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Systems Analysis in Electric Power Sector Modeling: Evaluating Model Complexity for Long-Range Planning

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Systems Analysis in Electric Power Sector Modeling: Evaluating Model Complexity for Long-Range Planning

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ABSTRACT

The literature review (Santen, et al., 2017) that preceded this report explains that “systems analysis” approaches to electric sector modeling aim to improve models’ representation of one or more kinds of complexity to support better decision-making. Such approaches are typically aimed at reducing costs, preventing system crises, avoiding unintended consequences, or improving other outcomes. However, there is often a tension between the complexity of a systems analysis approach and the need for simplicity to keep models computationally tractable and practically manageable within a project’s resource constraints. As a result, long-range models of electric sector capacity planning and dispatch require modelers to balance appropriate levels of temporal, spatial, and technical complexity with computational demands. Well-informed decisions in this balancing act can be important, because simplified representations of the power system may materially impact conclusions drawn from modeling exercises. For instance, they may lead to under- or overestimation of policy compliance costs or to suboptimal decision support about capacity investments.

The objective of this report is to test and examine the benefits of alternate approaches in four key systems analysis areas: *temporal resolution*, *spatial resolution*, *representation of end use*, and *representation of uncertainty*. The analysis calculates and examines potential impacts of using simplified models and methodologies in these areas, using intra-model comparison exercises with two U.S. capacity planning and analysis models: EPRI’s US-REGEN and RFF’s E4ST. The broader goal is to support more prudent and systematic consideration of model simplifications and tradeoffs between appropriate levels of temporal, spatial, and technical resolution.

On one hand, these analyses illustrate how simplifications of system features can lead to unrealistic evaluations of the effects of changes in technologies, polices, and markets. On the other hand, specific applications merit different tradeoffs and considerations in selecting an appropriate analysis framework, which requires modeler judgment and a thorough understanding of the decision context. This report offers insights to modelers assessing these tradeoffs and to consumers of model results as they evaluate outputs. The experiments in this report underscore how the effects of particular model simplifications can vary substantially based on regulatory and market conditions as well as other model simplifications.

Keywords

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Systems analysis

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PRIMARY AUDIENCE: Stakeholders, researchers, and agencies who develop, apply, or rely on electric sector capacity planning or policy analysis tools

KEY RESEARCH QUESTION

The literature review (Santen, et al., 2017) that preceded this report explains that “systems analysis” approaches to electric sector modeling aim to improve models’ representation of one or more kinds of complexity to support better decision-making. Such approaches are typically aimed at reducing costs, preventing system crises, avoiding unintended consequences, or improving other outcomes. However, there is often a tension between the complexity of a systems analysis approach and the need for simplicity to keep models computationally tractable and practically manageable within a project’s resource constraints. As a result, long-range models of electric sector capacity planning and dispatch require modelers to balance appropriate levels of temporal, spatial, and technical complexity with computational demands. Well-informed decisions in this balancing act can be important, because simplified representations of the power system may materially impact conclusions drawn from modeling exercises. For instance, they may lead to under- or overestimation of policy compliance costs or to suboptimal decision support about capacity investments. Although this tradeoff between accuracy and tractability is widely acknowledged, the modeling literature has been limited in systematically investigating the consequences of and best practices for domain-specific simplifications.

RESEARCH OVERVIEW

The objective of this report is to test and examine the benefits of alternate approaches in four key systems analysis areas: *temporal resolution*, *spatial resolution*, *representation of end use*, and *representation of uncertainty*. To better understand the most appropriate systems analysis treatments for different applications, the analysis in this report characterizes potential impacts of using simplified models and methodologies in these four areas. These characterizations use intra-model comparison exercises with two U.S. capacity planning and analysis models: EPRI’s US-REGEN and the E4ST model built by researchers at RFF, Cornell, and Arizona State. The broader goal is to support more prudent and systematic consideration of model simplifications and tradeoffs between appropriate levels of temporal, spatial, and technical resolution.

KEY FINDINGS

- These exercises highlight how critical *temporal resolution* can be for properly valuing power sector investments, including variable renewable energy, dispatchable technologies, and transmission (Chapter 2). These exercises underscore that it is not just how many intra-annual time blocks are included in a model that matters for capacity planning decisions and other outcomes but their method of selection.

- *Trading* – both of electricity and environmental compliance instruments – offers potentially important degrees of freedom in planning and policy compliance (Chapter 3.1). Models that omit trade neglect potentially significant opportunities to lower costs and/or emissions. Simplified trade representations in models exhibit different impacts across model regions in their direction and magnitude (some effects may be offsetting at a national level but have critical implications for regional planning), which requires explicit analysis across regions to evaluate. These differences alter how such simplifications may overstate or understate optimal deployment or costs depending on the circumstances of the region. Policy constraints and market conditions (e.g., renewable mandates, high gas prices) can amplify cost impacts of restricted electricity trade, which leads to an almost two-fold increase in percentage terms over a business-as-usual policy environment.
- Model representations of *spatial resolution* interact strongly with trade assumptions, especially regarding the role of transmission as a resource (Chapter 3.2). The spatial aggregation modeling exercises suggest that adding detail and more restrictions on trade flows with neighboring states show the challenges with renewable integration more clearly. In scenarios and locations where variable renewable deployment is driven primarily by policy incentives, the omission of intra-regional transmission constraints suggests that current results understate cycling challenges for in-region thermal generators (likely lowering their revenues) and understate economic value of balancing options (e.g., transmission, storage).
- The simulations that ignore the *price responsiveness of load* (Chapter 4) miss the load reduction that results from the projected increases in natural gas prices. This interacts with the phenomenon of the RPS making more coal-fueled generation marginal, to appreciably diminish the RPS-induced emission reductions. It also exaggerates the price-reducing effect of the RPS, and hence the benefit to consumers and the profit reduction for generators. The latter effect is chiefly a result of the simplification increasing the electricity price in the no-RPS case.
- *Uncertainty* (Chapter 5): Non-linearities can cause the average results from simulating with a range of input values to differ from the results from simulating with the average of those input values. Comparing the results of modeling exercises that assume different natural gas price paths illustrates two non-linearities related to the natural gas price. First, a change from medium to low natural gas prices causes a larger shift from other generation types to natural gas than does a change from high to medium natural gas prices, even though the latter price change is twice as large. The reason for this is likely that the lower the price of natural gas, the more competitive it is with other generation sources. Second, in a range below the medium natural gas price, each dollar of change in the natural gas price has a substantially smaller effect on the electricity price impact of the RPS than does each dollar of change in the natural gas price in a range above the medium natural gas price. The reason for this is likely that the lower the price of natural gas, the more time generators that do not use natural gas spend setting the price of electricity.

WHY THIS MATTERS

On one hand, these analyses illustrate how simplifications of system features can lead to unrealistic evaluations of the effects of changes in technologies, policies, and markets. On the other hand, specific applications merit different tradeoffs and considerations in selecting an appropriate analysis framework, which requires modeler judgment and a thorough understanding of the decision context. This report offers insights to modelers assessing these tradeoffs and to consumers of model results as they evaluate outputs. The exercises in this report underscore how the effects of particular model simplifications can vary substantially based on regulatory and market conditions as well as other model simplifications.

Given the rapid cost reductions and deployment of wind and solar in the power sector, it is important to accurately represent unique features of these resources, which requires more detailed temporal and spatial granularity. Omissions in many widely used models can prevent analysis of technical and economic implications of wind and solar deployment and the evaluation of related policies. If decision-makers anticipate that a high wind and/or solar state-of-the-world will obtain (regardless of the drivers), then this analysis suggests that modeling should account for:

- Hourly correlations between load, wind output, and solar output within and across regions (Chapter 2)
- Endogenous electricity trade across regional boundaries (Chapter 3)
- Flexibility provisions in policy design like renewable energy certificate markets for complying with renewable energy mandates (Chapter 3)
- The existing price responsiveness of load (Chapter 4)

The analysis also underscores how natural gas prices materially impact policy outcomes and planning decisions, which increases the importance of related model considerations. Key factors include assumed fuel price trajectories over time, incorporation of uncertainty, location-specific differences in the delivered price of natural gas and assumed changes of these price differences over time (which intersects with infrastructure assumptions), and how temporal resolution impacts the economics of flexible resources such as gas turbines, combined cycle units, and storage.

Ultimately, well-suited models should be capable of evaluating critical tradeoffs and of representing aspects of the system affected by a specific policy, technological development, or other scenario characteristics. Increases in energy systems integration, deployment of novel technologies, and prevalence of layered regulations and incentives at state, regional, and federal levels will increase the importance of considering not just the marginal cost of technologies in evaluating investments but also their marginal system value. Marginal system value estimates can require very detailed models capable of capturing these dynamics endogenously, which can require more work for modelers to construct and test additional model features. Adding those features may require other model features to be simplified or removed to keep models tractable or runtimes manageable. This report offers guidance to modelers about such decisions.

