energy throughout the night, unlike CAISO.

This selection of regional DSF operation in the context of future peak load changes show that DSF operation is strongly influenced by the underlying generation mix and net load conditions.

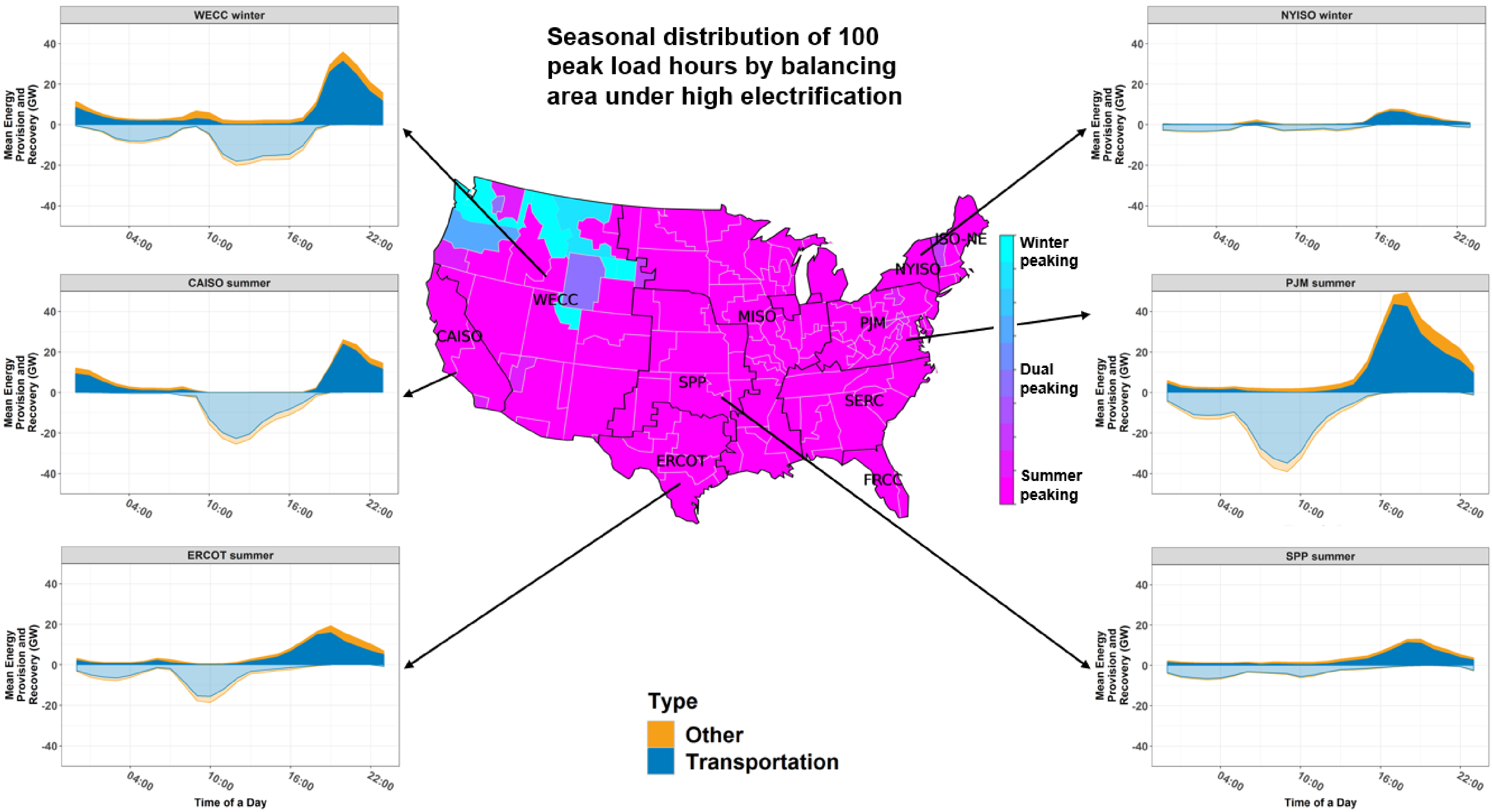

Figure 17. Simulated 2050 regional DSF operation and peak load seasonality

WECC refers to the non-CAISO WECC region. The WECC and NYISO figures show winter operation, while summer operations are shown in all other regions. Other = all non-transportation flexible demand.

5.2 Operating Reserves

The previous section describes how DSF provides energy services by shifting the timing of electricity demand. As with generators, demand sectors can also provide operating reserves by holding the shiftable capacity available to meet regular or unforeseen changes to supply and demand. Specifically, in our core scenarios (Table 3, page 17), we assume DSF can provide flexibility and contingency reserves (but not regulation reserves). This section shows the extent to which DSF is relied on for these services.

DSF reduces the need for other generators such as natural gas plants and storage to provide reserves. Figure 18 illustrates the changes in reserve provision with increasing amounts of DSF in the system. The impact is considerably greater for flexibility reserve where storage makes up about 63% of the total flexibility reserve provision in High-NoFlex; yet with high levels of DSF availability (High-HiFlex), storage's contribution is reduced to 11% while DSF provides about 71% of the flexibility reserve.

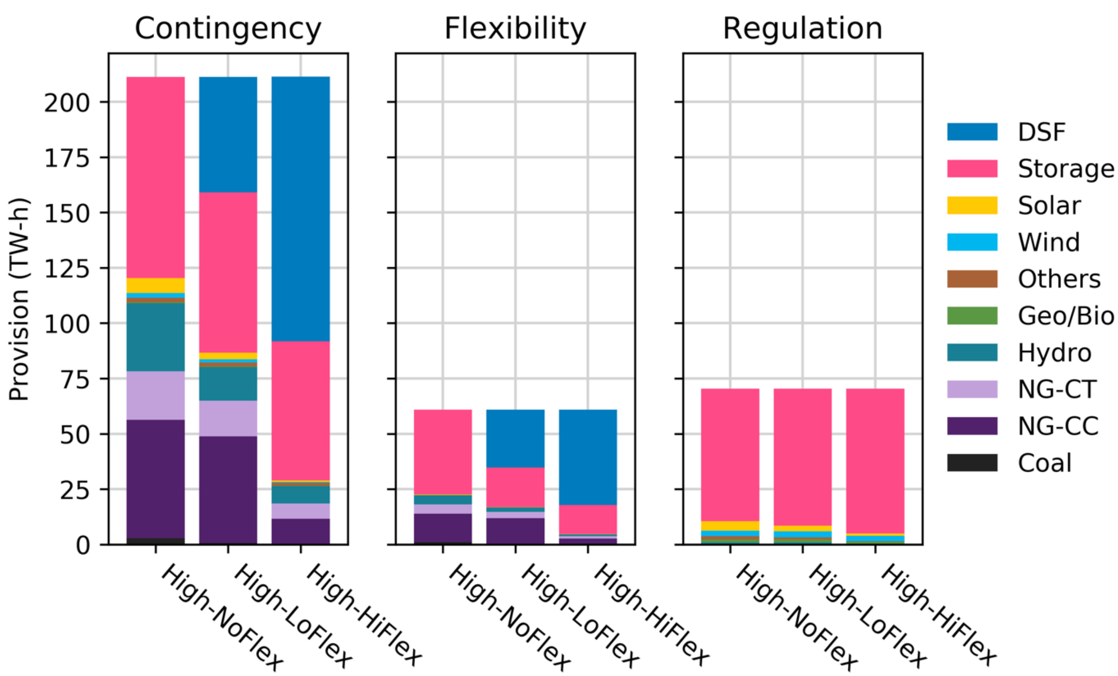

Figure 18. Total operating reserve provision by technology type in High-NoFlex, High-LoFlex, and High-HiFlex scenarios

Our analysis finds that DSF can provide operating reserves throughout the year. As we expect from our DSF availability inputs, Figure 19 (top) shows that DSF provides more energy and ancillary services during the summer months, and that energy service accounts for most of its provision. Figure 19 (bottom) shows that more reserve provision is available during the daytime period of 8 a.m. to 4 p.m., when DSF increases its energy consumption.