The comparisons in this report demonstrate the importance of accurate methods for estimating system costs and values, and their dependence on scenario-specific assumptions and regional heterogeneity. Given this planning context, a related takeaway is the importance of rigorously modeling provisions of complementary regulations and so-called “n^{th}-best” policies.

HOW TO APPLY RESULTS

Overall, the exercises in this report illustrate how model representations of temporal resolution, spatial resolution, end-use detail, and uncertainty can materially influence long-run planning and investment decisions. However, prioritizations for the most critical capabilities to include depend on the specific context, questions, and scenarios.

EXECUTIVE SUMMARY

LEARNING AND ENGAGEMENT OPPORTUNITIES

- Users of this report may be interested in EPRI's Project Set 178B (*Integrated Portfolio Planning and Market Analysis*), which helps members and the public to understand emerging resource planning issues and improved methods for integrated generation, transmission, and distribution planning and fuels management. Contact Adam Diamant at adiamant@epri.com for additional information.
- Users of this report may be interested in EPRI's Program 103 (*Analysis of Environmental Policy Design, Implementation, and Company Strategy*), which applies EPRI's U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model to understand impacts of state and federal policies, emerging technologies, and market uncertainties on company strategy. Contact David Young at dyoung@epri.com for additional information. Reports, articles, and presentations are available at http://eea.epri.com/research.html.
- This report is part of a larger collaborative project on systems analysis in electric power sector modeling between the Electric Power Research Institute and Resources for the Future, supported by the U.S. Department of Energy's Office of Energy Policy and Systems Analysis.
- Learn more about research at RFF that helps policymakers and stakeholders understand how domestic and international markets for electricity respond to government actions and consumer trends as well as varying market dynamics and uncertainties: http://www.rff.org/research/subtopics/electricity-markets-and-regulation.

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INTRODUCTION

Motivations and Scope

The literature review (Santen, et al., 2017) that preceded this report explains that "systems analysis" approaches to electric sector modeling aim to improve models' representation of one or more kinds of complexity to support better decision-making. Such approaches are typically aimed at reducing costs, preventing system crises, avoiding unintended consequences, or improving other outcomes. However, there is often a tension between the complexity of a systems analysis approach and the need for simplicity to keep models computationally tractable and practically manageable within a project's resource constraints. As a result, long-range models of electric sector capacity planning and dispatch require modelers to balance appropriate levels of temporal, spatial, and technical complexity with computational demands. Well-informed decisions in this balancing act can be important, because simplified representations of the power system may materially impact conclusions drawn from modeling exercises. For instance, they may lead to under- or overestimation of policy compliance costs or to suboptimal decision support about capacity investments.

Although this tradeoff between accuracy and tractability is widely acknowledged, the modeling literature has been limited in systematically investigating the consequences of and best practices for domain-specific simplifications. Such model specifications are not necessarily intended to capture physical processes of real-world systems directly but are designed to mimic relevant features through stylized and mathematically efficient representations.

The objective of this report is to test and examine the effects of simple versus complex representations of four key systems analysis areas: temporal resolution, spatial resolution, representation of end use, and representation of uncertainty. To better understand the most appropriate systems analysis treatments for different applications, the analysis reports and discusses potential impacts of using simplified models and methodologies. These quantitative comparisons use intra-model comparison exercises with two U.S. capacity planning and policy analysis models: US-REGEN and E4ST. The broader goal is to support more prudent and systematic consideration of model simplifications and tradeoffs between appropriate levels of temporal, spatial, and technical resolution.

Summary of Literature Review

This report is part of a larger collaborative project on systems analysis in electric power sector modeling between the Electric Power Research Institute (EPRI) and Resources for the Future (RFF), which is supported by the U.S. Department of Energy's Office of Energy Policy and Systems Analysis. It follows a literature review that summarizes research in electric sector systems analysis and capabilities of a selected set of long-range capacity planning models (Santen, et al., 2017).

The literature review surveys the strengths, shortcomings, and applicability of different approaches to integrating more complex power system dynamics into longer-term investment models. The takeaways in the four primary analysis areas are:

- **Role of model temporal resolution:** Accurate representations of system responses in long-term capacity planning models require consideration of hourly time-series data with greater coverage of underlying joint distributions of all relevant data, hourly and sub-hourly chronology, and unit-level detail. The relative importance of these features depends on the research question, but temporal resolution is especially important if the results depend significantly on multiple input parameters that vary over time, space, or both. These considerations make temporal resolution especially important for simulations involving variable renewable energy, large geographic scope, demand-side resources, or energy storage.
- **Role of model spatial resolution:** There is a need for better representations of transmission and electricity flow between disaggregated subregions and other non-electricity markets, especially for models with broad geographical coverage such as the contiguous U.S., owing to disparities between regions in existing resource bases, renewables potentials, market regimes, and policies.
- **Representation of end users and load:** Trends in changing end-use demand through distributed energy resources, price-responsive demand, and real-time pricing warrant more explicit model representations to understand how end-use details can impact long-term capacity planning decisions and policy impacts.
- **Capability of models to perform uncertainty analysis:** Improved methods for explicitly considering uncertainty and developing adaptable long-range capacity plans can guide the creation of systems that are more resilient to future uncertainties.

Overall, the literature review's conclusions highlight the need for additional modeling and analysis to help improve understanding of fundamental tradeoffs between model fidelity (i.e., the accuracy with which a model represents reality) and computational tractability (i.e., the ease with which a model can be constructed and efficiently solved), which is where the analysis in the current report is most valuable.

Model features examined in this report align with the power systems analysis features assessed in the literature review and with the structures of participating models, which lend themselves to rigorous review of these model characteristics.[1]

Methods

Each chapter in the report describes comparisons in different analysis areas between simple and complex versions of the same model. The experiments measure the effects of model capabilities by running one simulation with simplified analysis features (i.e., the "simple" model) and another with more detailed capabilities (i.e., the "complex" model).

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[1] Note that there are two distinct approaches to integrating detailed dynamics into reduced-form models: *soft-linking* (which involves passing information between models with different levels of detail) investment models with operational power systems models as a robustness check to leverage the complementary strengths of different models or *direct integration* (which involves bringing greater detail into a single model). This analysis focuses on the second category.

The impacts of using simplified models depend critically on how the model features are simplified and on the types of scenarios under investigation. Analyses in this report focus on a few prevalent cross-cutting issues in capacity planning models and attempt to capture common types of simplifications, but actual impacts are highly context dependent.

Table 1-1
Summary of modeling experiments to test complex and simple systems analysis areas. Each analysis area and scenario tests the effects of model capabilities by running simulations with more detailed analysis features ("complex" model) and simplified ones ("simple" model).

Analysis Area	Description	Model(s)	Scenarios	Section
Temporal Resolution	Representation of intra-annual variation of load and renewable output	US-REGEN, E4ST	Reference, National RPS, High Gas Prices (US-REGEN Only)	Chapter 2
Spatial Resolution (Trade and Spatial Aggregation)	Representation of electricity/REC trade and regional aggregation	US-REGEN	Reference, National RPS, High Gas Prices	Chapter 3
Representation of End Use	Representation of price-responsive load	E4ST	Reference, National RPS	Chapter 4
Representation of Uncertainty	Representation of fuel price uncertainty	E4ST	Reference, National RPS	Chapter 5

Comparisons across scenarios focus on national-level results in or through 2040. The metrics used to compare the results of the simpler and more complex models include the national generation mix, total electric sector costs, and emissions. Models report additional outputs of interest that are tailored to specific analysis questions. Insights underscore issues of model development, selection, and interpretation, though some takeaways are applicable for planning, technology strategy, and policy design.

Scenarios

A national (U.S. only) renewable portfolio standard (RPS) is represented in both models. In this policy, variable renewable energy requirements linearly increase from current levels to 35% by 2035, and thereafter linearly increase to 50% by 2050, as shown in Figure A-4. Targets are assumed to be the same for all regions, and the only eligible technologies are assumed to be wind and solar. No banking or borrowing is included, though some sensitivities vary assumptions about trading renewable energy certificates (RECs) across regions to satisfy compliance obligations. The US-REGEN analyses layer the national targets on top of state-level mandates, as discussed in Appendix A. The analysis is not intended to comment on efficacy of specific RPS proposals *per se* but to evaluate the effects of alternate model features (complexity) under different possible policy futures.

The RPS effectively causes the amount of wind and solar generation to equal a certain percentage of electricity consumption. Simulating this type of policy tends to greatly reduce the differences between the results of the complex and simple models, since it prescribes total wind and solar generation ex ante. Though this greatly reduces the magnitudes of many of the differences, the differences are still informative. Changes in model complexity would likely have had larger effects if the policy scenario implemented another type of policy, such as a renewable energy tax credit, emissions price, cap-and-trade program, or research that substantially increased the adoption of some technology. This is illustrated by the fact that, in the US-REGEN results, the effects of the high natural gas price are larger than the effects of the national RPS.

In this report, each comparison measures the impacts of complex versus simple representations of model features on the simulated effects of a national RPS. This requires groups of four scenarios: The simpler model with and without national RPS to assess the effects of the national RPS in the simpler model, and the more complex model with and without RPS to evaluate the effects in the more complex model. The effects of the national RPS are then compared in the more complex model with the effects in the simpler model. Technical readers will recognize that each such difference can be called a "difference in differences."

The US-REGEN scenarios also include experiments to test the effects of model complexity under higher natural gas prices. Assumptions about fuel price trajectories over time are included in Appendix A and Chapter 5 for US-REGEN and E4ST, respectively. Reference scenarios include on-the-books policies, and assumptions for these scenarios are described in the respective model appendices.

Brief Model Introductions

U.S. Regional Economy, Greenhouse Gas, and Energy (**US-REGEN**) model, developed by EPRI, is a regional model of the United States that represents detailed electricity sector capacity planning and dispatch decisions simultaneously. Joint variation in load, wind, and solar across regions is captured through the selection of representative hours. Each five-year time step includes capacity investment, retrofit, and retirement decisions as well as dispatch for installed capacity. The intertemporal optimization structure of US-REGEN determines investment and operational choices through 2050 while representing regional resource endowments, costs, demand, and regulations. Additional detail about the structure and assumptions of US-REGEN is provided in Appendix A and EPRI (2017).

US-REGEN experiments examine the impact of alternate systems analysis features for temporal variability of load and renewable energy output (Chapter 2), endogenous versus exogenous trade (Chapter 3), and spatial resolution (Chapter 3).

The Engineering, Economic, and Environmental Electricity Simulation Tool (**E4ST**, pronounced "East") is open-source software built to simulate in detail how the power sector will respond to changes in environmental and non-environmental policies and regulations, input costs, transmission investments, generation investments, and other factors. It determines operation, entry and exit of generators, prices including capacity/scarcity prices, all of the elements of social surplus (a measure of total net benefits), and other outcomes. E4ST is a large linear program that assumes perfect competition. Rather than using a zonal transport model like most capacity planning and policy analysis models, it uses grid models that contain the individual transmission lines and that model flows according to the laws of physics.[2] It models successive multi-year periods, with each multi-year period characterized by representative hours that capture the variation of demand, wind, and sun. E4ST's developers have also created detailed models of the three major U.S. and Canadian grids for simulations using E4ST. The models contain the 19,000 existing generators with their detailed individual characteristics, tens of thousands of buildable generators including location- and hour-specific wind and solar availability, and approximately 20,000 transmission line segments. The segments include all of the high-voltage (>200 kV) segments, selected lower-voltage segments in areas of chronic congestion, and equivalent lines to represent removed low-voltage lines. The models also include detailed generator emission rates and an air pollution fate-and-transport model to enable E4ST to calculate emissions and health effects. The models can be customized to represent phenomena such as policies, layered and complementary policies, storage operation, electric vehicles, other deferrable loads, increased dynamic pricing, and investment and retirement under uncertainty. E4ST is built on the foundation of the popular MATPOWER open-source optimal power flow software. Simulations can be run in large batches to consider various futures. Additional detail about the structure and assumptions of E4ST is provided in Appendix B and at e4st.org.

E4ST experiments in the present report examine the impacts of complex versus simple representations of temporal variability of renewables output (Chapter 2), price-responsive load (Chapter 4), and consideration of uncertain fuel prices (Chapter 5).

References

Santen, N., Bistline, J., Blanford, G., de la Chesnaye, F. (2017). Systems Analysis in Electric Power Sector Modeling: A Review of the Recent Literature and Capabilities of Selected Capacity Planning Tools, EPRI Technical Report #3002011102 (EPRI, Palo Alto, CA).

Electric Power Research Institute (2017). US-REGEN Model Documentation, EPRI Technical Update #3002010956 (EPRI, Palo Alto, CA).

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[2] A note for those with familiarity with power system engineering: Typically, the electrical model embedded in the larger E4ST optimization problem is a DC optimal power flow, though E4ST is also capable of using a full AC optimal power flow if the model is small enough for that to be tractable.

2

TEMPORAL RESOLUTION

The level of temporal granularity (i.e., intra-annual detail) can have important impacts on model outputs. For example, a fundamental economic feature of variable renewable energy like wind and solar is its hourly temporal variability. The degree to which the joint variability of renewable resources and load is represented will impact model outputs such as investments in wind, solar, and dispatchable capacity. However, many planning models use a limited amount of detail in this dimension and focus on capturing the variability of demand alone. This chapter reports the benefits of advanced representations of temporal resolution through quantitative experiments using **US-REGEN** (Section 2.1) and **E4ST** (Section 2.2).

US-REGEN Temporal Resolution Modeling Exercises

Scenario Overview

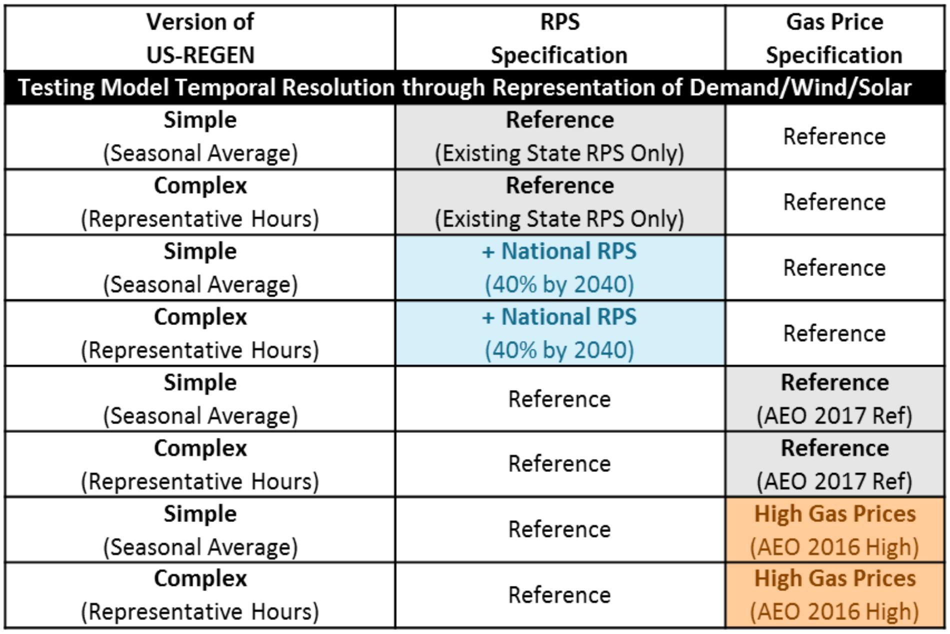
The experiments in this subsection compare the effects of two approaches to representing intra-annual variation:

- **Representative Hours (Complex):** US-REGEN uses a novel representative hours approach for strategically selecting intra-annual hours to satisfy key distributional requirements for time-series data like load and renewable output across multiple interconnected regions. This method includes the selection of relevant extremes of not only the peaks and minimums of individual series but also the joint extremes, which recognizes the importance of boundary events for system operations (e.g., capacity shortfalls, periods of wind or solar overgeneration), very high or low prices, and ultimately returns on investments. This approach is described in Blanford, et al. (2016).
- **Seasonal Average (Simple):** The simple but commonly employed seasonal average approach focuses on capturing the load duration curve in different annual periods (e.g., peak, shoulder, and base demand across seasons). This method assigns renewable capacity factors to each model segment based on the average hourly resource availability across the associated load periods. Variants of the seasonal average approach are common in national-scale capacity planning models like EPA's Integrated Planning Model (IPM) (EPA, 2010) and multisector models like the EIA's National Energy Modeling System (NEMS) (EIA, 2014). Such approaches often use a smaller number of total segments, but their most significant shortcomings are that they inadequately capture the distribution and covariation of renewable resources and load (as well as correlations across regions). Although this is an active area of energy modeling research, many widely used capacity planning tools incorporate variability in stylized ways similar to such seasonal average approaches, prioritizing increased resolution in other modeling dimensions at the expense of intra-annual temporal detail (Santen, et al., 2017).

This section uses US-REGEN to test the effects of selecting "representative hours" to more effectively capture the joint variability of demand and renewable resources, rather than using "seasonal average" values of wind and solar output that simply focus on representing demand variability. Both approaches yield a similar number of segments (109 for the representative hour approach and 108 for the seasonal average approach).[3]

Scenario combinations are enumerated in Table 2-1. More detailed descriptions of the scenarios and key modeling assumptions can be found in Appendix A.

Table 2-1
Modeling experiments to test temporal resolution capability in US-REGEN. Results compare the intra-annual temporal representation of demand and renewable resource variability.