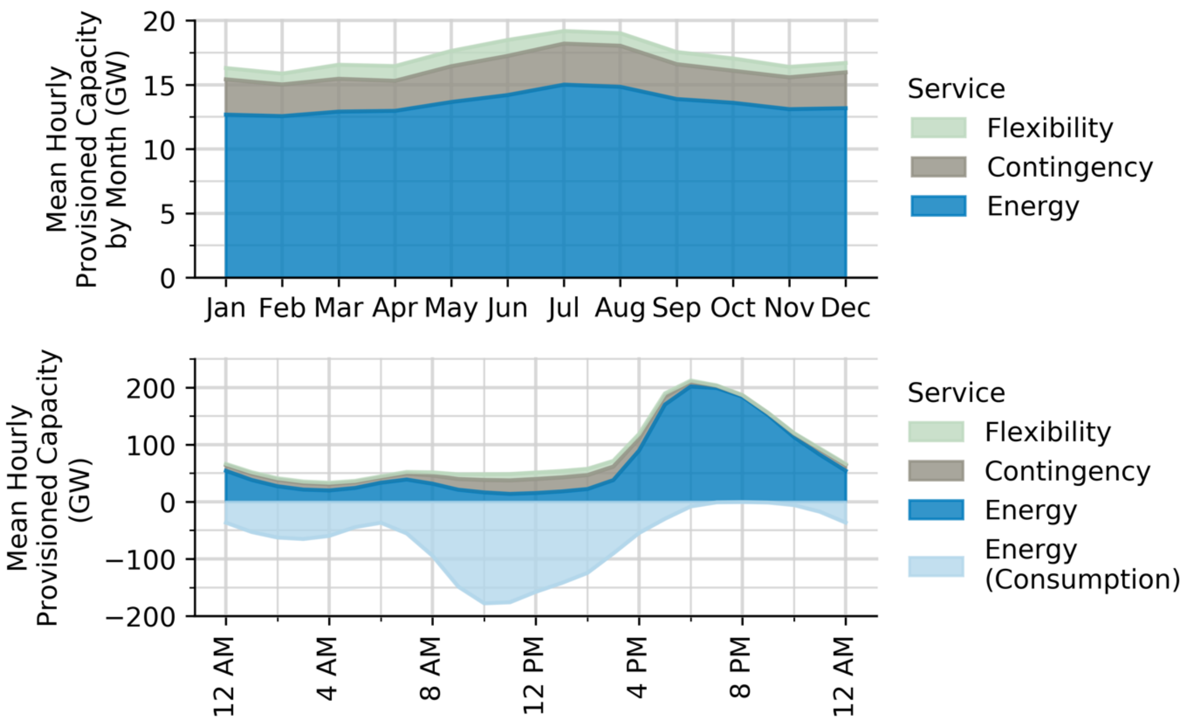

Figure 19. Total DSF hourly mean provisioned capacity by service type by month (top) and by hour of the day (bottom) in the High-HiFlex scenario

5.3 Impacts on Fossil Generators

In this section, we describe the impact of flexible loads on generator dispatch and utilization, including fossil fuel and renewable generators. We first examine the impact of DSF energy-shifting on fossil fuel power plant utilization, plant load factors, and unit starts. Figure 20 focuses on a one-week operation of the coal fleet and the natural gas combined cycle fleet with and without demand-side flexibility under high electrification. The figure illustrates that the generation (red area) from both coal and natural gas combined cycle fleets increases under High-HiFlex, even though less natural gas combined cycle capacity in total is committed (comparing the top of yellow lines) in High-HiFlex than in High-NoFlex.

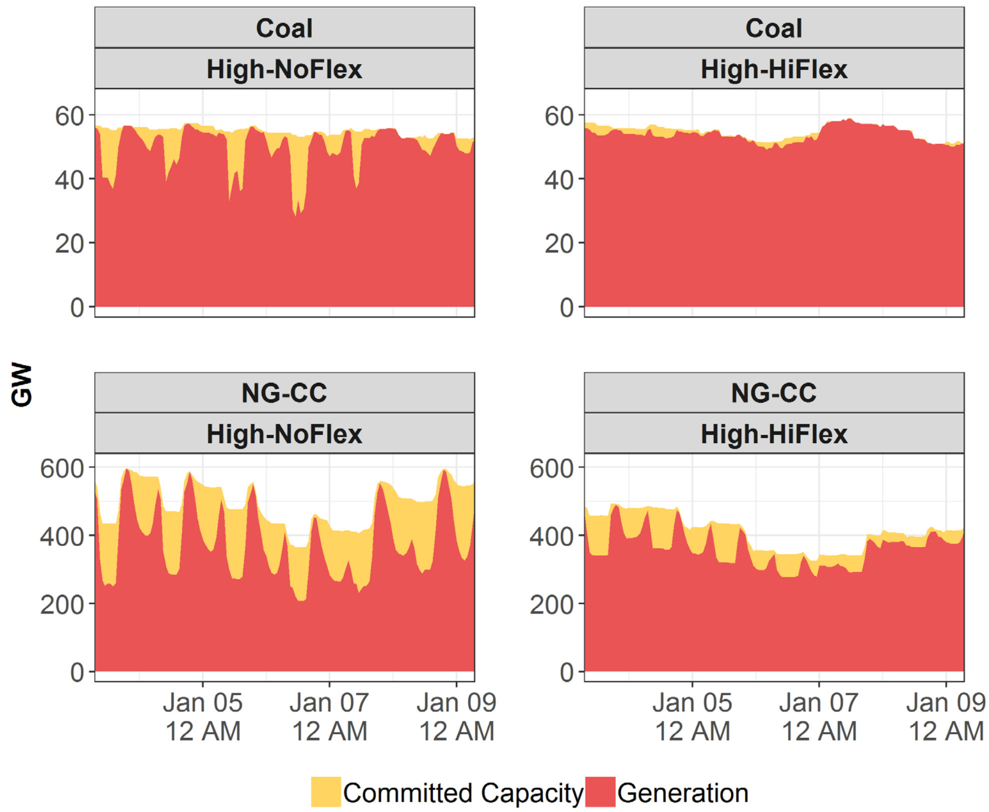

Figure 20. Committed capacity and generation from coal and natural gas combined cycle units in a sample week in January

The observations from the weekly operation holds true in the aggregated annual results. By shifting energy consumption from high-energy-cost hours to low-energy-cost hours, the system can utilize technologies with the lowest generation costs (which includes a combination of fuel costs, start and ramping costs, variable operation and maintenance costs). Because the generation cost of coal is less than that of natural gas in these 2050 scenarios,[38] DSF tends to increase coal generation at the expense of natural gas-fired generation (Figure 21). Different relative fuel prices or policies could yield an opposite effect.

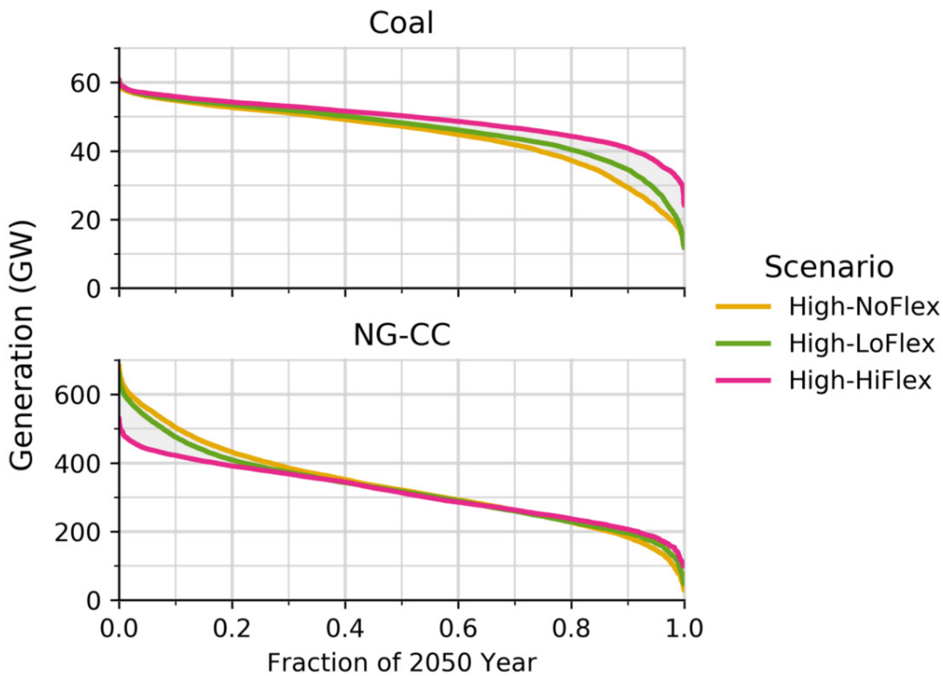

Figure 21. Generation duration curve of coal and natural gas combined cycle units in High-NoFlex, High-LoFlex, and High-HiFlex scenarios

The x-axis shows the fraction of time within the 2050 simulation year.

[38] Fuel prices are based on the AEO2018 Reference case with adjustments made from the ReEDS modeling (Murphy et al. 2021; Sun et al. 2020). Note that no emissions price or limit are enforced in these scenarios.

Our analysis also shows that DSF can reduce the number of low-load hours for fossil fuel generators. The plant load factors for coal units increase with the added DSF (Figure 22). A number of natural gas combined cycle units are never turned on in the High-HiFlex scenario (shown as the small grey dots converging along the zero value in the right panel of Figure 22). Even though the average plant load factor of the natural gas combined cycle units decreases in High-HiFlex, for the natural gas combined cycle units that are committed, their plant load factors rise (shown as the small grey dots above the upper edge of the pink box indicating the 75th percentile). This is also shown by the week-long example from Figure 20 (page 38).