Version of US-REGEN	RPS Specification	Gas Price Specification
Testing Model Temporal Resolution through Representation of Demand/Wind/Solar		
Simple (Seasonal Average)	**Reference** (Existing State RPS Only)	Reference
Complex (Representative Hours)	**Reference** (Existing State RPS Only)	Reference
Simple (Seasonal Average)	**+ National RPS** (40% by 2040)	Reference
Complex (Representative Hours)	**+ National RPS** (40% by 2040)	Reference
Simple (Seasonal Average)	Reference	**Reference** (AEO 2017 Ref)
Complex (Representative Hours)	Reference	**Reference** (AEO 2017 Ref)
Simple (Seasonal Average)	Reference	**High Gas Prices** (AEO 2016 High)
Complex (Representative Hours)	Reference	**High Gas Prices** (AEO 2016 High)

Results

The two approaches described in the overview capture temporal variability in different ways. Figure 2-1 compares the representative hour and seasonal average duration curves (i.e., annual values sorted from high to low) for load and wind resources with the underlying hourly data, which are important model inputs. Both methods reasonably replicate the load duration curve (left panel of Figure 2-1), even though the number of segments is an order of magnitude less than the 8,760 hourly dataset.

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[3] One common downside to approaches like these is that chronological information is lost or is in tension with retaining more a complete spectrum of variability from the joint time-series distribution, which are important considerations in jointly capturing renewables, storage, and unit-commitment costs and constraints in a single model (Bistline, 2017).

In contrast, the representative hour approach offers a considerably more accurate approximation of the wind resource duration curve than the seasonal average approach, as shown in the right panel of Figure 2-1.[4] Seasonal average methods do a poor job of replicating marginal distributions for resource availability, as the averaging approach tends to underestimate the variation of wind and solar while neglecting maximum and minimum output events (including their correlations, as shown in Figure C-3). The seasonal average approach typically results in a much flatter profile relative to the underlying data, and although the seasonal average method approximates the annual average capacity factor almost exactly, it nevertheless leads to errors in the intra-annual variability. These omissions have important implications for accurately assessing the capacity value of resources (Blanford, et al., 2016).

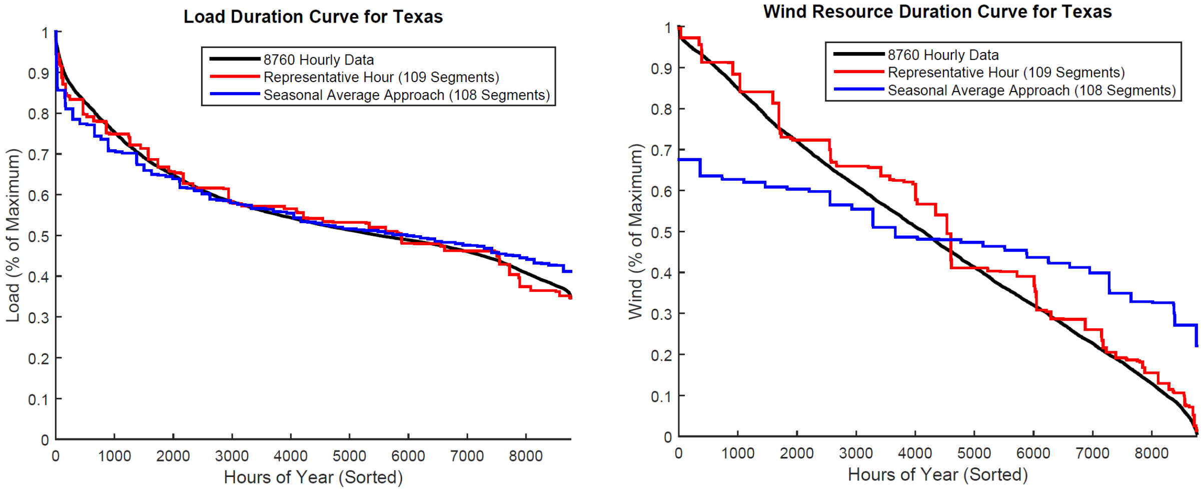

Figure 2-1
Sorted duration curves for load (left) and wind (right) in Texas. Load and wind are normalized as a fraction of their respective maximum annual values. Curves represent the complete hourly data (black), representative hour approach for capturing intra-annual temporal variability (red), and simplified seasonal average approach (blue).

Apart from the seasonal average approach's poor replication of marginal distributions for non-load time-series data (e.g., wind and solar output), an additional shortcoming is its inadequate approximations of the joint distribution for time-series data. Unlike the representative hours approach, the seasonal average procedure does not guarantee that covariation across load, wind output, and solar output is preserved, which may miss periods where load is high but wind and solar are low (and vice versa). The covariation of load and renewable resource output is a primary driver of the economic potential of wind and solar (Blanford, et al., 2016). The representative hours approach also does a better job of representing covariation across regions as well, which is important for modeling transmission and trade flows and highlights interactions between temporal and spatial resolution. Figure C-3 and Figure C-4 contrast the preservation of time-series and regional correlations between methods.

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[4] Additional comparisons in Appendix C demonstrate how this trend holds across other time-series data like solar resource duration curves and other regions.

Temporal Resolution

These differences in fidelity to the underlying joint distribution of intra-annual variability have important implications for model capacity planning decisions. The representation of temporal variability greatly impacts electric sector model outcomes, as illustrated in Figure 2-2. In particular, the simplified seasonal average approach tends to overstate wind, solar, and coal generation while understating gas deployment.[5] The marginal value of wind and solar investments is higher for the seasonal average approach than the representative hour approach, which leads to greater renewable investment than would be economic.[6]

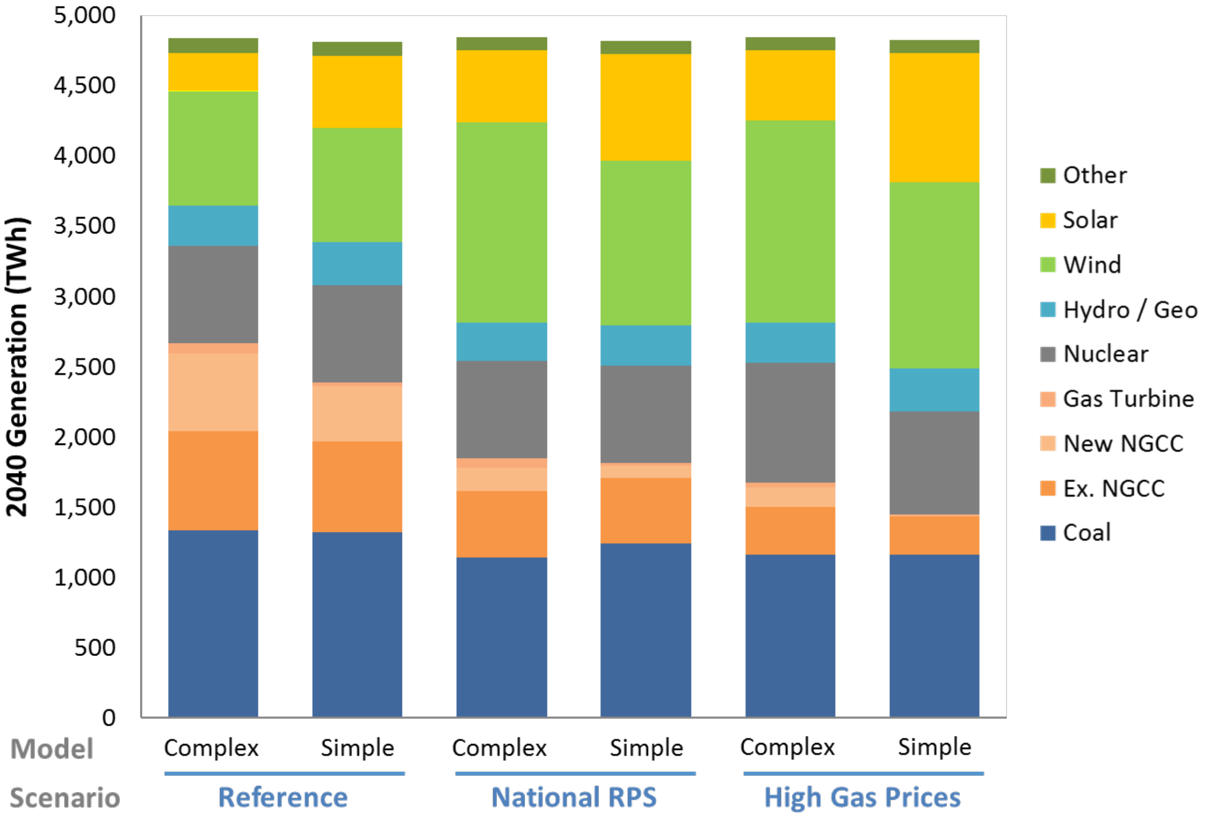

Figure 2-2
National generation (TWh) in 2040 by technology and scenario from US-REGEN model results. "Complex" scenarios use the representative hour approach for capturing intra-annual temporal variability, and "Simple" scenarios use the simplified seasonal average method.

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[5] While it is prima facie ambiguous as to whether seasonal average approaches bias wind and solar investments upward or downward relative to a model with higher temporal resolution (Merrick, 2016), these experiments consistently suggest that the seasonal average specification overvalues variable renewables. The effect size likely depends on the simplifications used for temporal resolution (e.g., Mai, et al., 2015), and future work should quantify how alternative specifications impact capacity planning decisions.

[6] Detailed marginal value curve comparisons between the 8,760 hourly data, representative hour approach, and seasonal average approach are provided in Blanford, et al. (2016).

Table 2-2 summarizes cost and emissions differences across the temporal resolution scenarios.

Table 2-2
Implications of model specifications of temporal resolution in US-REGEN. "Complex" scenarios use the representative hour approach for capturing intra-annual temporal variability, and "Simple" scenarios use the simplified seasonal average method. All values are relative to the reference model features under the reference scenario.

Metric	Units	Scenario	Complex (Rep. Hour)	Simple (Seas. Avg.)	Difference
Incremental Electric Sector Costs (NPV 2016–2050)	Billion $	Reference	0.0	-25.9	-25.9
		National RPS	61.2	-3.3	-64.5
		High Gas Prices	305.1	198.8	-106.3
Cumulative CO_2 Reductions from Reference	Billion Metric Tons	Reference	0.0	4.4	4.4
		National RPS	10.1	9.8	-0.3
		High Gas Prices	12.7	15.1	2.3

Model specifications also impact other technical and economic outcomes (e.g., compliance cost of policies, fleet flexibility needs). The simple seasonal average approach biases incremental compliance costs downward for the national RPS due to the higher renewables deployment in the reference scenario relative to the complex representative hour approach. Additionally, RPS-induced emissions reductions are biased downward under the seasonal average method due to its lower reference emissions than the representative hour method (owing again to higher wind and solar investments in the reference under the seasonal average approach).

E4ST Temporal Resolution Modeling Exercises

Scenario Overview

The experiments in this subsection include two approaches to representing intra-annual variation of wind and solar resources:

1. **Variable Wind and Solar (Complex):** Currently, E4ST uses 38 representative hours to represent the year in the Eastern Interconnection version of the model, and similar numbers of representative hours in the Western and Texas models. Each representative hour represents between 4 and 430 real hours. A method was developed to choose 38 hours out of the 8,760 hours in the year from which the data came, and assign weights or frequencies (i.e., the number of hours each one represents) to them, in such a way that the frequency distribution of system-wide electricity demand, wind, and solar generation in the 38 selected hours is almost the same as in the original 8760 hours.

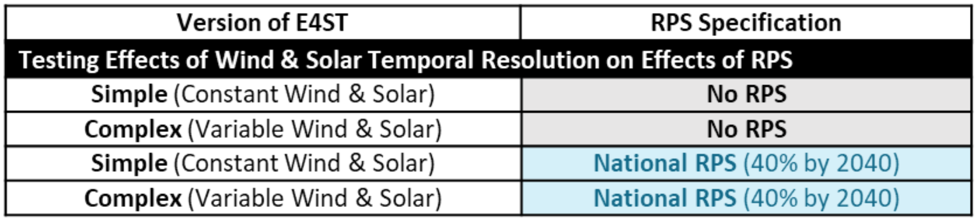
   Each generator has an "availability factor" in each hour. For wind farms and solar generators, the availability factor measures the proportion of its maximum possible hourly output in MW that it can generate in that hour, given the wind or sunlight available. For each of the thousands of buildable wind farms in the model, that availability factor comes from the hourly, site-by-site generation estimates produced for the Eastern Wind Integration and

Transmission Study (Corbus, et al., 2010). For each of the thousands of buildable solar generators in the model, that availability calculation comes from the nearest high-quality solar measurement station, assuming a fixed-tilt solar array.

2. **Constant Wind & Solar (Simple):** The simpler temporal resolution version of E4ST uses the same 38 representative hours, but replaces the availability factor of each existing or buildable wind farm in each representative hour with the annual average availability factor of that wind farm. Likewise, this version of the model replaces the availability factor of each existing or buildable solar array in each representative hour with the annual average availability factor of that solar array. For solar, the effects of this simplification may be quite different from the effects of the particular type of "seasonal average" wind and solar availability factors tested in US-REGEN in the preceding subsection, because the simplification tested with E4ST does not preserve a positive correlation between solar availability factors and demand, while the seasonal average solar availability factors tested in US-REGEN do.

The list of cases that are used to examine effect of wind and solar temporal resolution is shown in Table 2-3.

Table 2-3
List of cases used to examine effects of considering wind and solar variability on simulated effects of RPS in E4ST.



Version of E4ST	RPS Specification
Testing Effects of Wind & Solar Temporal Resolution on Effects of RPS	
Simple (Constant Wind & Solar)	**No RPS**
Complex (Variable Wind & Solar)	**No RPS**
Simple (Constant Wind & Solar)	**National RPS** (40% by 2040)
Complex (Variable Wind & Solar)	**National RPS** (40% by 2040)

Results

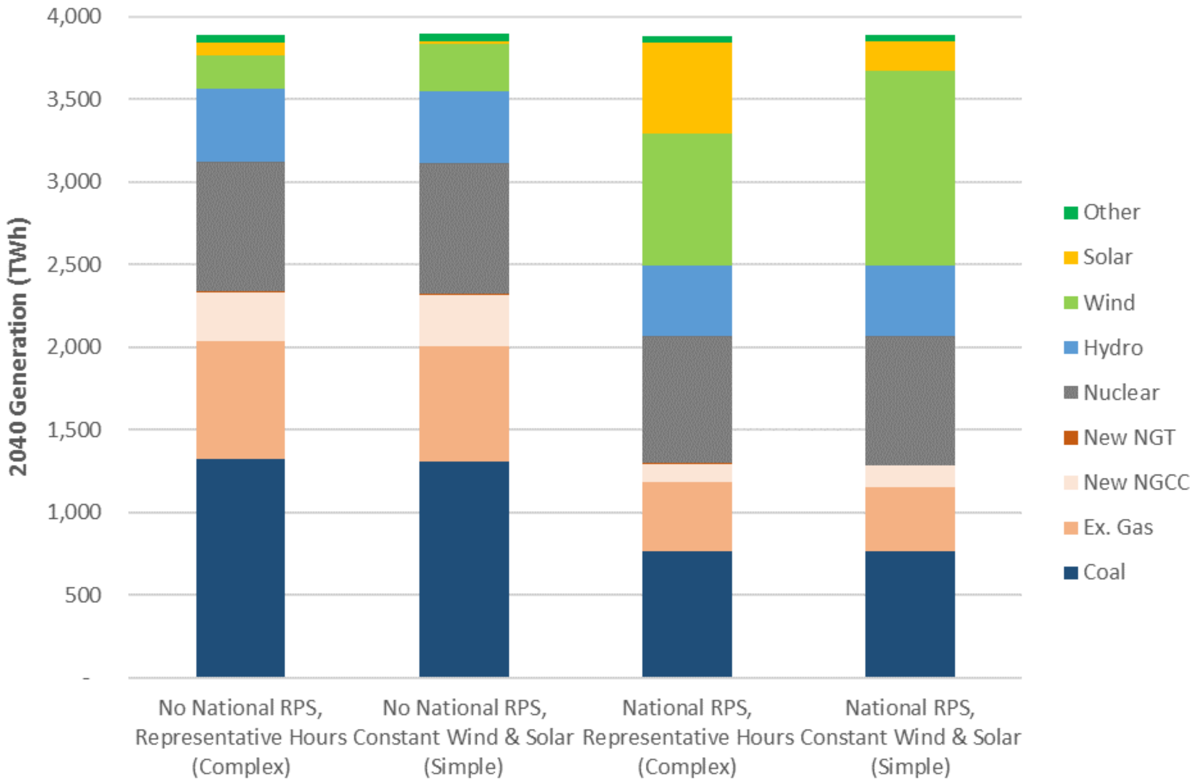


Figure 2-3
Generation (TWh) in 2040 by technology and scenario, in the E4ST Simulation of the Eastern Interconnection. “Representative Hours” scenarios use the representative hour approach for capturing intra-annual temporal variability, and “Constant Wind & Solar” scenarios use the simpler annual average method.

In the E4ST simulations, there are two main effects of using an annual average availability factor for each wind farm and solar array in every hour, instead of using the availability factor specific to that hour. The first effect is to understate the adoption of solar generators. Applying annual average availability factors in every hour makes solar generators less valuable, because their hour-specific availability factors are positively correlated with demand. Making solar generators less valuable is the opposite of what occurs in the US-REGEN simulations because the particular type of seasonal average representation of solar availability factors used in the US-REGEN simulations preserves the positive correlation between solar availability factors and demand, while the annual average representation used in the E4ST simulations does not. This illustrates that two different simplifications of the same parameter can have opposite effects on the results. The second effect is to overstate the adoption of wind generators. Applying annual average availability factors in every hour makes wind generators more valuable to the system because it reduces the amount of dispatchable generation capacity that must exist to complement the added wind generators in high-demand, low-wind hours.