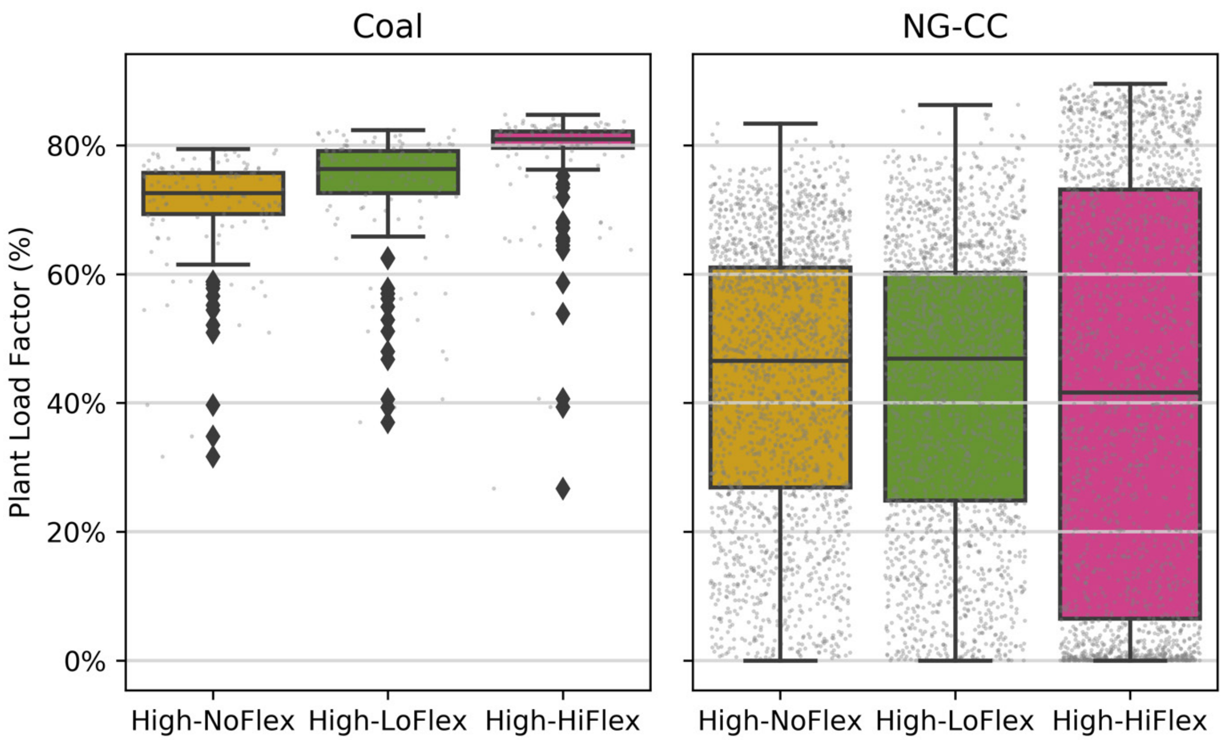

Figure 22. Plant load factor distribution of coal and natural gas combined cycle plants under High-NoFlex, High-LoFlex, and High-HiFlex scenarios

Each box extends from the lower to upper quartile of plant load factors with a line at the median; whiskers extend from Q1-1.5*(Q3-Q1) to Q3+1.5*(Q3-Q1); flier points are those that pass the whiskers. The grey dots show individual plant's load factors.

DSF also considerably lowers the number of starts and shutdowns of natural gas combined cycle units, but the impact on coal starts is negligible (Figure 23). Natural gas combined cycle units require shorter start time and can conduct daily start and stop operations – indeed this is what they are called to do under High-NoFlex. But coal units typically require longer start time and minimum up periods. Increasing DSF in the system drives down the overall ramping needs (Figure 15, page 33), and thereby lowering the number of starts for natural gas combined cycle units and increasing their plant load factor, despite lower committed capacity. The impacts of energy-shifting DSF in reducing the number of low-load hours for fossil fuel generators and reducing the starts of gas generators are consistent with previous demand response studies (Stoll, Buechler, and Hale 2017; Perlstein et al. 2012).

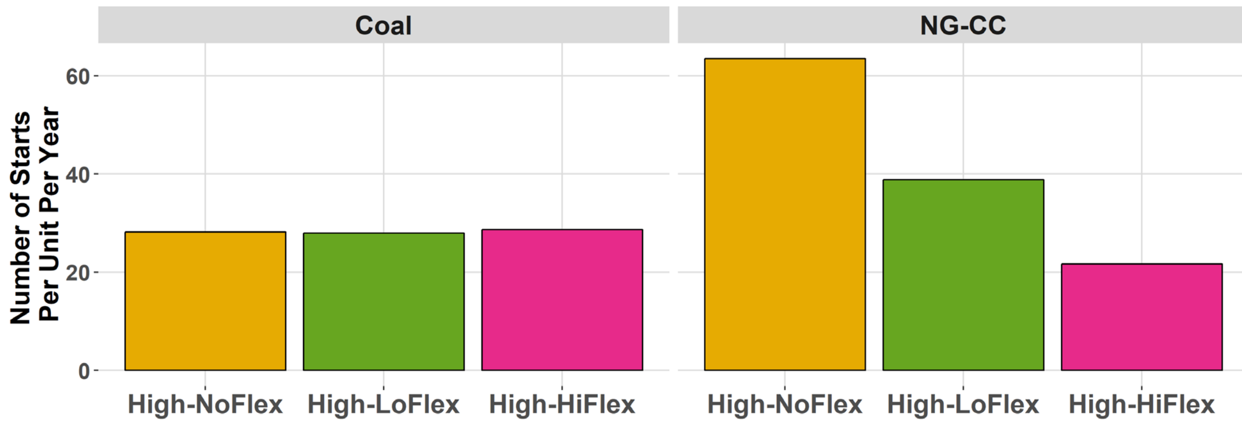

Figure 23. Number of starts per unit per year in High-NoFlex, High-LoFlex, and High-HiFlex scenarios

Consistent with previous studies, we also find DSF impacts the operation of renewable energy generators, particularly by reducing curtailment (McKenna, Grünewald, and Thomson 2015; Bitaraf and Rahman 2018; Gils 2016). Figure 24 shows a comparison of annual renewable curtailment for the reference and high electrification scenarios with different levels of DSF. Compared to the Ref-NoFlex scenario, renewable curtailment under Ref-HiFlex is reduced by 24 TWh; compared with High-NoFlex, High-LoFlex and High-HiFlex have 41 TWh and 54 TWh lower renewable curtailment respectively. In terms of VRE curtailment rate, these quantities translate to reducing the national annual average rate from 3.3% in Ref-NoFlex to 2.2% in Ref-HiFlex, and from 9.0% in High-NoFlex to 7.8% in High-LoFlex and 7.4% in High-HiFlex.

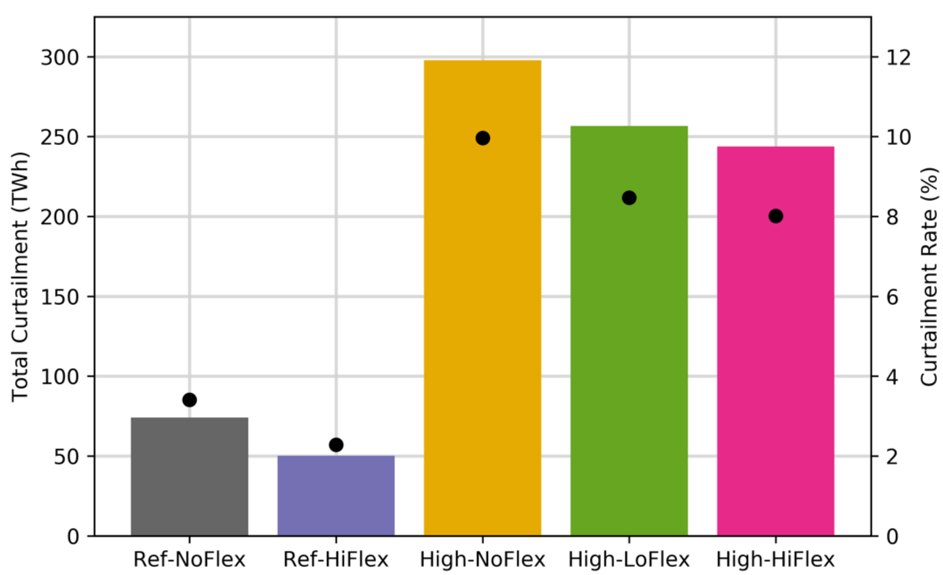

Figure 24. Total curtailment (bars) and average curtailment rate (dots) in the Ref-NoFlex, Ref-HiFlex, High-NoFlex, High-LoFlex, and High-HiFlex scenarios

The reduction in curtailment is achieved through shifting load from the low-renewable-output periods to the high-renewable-output periods. Figure 25 illustrates the system dispatch during the peak load, peak net load ramp, and highest hourly VRE penetration days[39] under High-NoFlex, High-LoFlex, and High-HiFlex. The dashed line in the figure shows the original load before DSF energy shifting, which peaks around 5 p.m. In all the high-stress periods, DSF reduces the evening load and increases the daytime load. For the peak load day, the result of the shifting is reduced total peak load. In the peak net load ramp day, shifting early morning load later and shifting evening load earlier significantly reduces the ramp for the conventional generation fleet. For the highest VRE penetration day, the result is a significant reduction in renewable curtailment (shown in grey).