Table 2-4
Monetized net benefits of RPS with and without considering variability of wind and solar.

	Net Present Value of Effects of RPS from 2018 through 2040		
Outcome	Considering Variability of Wind & Solar (Complex)	Ignoring Variability of Wind & Solar (Simple)	% Difference
	In billions of 2013 US $		
Total Production Cost	193	161	-17%
Constituents of Net Benefits (Social Surplus)			
Consumer Welfare (Net Consumer Surplus)	455	386	-15%
CO2 Benefit (Damage Reduction from less CO2)	297	292	-2%
SO2 Benefit (from lives saved from less airborne sulfates)	210	189	-10%
NOX Benefit (from lives saved from less airborne nitrates)	73	70	-3%
Generators' Profits	-608	-542	-11%
Government Net Revenue	-28	-14	-50%
Congestion Revenue (Merchandising Surplus)	16	25	58%
Total Social Surplus	414	406	-2%
Discounted net present values are from the perspective of the middle of 2016, and are calculated using a real discount rate of 3%.			

The numbers in Table 2-4 are net present values, using a 3% real discount rate. The first row of numbers shows total production cost. Assuming constant wind and sun leads to understating the effect of the RPS on production costs by $32 billion, or 17%. There are two reasons. First, it results in understating the amount of dispatchable capacity needed for times when, in some major part of the system, demand is high and wind and solar generation together are low. Second, it results in overstating wind generator construction and understating solar generator construction. In the cost assumptions used in the modeling, wind generators on average are less expensive, per MWh, than solar generators.

The rest of Table 2-4 shows the projected effects of the RPS on the components of total social surplus, which is a standard measure of net benefits to society. By comparing the first and second columns of numbers, one can see that the simplifying assumption has relatively little effect on the estimated total welfare effect of the RPS, understating it by just 2%, or $8 billion, but it has much larger effects on the individual components of total welfare. Compared with the complex model, the simplification reduces the number of hours with very low electricity prices, raising the average price of electricity (including capacity/scarcity prices). This understates the predicted consumer benefit by $69 billion (15%) and the predicted negative impact on generators' profits by almost the same amount, $67 billion (11%). The simplification also understates the predicted environmental benefit by $29 billion (5%). It understates the predicted expense to governments by $14 billion (50%), because it reduces the amount of solar capacity built in the years when solar is slated to receive larger tax credits than wind will. Assuming constant wind and sun also leads to understating the merchandising surplus by $9 billion (58%), because the renewable energy projects are more geographically concentrated in the locations with the highest average capacity factors, and consequently produce more consistent predicted congestion.

In summary, in this case study, assuming constant wind and sun results in understating the production cost increase, consumer benefits, environmental benefits, producer profit reductions, government fiscal cost, and total social surplus increase that results from the RPS. However, it results in overstating the increase in transmission congestion that results from the RPS.

Summary of Insights

This chapter examines temporal resolution in models, specifically focusing on how intra-annual periods are chosen and how these modeling choices influence investments and system operations. These experiments highlight how critical temporal resolution can be for properly simulating the effects of potential policy changes on power sector investments, including variable renewable energy, dispatchable technologies, and transmission.

In US-REGEN experiments, compared to a “representative hours” approach for incorporating intra-annual temporal variation, the simplified “seasonal average” approach tested here can:

- Overstate suggested variable renewable investments and understate the need for dispatchable generation, especially for joint extremes of demand, wind output, and solar output
- Favor solar over wind
- Understate incremental electric sector costs associated with a national RPS

The seasonal average approach fails to account for key variability impacts on the value of renewables. Using intra-annual segments based on averaging underestimates the variability of wind and solar output, which artificially smooths periods of high and low output. In contrast, the representative hours approach avoids omitting solution-constraining extreme hours in the marginal and joint distributions. The marginal value of wind and solar investments is higher for the seasonal average approach than the true 8,760 hourly data (or the representative hour approach that tracks the underlying data closely), which leads to greater renewable investment than would be economic (Blanford, et al., 2016).

In the E4ST experiments, assuming constant instead of variable wind and solar can:

- Understate the amount of solar generation capacity that will be built, and overstate the amount of wind generation capacity that will be built
- Understate the production cost increase, electricity price reduction, consumer benefits, environmental benefits, producer profit reductions, government fiscal cost, and total social surplus increase that would result from the RPS
- Overstate the increase in transmission congestion that would result from the RPS

The results show that simplification of the availability pattern of solar and wind generators can cause their adoption to be greatly overstated or understated in simulation results. The differences between the US-REGEN and E4ST results illustrate that the form of simplification of the representative hours matters. In particular, eliminating the positive correlation between solar availability factors and demand tends to cause simulations to understate solar construction.

Otherwise, reducing the output variability of wind and solar generators tends to cause simulations to overstate wind and solar construction.

These experiments underscore that it is not just how many intra-annual segments are included in a model (i.e., not only increasing temporal resolution) that matters but their method of selection (Ludig, et al., 2011). Such considerations are shown to be increasingly important in settings where variable renewable energy is expected to be a more significant portion of the electricity generation portfolio.

Note how experiments in this section on temporal resolution focus on intra-annual variability of supply and demand to integrate short-run dynamics in long-run power system models. However, longer time horizon temporal issues can be important in long-term capacity planning models, especially in terms of treating end effects in the time horizon. Additionally, modeling decisions about temporal resolution interact with spatial resolution choices, both in terms of model results (e.g., impacts of transmission and trade) and in terms of model size (e.g., to maintain similar runtimes, increasing a model's spatial resolution may require decreasing temporal resolution). Chapter 3 explores questions about appropriate levels of spatial resolution in models.

References

Bistline, J.E. (2017). "Economic and Technical Challenges of Flexible Operations under Large-Scale Variable Renewable Deployment," Energy Economics **64:363–372.**

Blanford, G.J., Merrick, J.H., Bistline, J.E., Young, D. (2016). Simulating Annual Variation in Load, Wind, and Solar by Representative Hour Selection, EPRI Technical Update #3002008653 (EPRI, Palo Alto, CA).

Corbus, D., King, J., Mousseau, T., Zavadil, R., Heath, B., Hecker, L., Lawhorn, J., Osborn, D., Smit, J., Hunt, R. (2010). Eastern Wind Integration and Transmission Study, CP-550-46505 (NREL, Golden, CO). Available at: http://www.nrel.gov/docs/fy09osti/46505.pdf.

Electric Power Research Institute (2017). US-REGEN Model Documentation, EPRI Technical Update #3002010956 (EPRI, Palo Alto, CA).

Ludig, S., Haller, M., Schmid, E., Bauer, N. (2011). "Fluctuating Renewables in a Long-term Climate Change Mitigation Strategy," Energy **36(11):6674–6685.**

Mai, T., Barrows, C., Lopez, A., Hale, E., Dyson, M., K. Eurek (2015). Implications of Model Structure and Detail for Utility Planning: Scenario Case Studies Using the Resource Planning Model, NREL/TP-6A20-63972 (NREL, Golden, CO).

Merrick, J. (2016). "On Representation of Temporal Variability in Electricity Capacity Planning Models," Energy Economics **59:261–274.**

Santen, N., Bistline, J.E., Blanford, G., de la Chesnaye, F. (2017). Systems Analysis in Electric Power Sector Modeling: A Review of the Recent Literature and Capabilities of Selected Capacity Planning Tools, EPRI Technical Report #3002011102 (EPRI, Palo Alto, CA).

U.S. Energy Information Administration (2014). The Electricity Market Module of the National Energy Modeling System: Model Documentation 2014 (EIA, Washington, DC).

U.S. Environmental Protection Agency (2010). Valuing Mortality Risk Reductions for Environmental Policy: A White Paper (EPA, Washington, DC).

U.S. Environmental Protection Agency (2010). Documentation for Integrated Planning Model (IPM) Base Case v.4.10 (EPA, Washington, DC).

3

SPATIAL RESOLUTION

The representation of a region and its connections with broader markets is critical to assessing the integrated nature of the electric system. For instance, the ability to trade electricity across regional borders can provide resource adequacy, reliability, and lower-cost system planning and operations. Such trading can include electricity, emission credits, and renewable energy certificates. In addition, regional heterogeneity in resources and costs means that the geographical scope on environmental compliance can impact the economic and environmental impacts of policies. Existing analyses underscore the importance of capturing spillover effects of neighboring policies (e.g., Bowen and Lacombe, 2017; Heeter, et al., 2015), but there is little systematic guidance about how more complex model representations of trade may impact capacity planning decisions. Studies also suggest that spatial aggregation can impact investment decisions for specific technologies and other model outputs (e.g., Mai, et al., 2013; Shawhan, et al., 2014) but have not investigated interactions between spatial resolution and trade. This chapter assesses the benefits of increased spatial resolution using US-REGEN in two areas: **trade** (Section 3.1) and **spatial aggregation** (Section 3.2).