[39] DSF can change the net load ramp and the instant VRE penetration, so in this figure, we fix the days to the key period days in the High-NoFlex scenario for direct comparison.

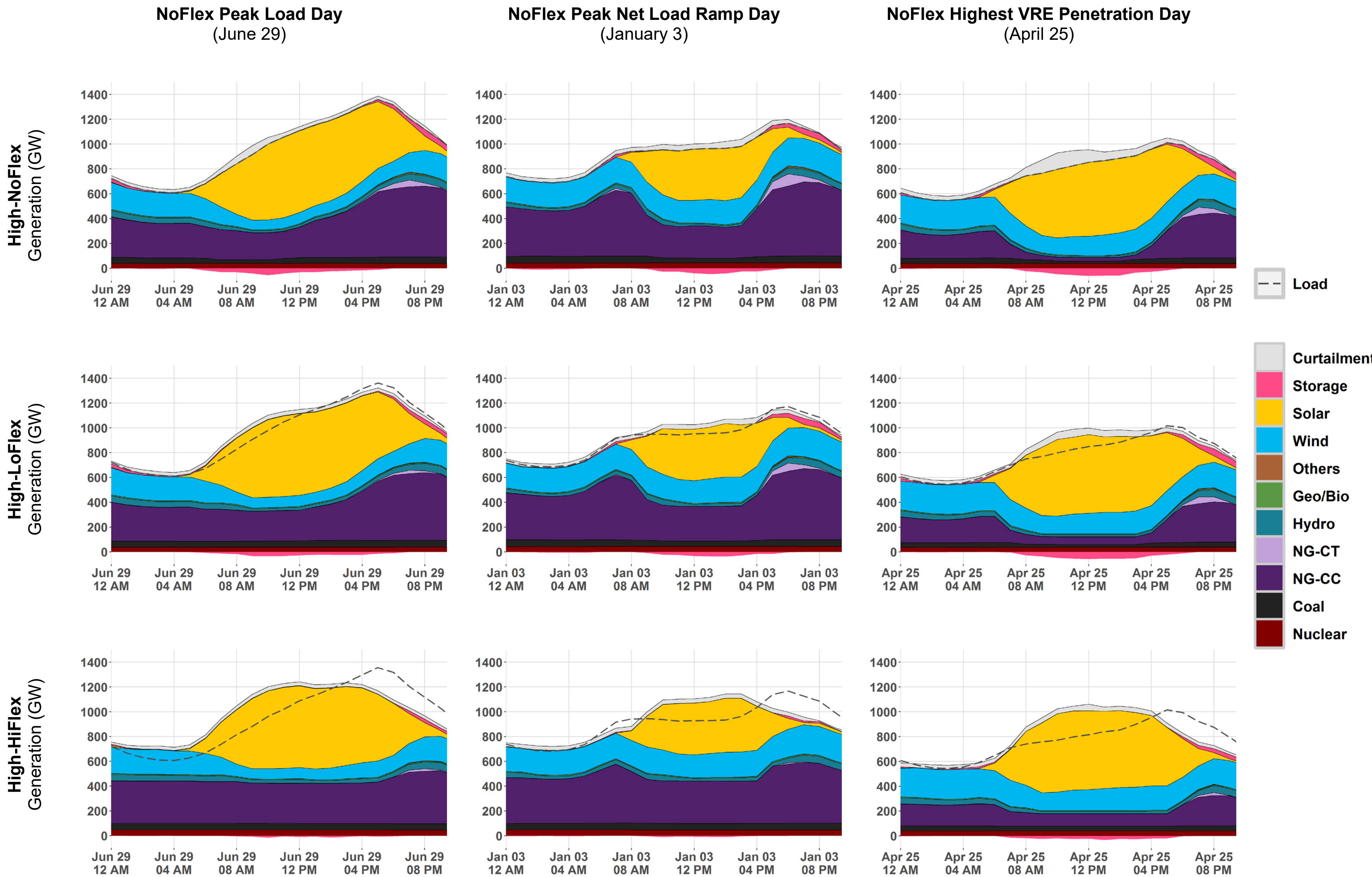

Figure 25. Daily dispatch for high potential stress days in 2050 in High-NoFlex, High-LoFlex, High-HiFlex scenarios

Dotted line shows the original static load from the NoFlex scenarios. Pink area below the x-axis indicates storage charging.

5.4 Production Costs and Price Variations

The previous sections describe the dispatch behavior of DSF and the consequential impacts to generators. These DSF outcomes—including reduced magnitude of system ramps, increased use of low-cost generation, and reduced renewable curtailment—help reduce overall system operating costs. In this section, we report the *gross*[40] production cost savings associated with DSF, which, as we expected, are greater under high electrification than reference electrification (Table 6). For example, total annual production cost in the Ref-HiFlex scenario is $2.8 billion (4.2%) lower than in the Ref-NoFlex scenario. Similarly, total production cost is $4.7 billion (4.3%) lower in the High-LoFlex and $10 billion (9.3%) in the High-HiFlex scenarios (relative to High-NoFlex). These cost savings are primarily from reduced fuel and startup/shutdown costs; smaller savings come from avoided variable operation and maintenance (O&M) costs.

Table 6. Simulated 2050 Total Operation Cost by Type (Billion $)

Scenario	Fuel Cost	Start and Shutdown Cost	Variable O&M Cost	Total Cost	Cost Difference from NoFlex
Ref-NoFlex	56.86	2.79	5.54	65.18	Ref-NoFlex
Ref-HiFlex	55.32	1.70	5.41	62.42	-2.76 (-4.24%)
High-NoFlex	93.60	5.50	8.90	108.00	High-NoFlex
High-LoFlex	91.09	3.60	8.63	103.31	-4.69 (-4.34%)
High-HiFlex	87.72	2.01	8.24	97.96	-10.04 (-9.30%)

The production cost value per unit of DSF[41] can be calculated by dividing these annual production cost savings by the annual amount of DSF energy shifted (Table 7). By this calculation, we estimate that the annual average of the gross operational value of DSF ranges from $16/MWh in Ref-HiFlex to $22/MWh in High-LoFlex and to $17/MWh in High-HiFlex. These results suggest DSF can have greater value under higher electrification. High electrification leads to sharper demand peaks and more variability in the net load that can be mitigated with DSF. The results also suggest there are diminishing returns with DSF as shown by the lower DSF value under HiFlex versus LoFlex scenarios. The declining marginal value of DSF with increasing participation is consistent with findings from the demand response literature (Arteconi et al. 2016) and in the prior EFS analysis (Murphy et al. 2021).

[40] Costs (operating and fixed) costs for DSF are excluded in this analysis hence net costs are not estimated.
[41] The resulting value includes both the energy and the reserve values from DSF.

Table 7. Simulated 2050 Annual Average Value of DSF

Scenario	Total Cost Saving (Billion $)	DSF Availability (TW-h)	DSF Energy Shifted (TWh)	DSF Value ($/MW-h Availability)	DSF Value ($/MWh)
Ref-NoFlex	Ref-NoFlex	—	—	—	—
Ref-HiFlex	2.76	357.00	171.20	7.74	16.14
High-NoFlex	High-NoFlex	—	—	—	—
High-LoFlex	4.69	299.00	216.99	15.68	21.60
High-HiFlex	10.04	1,151.00	592.27	8.72	16.95

Table 7 also shows a slightly different measure of DSF value. Instead of dividing the production cost savings by the amount of energy shifted, one can divide by the total amount of DSF available, even though a good portion of shiftable load is not used, especially in the Ref-HiFlex and the High-HiFlex scenarios. By this calculation, we estimate an operational value ranging from $8/MW-h to $16/MW-h for the available DSF in all the scenarios shown. The same qualitative relationships between scenarios exists whether DSF value is measured based on energy shifted or available capacity. These estimates are consistent with a previous study of demand response in the Western Interconnection (Ma and Cheung 2016), which finds a value of $9.5/MW-h for available DSF in scenarios with about 33% VRE penetration.[42]

These results can also be compared with the value of DSF estimates from a prior EFS report (Murphy et al. 2021). The prior estimates, which include both the operational and capacity value of DSF from 2018 to 2050, range from $11/MW-h to $19/MW-h on a levelized basis.[43] The present analysis measures DSF's operational value in 2050 only, but does so with higher temporal resolution than in the prior analysis. Despite these differences, the current set of detailed estimates confirms the prior finding that DSF can have significant value particularly when combined with electrification; however, this value declines with increasing amounts of DSF.

In addition to reducing gross system operational cost, DSF can also reduce electricity price variability and volatility. As Figure 26 shows, the addition of DSF allows the price[44] to stabilize at around $30/MWh for more hours of the year. And the addition leads to fewer hours of both extreme high prices caused by reserve or energy shortage and very low prices caused by renewable curtailment. The role of DSF in reducing price volatility is consistent with previous observations (Albadi and El-Saadany 2007).

[42] This result is from the high renewable scenario in the study; the reference scenario from Ma and Cheung (2016) has a VRE penetration of 15% and is not comparable to the system in our present analysis and is therefore not used.
[43] Specifically, Murphy et al. (2020) calculated the ratio of the present value of system cost savings to the present value of available DSF over the 2018–2050 period, using a 3% real discount rate.
[44] The electricity prices reported are the marginal, or shadow, prices of the load balancing constraint in the model. These prices represent the operating costs to serve the marginal unit of electricity.

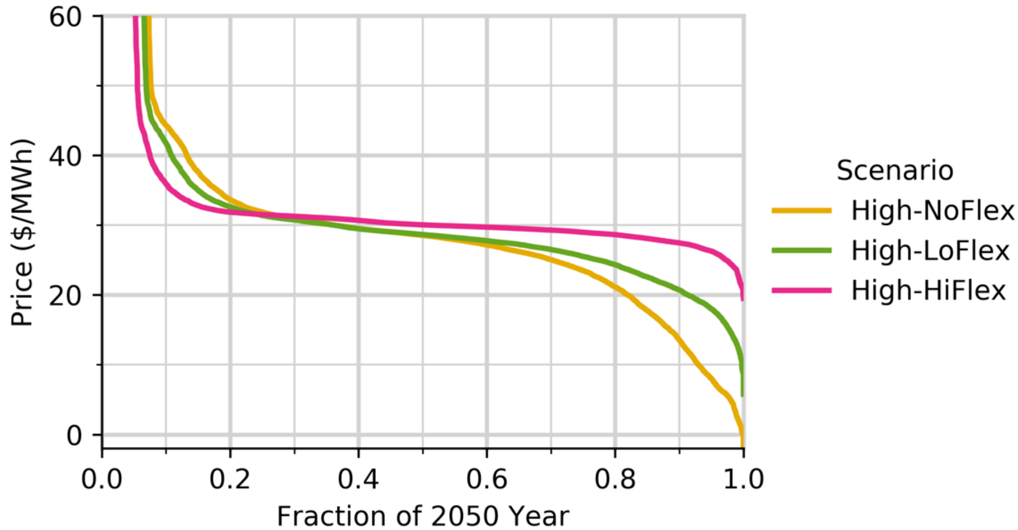

Figure 26. Duration curve for the national average marginal hourly price from each balancing area, weighted by load

6 Results: Envisioning High Renewable High Electrification Futures

The previous section investigates the operation and impacts of DSF in systems with varying levels of electrification. In this section, we examine the grid integration of VRE in power systems of highly electrified energy futures and analyze the role of DSF in such systems. Specifically, this section is focused on the operation strategies of the High-HiRE scenarios, which include about 4600 TWh of VRE generation—equivalent to 66% of total 2050 generation in the scenarios and in excess of annual U.S. load in 2020. Where appropriate, we compare results with the High scenarios (High-NoFlex, High-LoFlex, and High-HiFlex), which had lower (about 42%) VRE penetration.

6.1 Operational Feasibility

Section 4 describes the operational feasibility of the NoFlex scenarios by examining the amount of unserved load and unserved reserves. Among all NoFlex scenarios, the most unserved load was found under the scenario with the largest share (66%) of VRE (High-HiRE-NoFlex). Without DSF in this scenario, 852 MWh of electricity demand was unmet, and even though this quantity represents less than 0.01% of annual demand, it is the largest of all scenarios modeled. However, when DSF is added to the mix, we find that the amount of annual unserved load can be reduced to only 0.5%–2.0% of that found in the NoFlex scenario (to 16 MWh in High-HiRE-LoFlex and to 4 MWh in High-HiRE-HiFlex).

In addition to unserved load, we also find that the amount of unmet operating reserves declines with DSF. For example, High-HiRE-NoFlex has a total of 15 gigawatt-hours (GW-h) of unmet reserves and High-HiRE-HiFlex only has 0.46 GW-h. These results show how DSF can help increase system adequacy, especially in power systems with high VRE shares. These results are consistent with previous studies (Hurley, Peterson, and Whited 2013; F. Wang et al. 2017) that explore demand response as a resource for improving system reliability.

The dispatch stacks in Figure 27 show how DSF can help support system operation during stressful periods. Specifically, it shows economic dispatch of the generators and flexible loads during three potentially high-stress days, peak load, peak ramp, and highest VRE penetration for the set of High-HiRE scenarios. DSF shifts the load from the dashed line (indicating the original load without DSF) to one that is better aligned with net load to better match the generation pattern of wind and solar, thereby reducing the risk of unserved energy and reducing renewable curtailment.

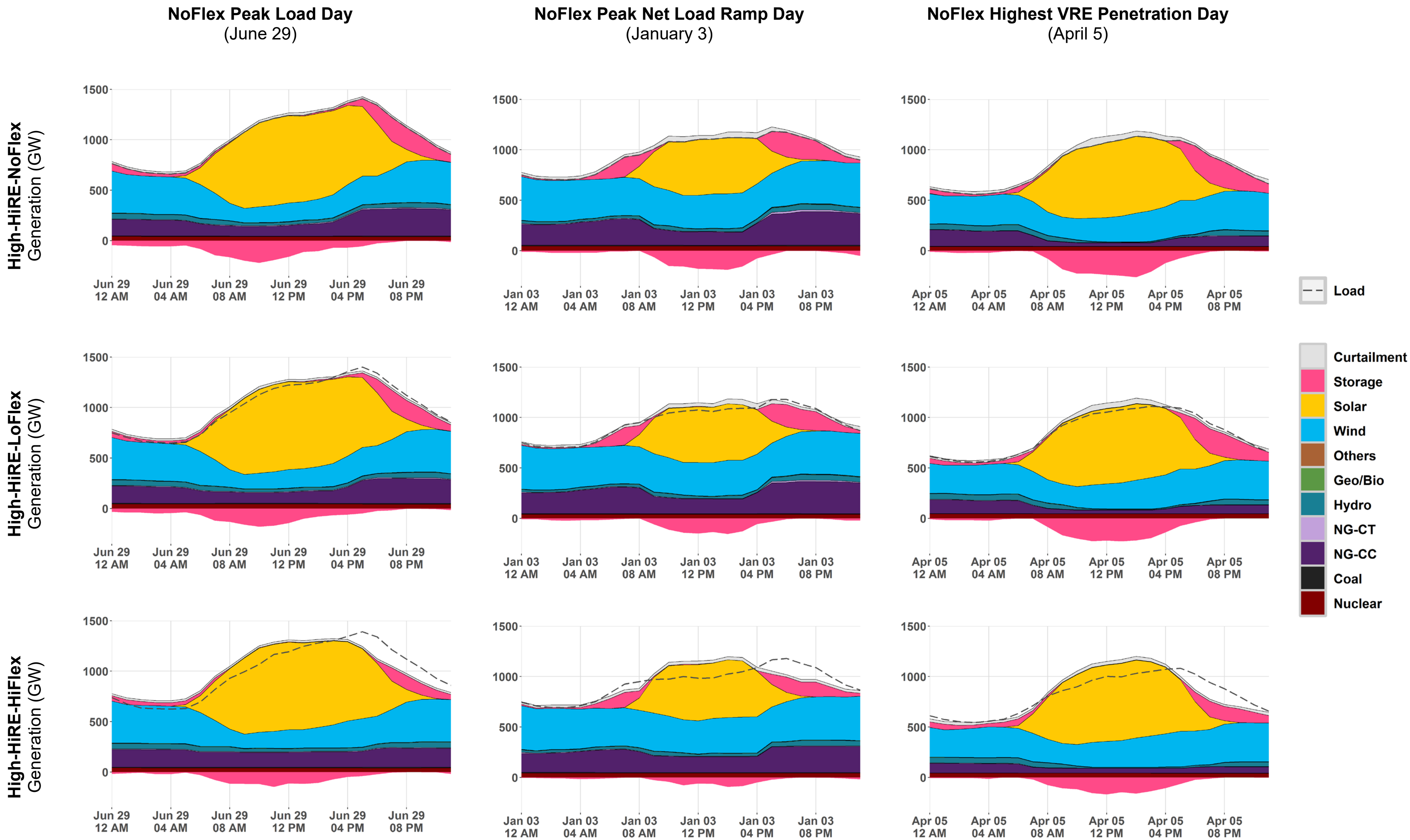

Figure 27. Dispatch during potential high stress days in 2050 in High-HiRE scenarios

Dotted line shows the original static load from the NoFlex scenarios. Pink area below the x-axis indicates storage charging.