US-REGEN Trade Modeling Exercises

Scenario Overview

Many capacity planning models simplify the representation of trade with broader markets by assuming pre-specified levels of interaction between regions. To understand the effect of broader trade on regional planning, this section uses US-REGEN with constrained trading between regions, and then again with the model's fully endogenous inter-regional trading capability with co-optimized transmission investment.[7] The simplified (fixed) trade case assumes that segment-level flows are constrained to be less than or equal to their base year values.

A second set of scenarios tests model simplifications about trading renewable energy certificates (RECs) under a national RPS. RECs are the tradable currency of RPS markets and provide increased flexibility in compliance by allowing covered entities to buy and sell these environmental attributes of generated power without necessarily taking physical delivery.[8] Existing state renewable mandates exhibit differences in their geographical or deliverability requirements, timing, stringency, and eligible technologies, which are captured in US-REGEN. National RPS scenarios generally assume full trading so that unbundled RECs can be exchanged across regions, which gives rise to the optimal regional allocation of renewable generation.[9] In contrast, the limited REC trade case is similar to many on-the-books RPS provisions by prohibiting unbundled REC exchange.

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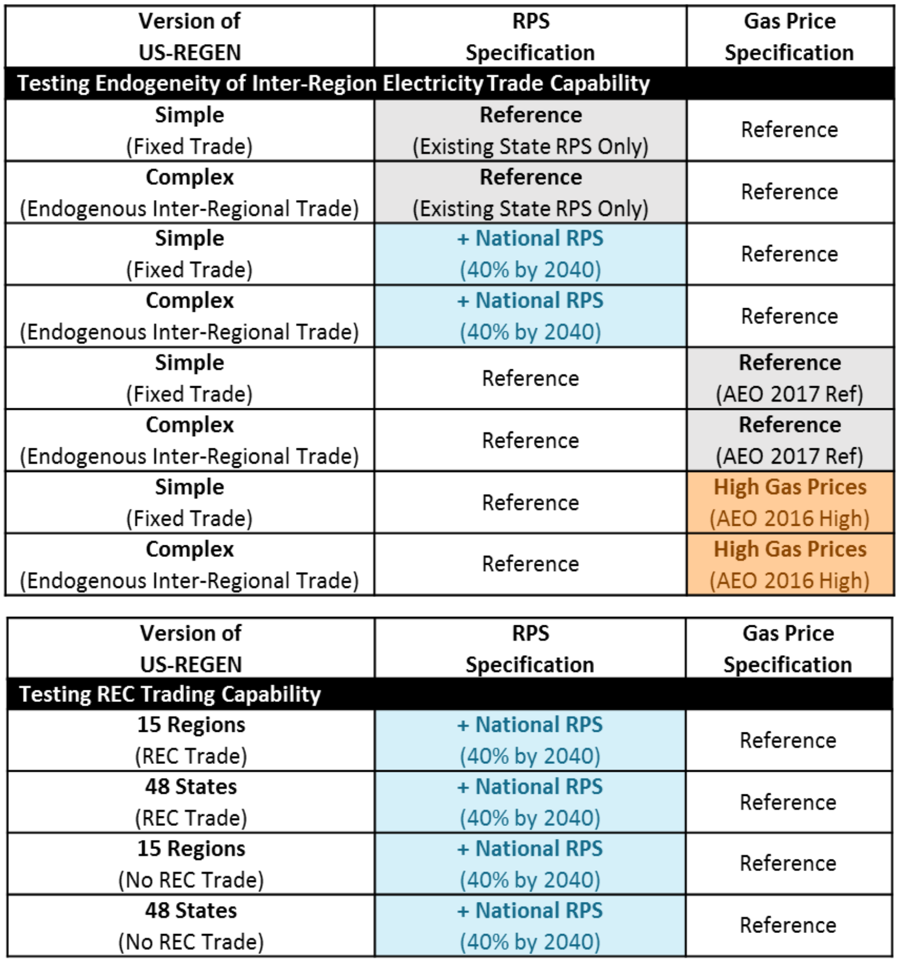
[7] US-REGEN represents co-optimized inter-regional transmission investment and electricity trade across regions but does not capture intra-regional transmission constraints.

[8] "Unbundled" RECs are sold separately from electricity and can be traded across any region.

[9] Such "where" flexibility ensures a least-cost equilibrium that meets exogenously specified renewable mandates.

The impacts of alternate model formulations are tested across market and policy assumptions to investigate whether insights are robust across these dimensions. Scenario combinations are enumerated in Table 3.1.[10] Detailed scenario descriptions and key modeling assumptions can be found in Appendix A.

Table 3-1
Modeling experiments to test trade-related spatial resolution capabilities in US-REGEN. Electricity trade (top) and REC trade (bottom) results are presented in Section 3.1.



Version of US-REGEN	RPS Specification	Gas Price Specification
Testing Endogeneity of Inter-Region Electricity Trade Capability		
Simple (Fixed Trade)	**Reference** (Existing State RPS Only)	Reference
Complex (Endogenous Inter-Regional Trade)	**Reference** (Existing State RPS Only)	Reference
Simple (Fixed Trade)	**+ National RPS** (40% by 2040)	Reference
Complex (Endogenous Inter-Regional Trade)	**+ National RPS** (40% by 2040)	Reference
Simple (Fixed Trade)	Reference	**Reference** (AEO 2017 Ref)
Complex (Endogenous Inter-Regional Trade)	Reference	**Reference** (AEO 2017 Ref)
Simple (Fixed Trade)	Reference	**High Gas Prices** (AEO 2016 High)
Complex (Endogenous Inter-Regional Trade)	Reference	**High Gas Prices** (AEO 2016 High)

Version of US-REGEN	RPS Specification	Gas Price Specification
Testing REC Trading Capability		
15 Regions (REC Trade)	**+ National RPS** (40% by 2040)	Reference
48 States (REC Trade)	**+ National RPS** (40% by 2040)	Reference
15 Regions (No REC Trade)	**+ National RPS** (40% by 2040)	Reference
48 States (No REC Trade)	**+ National RPS** (40% by 2040)	Reference

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[10] Comparing model runs 1/2, 3/4, and 5/6 provides insight about the effect of *electricity trade* on generation, system costs, and emissions (top of Table 3.1). Runs 3/8 and 7/9 focus on *REC trade* sensitivities.

Results

As illustrated in Figure 3.1, the explicit representation of electricity trade across regions impacts the economic value of renewables and dispatchable assets, which leads to different generation mixes at regional and national levels. For the reference scenario, simplified (fixed) trade lowers total wind and solar generation by lowering potential revenues to these generators through restrictions on export markets. For a national RPS scenario, restricting electricity trade changes the portfolio of renewable technologies, with more solar capacity relative to wind. The increases in NGCC generation under the fixed trade scenarios indicate a flexibility premium when inter-regional transactions and geographical pooling are restricted.

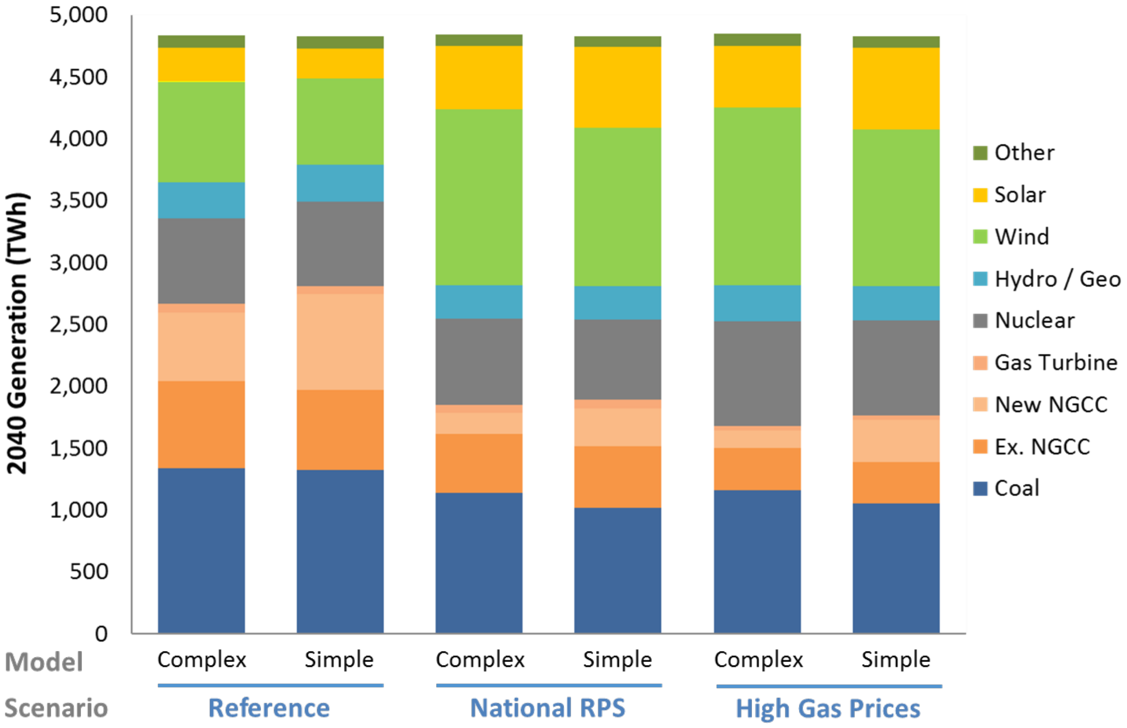

Figure 3-1
National generation (TWh) in 2040 by technology and scenario from US-REGEN model results. "Complex" scenarios assume endogenous inter-regional electricity trade, and "Simple" scenarios assume trade levels are constrained by their base year values.