6.2 Curtailment

With more RE capacity and available generation, estimated curtailment under the High-HiRE scenarios is greater than that from the High scenarios in absolute terms. Table 8 shows how this applies across all demand-side flexibility scenarios. For example, a difference in annual curtailment of 79 TWh (377 TWh vs. 298 TWh) is estimated between the High-HiRE-NoFlex and High-NoFlex. However, the VRE curtailment *rate*—curtailment as a fraction of available annual RE generation—under the High-HiRE scenarios are actually lower than under the High scenarios with the corresponding level of DSF. As mentioned in Section 4.3, lower curtailment rates under the HiRE scenarios are realized due to the greater storage deployment and transmission capacity expansion in these scenarios. In fact, when including the losses from storage with curtailment (see Table 8), the rates under the High-HiRE and High scenarios are more similar (7.5%–9.3% under the High scenarios and 6.8%–8.8% under the High-HiRE scenarios). As a side note, the decreasing storage losses with the addition of DSF in Table 8 indicates a reduction in storage utilization. Some types of DSF, such as thermal loads, avoid conversion losses because cooling or heating is used directly (Robert, Sisodia, and Gopalan 2018), and changing the charging hours of electric vehicles (*not* vehicle-to-grid) does not incur an efficiency loss either. In such cases, the use of DSF usually represents an efficiency gain over for example, battery storage that needs to be converted back and forth into chemical storage.

Table 8. Simulated 2050 VRE Curtailment in High and High-HiRE Scenarios

Scenario	Curtailment (TWh)	Curtailment Rate (%)	VRE Penetration (after curtailment)	Storage Loss (TWh)
High-NoFlex	298	9.1%	42.4%	7
High-LoFlex	257	7.8%	43.0%	4
High-HiFlex	244	7.4%	43.2%	2
High-HiRE-NoFlex	377	7.5%	65.5%	66
High-HiRE-LoFlex	346	6.9%	66.0%	56
High-HiRE-HiFlex	317	6.3%	66.4%	25

Figure 28 also shows how DSF can help lower curtailment in all high electrification scenarios. VRE curtailment is 54 TWh (18%) lower in High-HiFlex and 60 TWh (16%) lower in High-HiRE-HiFlex relative to the corresponding NoFlex cases. Figure 28 (page 50) shows how DSF helps avoid curtailment during all months, but curtailment remains high during the spring months, partly because only daily or weekly flexible loads are considered. The monthly and seasonal variations in curtailment are greater in the High-HiRE scenarios, where curtailment can be three times larger than under the High scenarios. This result highlights how longer-duration sources of flexibility, such as electrolytic hydrogen production, have the potential to reduce the seasonal mismatch between supply and demand under these high electrification and high renewable scenarios but such options are not included in the current analysis.

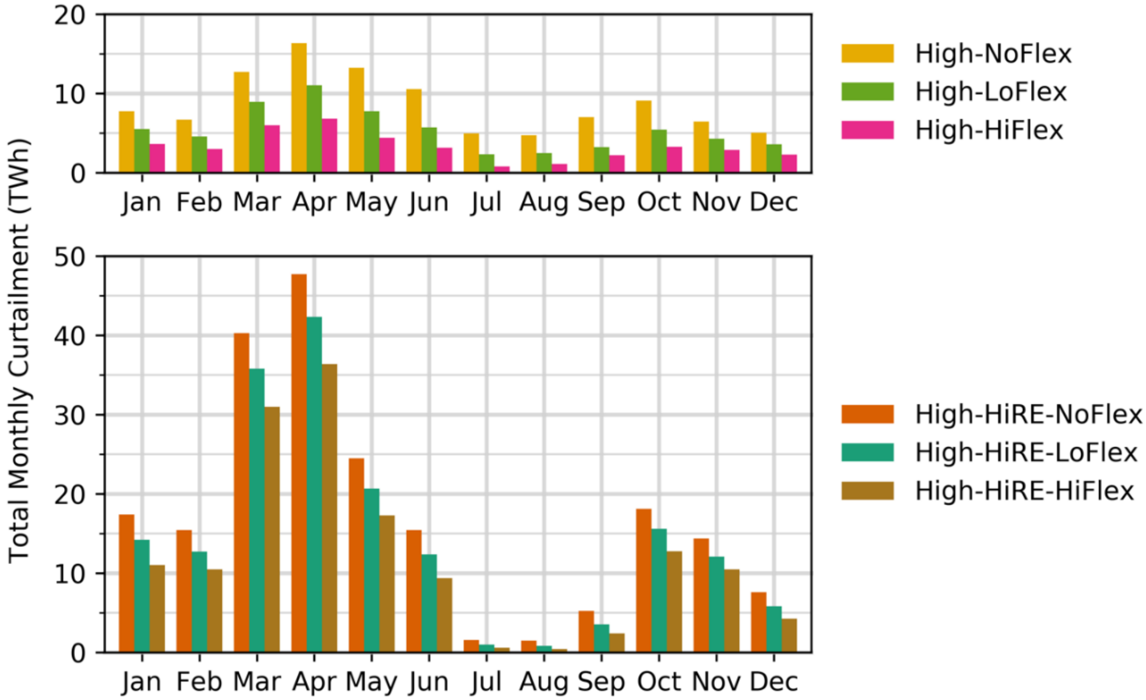

Figure 28. Total monthly VRE curtailment in High-No/Lo/HiFlex scenarios (top) and High-HiRE-No/Lo/HiFlex scenarios (bottom)

Diurnal patterns for curtailment are similar in the High and High-HiRE scenarios with curtailment closely following daytime solar production pattern (Figure 29, page 51). However, as with the seasonal trends, diurnal curtailment patterns are starker in the High-HiRE scenarios. As described above, demand-side flexibility can reduce curtailment by shifting load to daytime hours to align with solar generation and away from evening hours. Conversely, DSF has a more limited impact on nighttime curtailment. This is, in part, because there is less nighttime curtailment to avoid, but also because DSF is more limited during nighttime hours under our assumptions (Section 3.2). Overall, these findings suggest a synergy between VRE, particularly PV, generation and flexible loads, particularly electric vehicle charging.

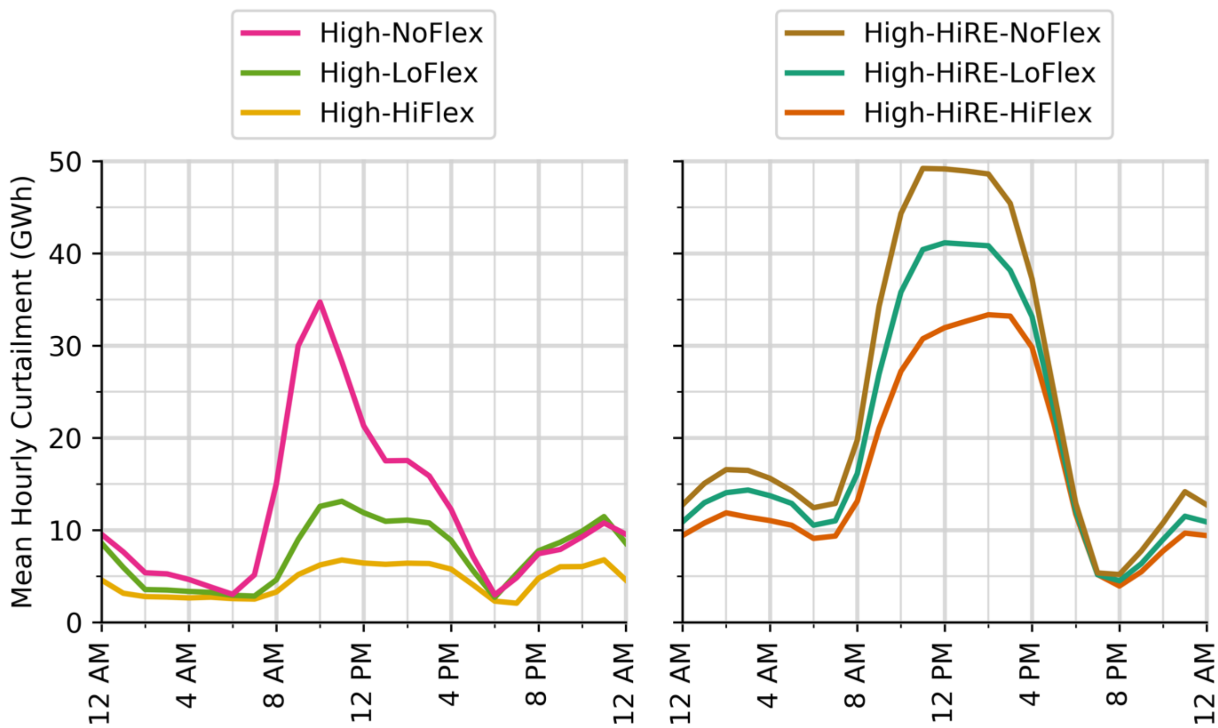

Figure 29. Mean hourly renewable curtailment in High-No/Lo/HiFlex scenarios (left) and High-HiRE-No/Lo/HiFlex scenarios (right)

6.3 Production Costs

The High-HiRE scenarios have lower total system operation cost than the High scenarios because of the greater amount of renewable energy generation with zero operating costs. Capital or other fixed costs are not included in the PLEXOS modeling, but they are considered in the prior EFS analysis (Murphy et al. 2021). Table 9 (page 52) shows these differences in production costs between scenarios with different VRE penetrations as well as how DSF can reduce total production costs for any given VRE penetration system.

Total production costs of the High-HiRE scenarios are less than half of the costs in the High scenarios. Correspondingly, the value of DSF is lower in the High-HiRE scenarios than in the High scenarios. Under the High-HiRE scenarios, DSF value per megawatt-hour of available flexible load ranges from \$4/MW-h to \$7/MW-h under the High-HiRE scenarios compared with \$9/MWh-h to \$16/MWh-h under the High scenarios. In terms of DSF value per megawatt-hour of load shifted, DSF has a value of around \$8/MWh–\$12/MWh under the High-HiRE scenarios. The decline in the absolute value of DSF with the increase in renewable penetration is also observed by Ma and Cheung (2016). However, it is important to note that in the high renewable scenarios, DSF generates more cost saving as a *percentage* of total cost—up to 4.66% of total system operation cost in High-HiRE-LoFlex and 10.35% in High-HiRE-HiFlex, relative to High-HiRE-NoFlex (Table 9).

Table 9. Simulated 2050 Gross Cost Savings in High Electrification Scenarios[a]

Scenario	Total Cost (Billion $)	Total Cost Saving (Billion $)	Cost Saving Percentage (%)	DSF Value ($/MW-h Availability)	DSF Value ($/MWh Energy Shifted)
High-NoFlex	108.00	—	—	—	—
High-LoFlex	103.31	4.69	4.34%	15.68	21.60
High-HiFlex	97.96	10.04	9.30%	8.72	16.95
High-HiRE-NoFlex	45.03	—	—	—	—
High-HiRE-LoFlex	42.93	2.10	4.66%	7.02	11.52
High-HiRE-HiFlex	40.37	4.66	10.35%	4.05	8.20

[a] The cost of DSF is assumed to be zero, so the cost savings reported here are gross savings without accounting for any implementation or operation cost.

Systems with higher RE penetration can have greater (short-run) energy price variability due to the greater variations with net load. In addition, more low-price hours are also commonly found and reflected by the greater curtailment as discussed above. Figure 30 and Figure 31 (page 53) show the number of hours of high- (top) and low- (bottom) price hours, respectively, for the High-HiRE-NoFlex (left) and High-HiRE-HiFlex (right) scenarios. Without DSF, regions in the Southeast, Southwest, and Northeast experience tens or a hundred hours with high prices, which we define as hours with prices >$100/MWh. On the other hand, low price (<$1/MWh) hours are common throughout the country but are most prominent in the central wind belt, where many regions experience thousands of low-price hours during the year in our simulations. As discussed in Section 5, hourly prices typically fall between $20/MWh and $40/MWh under the High scenarios.

The right sides of Figure 30 and Figure 31 show how DSF can mitigate some of the extreme price periods under the high renewable and high electrification scenarios. As Figure 30 shows, DSF can be effective in avoiding the highest price peaks: hours with a price higher than $100/MWh are almost eliminated across all BAs in High-HiRE-HiFlex. And by reducing curtailment, DSF also reduces the number of hours with low prices although the differences are less pronounced in Figure 31.

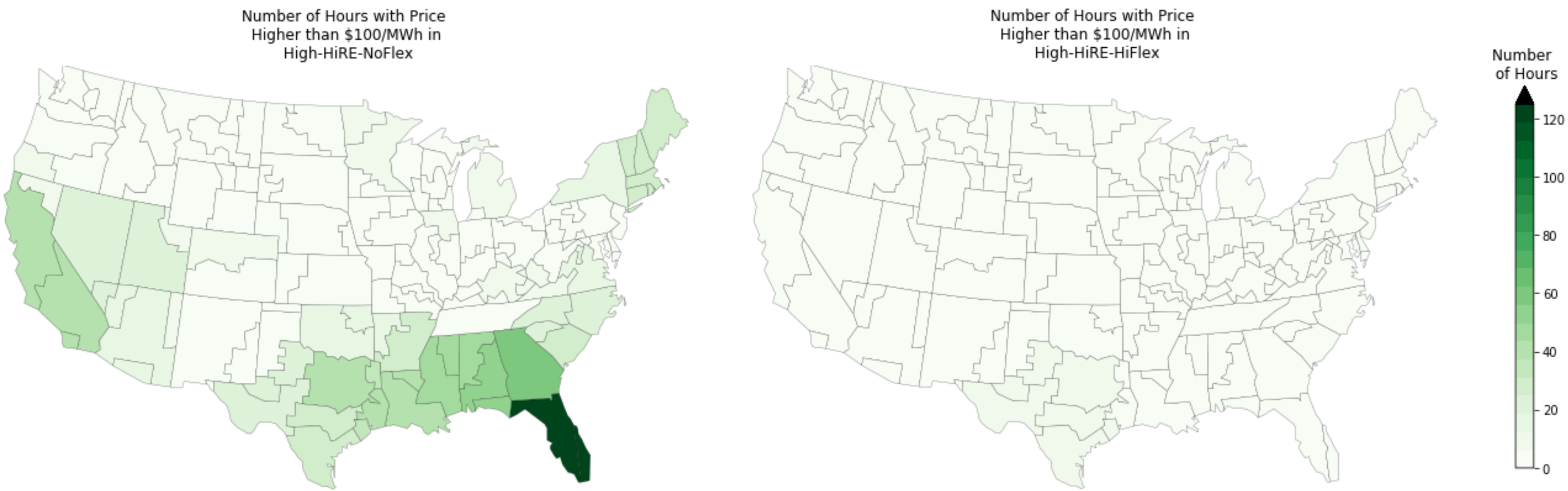

Figure 30. Number of hours with price higher than $100/MWh in High-HiRE-NoFlex (left) and High-HiRE-HiFlex (right) scenarios by balancing area

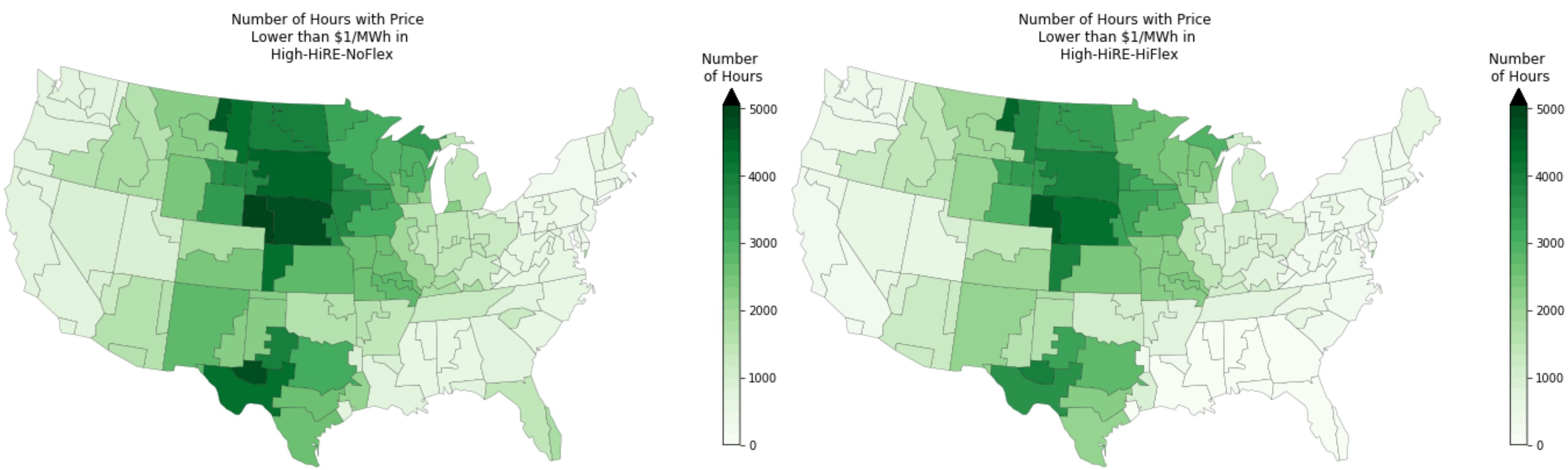

Figure 31. Number of hours with price lower than $1/MWh in High-HiRE-NoFlex (left) and High-HiRE-HiFlex (right) scenarios by balancing area

6.4 Emissions

Electrification reduces carbon emissions in the energy sector. Due to the energy efficient nature of many electrified technologies, the energy-sector wide carbon emissions are reduced by 23% (1.1 billion tonnes of CO_2) in 2050 going from reference to high electrification (Murphy et al. 2021). But because high electrification scenarios serve 40% more electric load than reference scenarios in 2050, it results in an increase of carbon emissions in the electricity sector (Figure 32). High VRE can reduce carbon emissions in the electricity sector by around 50% under high electrification, bringing the amount to below reference electrification levels. This is why many electrification studies (Dennis, Colburn, and Lazar 2016; Jones et al. 2018) also call for the reduction of the carbon intensity level in the electricity sector.

Demand-side flexibility increases the ability of VRE to lower CO_2 emissions in electrification futures (Figure 32). We find that under high electrification, higher amounts of DSF can reduce carbon emissions by 5.4% (58.7 million tonnes of CO_2) compared with High-NoFlex; under high electrification plus high VRE, high DSF can reduce carbon emissions by 8.3% (44.4 million tonnes of CO_2) compared with High-HiRE-NoFlex. On the surface, these results seem to contradict previous demand response studies (Hummon et al. 2013; E. T. Hale, Stoll, and Novacheck 2018), which find that when the objective function minimizes costs, load flexibility increases total carbon emissions. This is because the generation mixes and operation conditions in those studied systems are similar to the system we have today. As several studies (Denholm et al. 2013; E. Hale et al. 2018) point out, flexibility from storage and demand response could decrease carbon emissions at high VRE penetrations and our results support such an hypothesis.

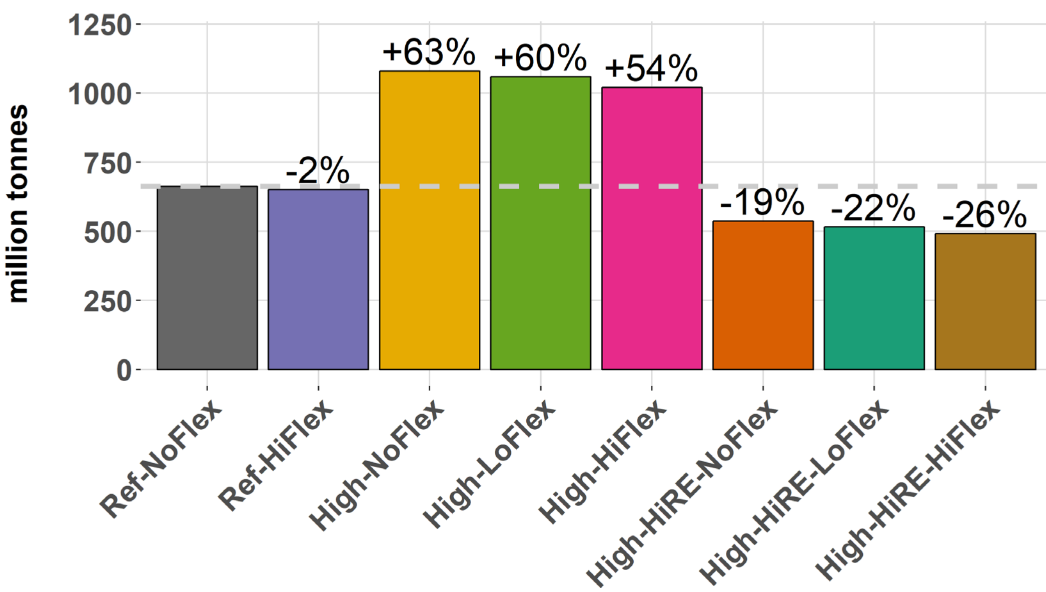

Figure 32. Annual power system CO_2 emissions (million tonnes) and difference from Ref-NoFlex emissions

7 Conclusion

This analysis presents high-resolution grid simulations of U.S. power systems in 2050 under scenarios with various levels of electrification, demand-side flexibility, and penetration of variable renewable energy (VRE). The overarching finding from this analysis is that the operation of the power system under high levels of electrified demand is feasible at the hourly level—even with unprecedented amounts (total installed capacity of 1.3 TW) of VRE for the United States—and that the operational efficiency of such systems can be enhanced through the expansion of demand-side flexibility, especially flexibility from newly electrified loads.

We identify four other primary findings:

1. The U.S. power system can operate under scenarios with widespread electrification—and associated changes to electricity demand patterns—with high levels of VRE penetration (66% of annual national generation) through the expansion and investment in existing commercial technologies.
2. Demand-side flexibility—mainly from optimized vehicle charging but also from flexible operations of other end-use equipment used in buildings and industry—can result in observable changes in how the power system operates, such as reduced system net load ramps and reduced thermal plant cycling. And it can alleviate the challenges of operating a high VRE power system under high electrification by providing energy shifting and operation reserves, resulting in improved operational reliability and lowered VRE curtailment (up to 60 TWh or 16% less curtailment in High-HiRE-HiFlex compared to High-HiRE-NoFlex) .
3. Assuming no or low operating costs with demand-side flexibility, flexible loads in highly electrified futures can lower power system operation costs by providing high-value grid services during periods of system stress and by increasing the utilization of more-efficient lower-cost units. This results in gross operational values of \$9/MW-h to \$16/MW-h of available flexible load *capacity* and \$17/MWh–\$22/MWh of shifted load.
4. Coupling demand-side flexibility with VRE enhances the ability of electrification to decarbonize the energy sector, because demand-side flexibility is effective in boosting generation from the least-cost sources. High-HiRE-HiFlex can result in 8.3% carbon emission reduction (44.4 million tonnes of CO_2) compared to High-HiRE-NoFlex.

The scenario-specific quantitative estimates that lead to these findings are described in the main body of the report. Despite the detailed grid simulations used to develop these estimates, there are several areas where modeling and analysis improvements could enable refined numerical estimates as well as improve confidence in the overall qualitative findings. Here, we list a few select research areas that would improve grid modeling of power systems under highly electrified futures.

With electrification, the demand sectors may become increasingly dynamic and important participants in the operation of the power system. Co-optimizing supply-and demand-side flexibility resources is a growing area of research, and the present analysis contributes to this body of work. However, additional research on flexible load operation, cost and value—including across a wide range of subsectors and end uses in commercial and residential buildings, transportation, and industry—can support more robust and granular modeling of demand-side flexibility. A related research area where further efforts are also likely needed includes the markets, regulations, business models, and practices needed to incentivize or enable flexible loads to provide the types of services envisioned in our analysis.

Future studies of electrification can also benefit from a more detailed and realistic representation of the transmission network and generation fleet. Such detailed examinations will likely face computational challenges; therefore, judicious use of decomposition (e.g., Novacheck, Brinkman, and Porro 2018) and innovative approximation methods for high-dimension dynamic programming (Anderson, Zéphyr, and Cardell 2017) may be needed. Additionally, further high-fidelity analysis is needed to further assess grid reliability of high electrification systems at the transmission and distribution levels. Such detailed examinations are needed for both nationwide and regional analyses of electrification.

Given the complexities of electrification and the broader energy system, these suggested areas represent only a small subset of the research needed to better understand electrification's future impacts.[45] Nonetheless, improvements to power system models are an important subset given the more-integral role of electricity under potential high electrification scenarios for the United States.

[45] See Mai et al. (2018), Murphy et al. (2021), and Sun et al. (2020) for further discussion of research needs related to electrification analysis.

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Appendix. Operating Reserve Parameters

The tables in this appendix documents two sets of parameters used in the production cost modeling for reserves.

Table A-1. Ancillary Service Products Representation in PLEXOS

Ancillary Service Product	Time Frames	Value of Reserve Shortage ($/MW)
Regulation	300	9,500
Contingency	600	9,000
Flexibility	1,200	8,500

Table A-2 represents the wear and tear costs and heat rate degradation of the conventional units associated with non-steady state operation when providing regulation reserves.

Table A-2. Assumed Additional Operating Costs for Regulation Service Provision

Generator Type	Cost ($/MWh)
Coal	15
Combined Cycle	6
Gas/Oil Steam	4
Hydro	2
Pumped Storage	2


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