National-level generation results belie significant regional variation across these scenarios. Figure C-7 (Appendix C) presents regional comparisons for Texas, Southeast Central, and California. Scenario assumptions and model representations of trade significantly alter the size and composition of regional grids. The net trade balance of electricity and RECs reflect economic prospects across scenarios. For instance, Texas is a net exporter of electricity and RECs for many scenarios due to the favorable economics of wind development in the state. Restricting electricity trade consequently erodes the value of Texas wind generators, leading to lower investment in new capacity. On the other hand, net importers of electricity and RECs (e.g., the Southeast Central region) are impacted differently by model trade simplifications. For instance, prohibitions on REC exchange lead to higher in-region renewable builds for regions that would otherwise import RECs, higher in-region costs, and lower output from existing generators like coal and nuclear.

The regional distribution of capacity additions, generation, and welfare impacts vary dramatically across scenarios, as some regions benefit from trading while others lose. Figure 3-2 compares regional generation in 2040 with and without REC trading under a federal RPS. Net REC exporters like NW-Central and Texas have lower in-region renewable generation and higher fossil-based generation when REC trading is prohibited. Net REC importers like SE-Central and South Atlantic exhibit opposing trends, though regional heterogeneity alters marginal emissions impacts.

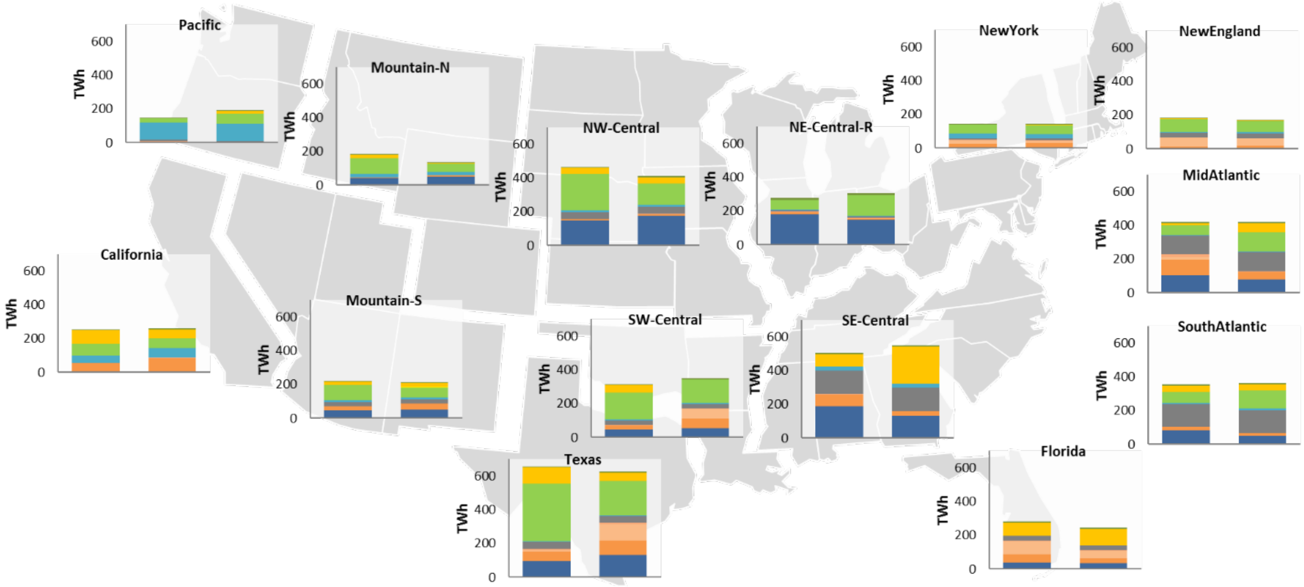

Figure 3-2
Regional generation (TWh) in 2040 by technology and REC trading scenario. All scenarios assume a national RPS requiring 40% of 2040 generation come from wind and solar. Scenarios vary whether REC trading is possible across regions (left bar) or whether each region must meet the RPS requirement individually (right bar).

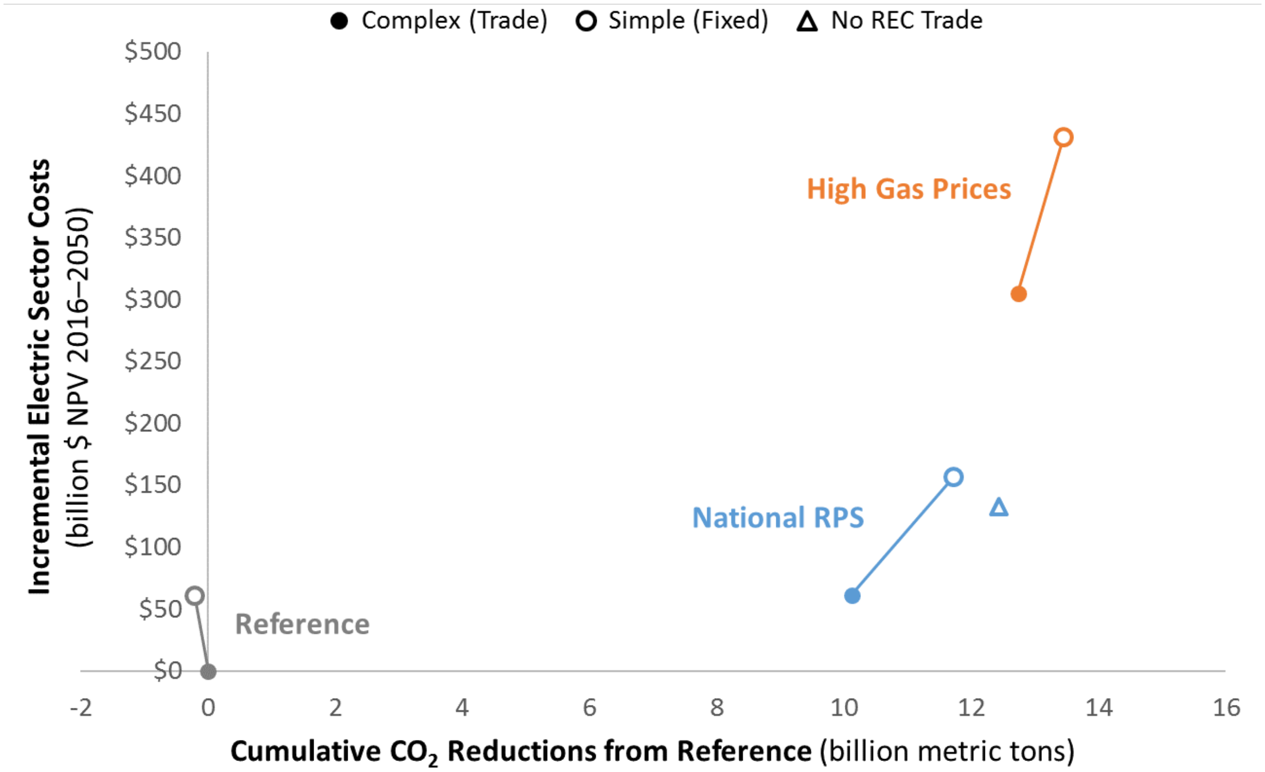

Figure 3-3
Comparison of incremental electric sector costs and cumulative CO_2 emissions reductions relative to the reference case. "Complex" scenarios assume endogenous inter-regional electricity trade, and "Simple" scenarios assume trade levels are constrained by their base year values. Incremental costs are relative to the reference scenario with trading, and the net present value of electric sector costs is summed across the model's time horizon (i.e., 2016–2050). Cumulative CO_2 reductions are also relative to the reference scenario.

Cost metrics provide additional insights into potential economic impacts of using simplified models or restricting flexibility in planning or policy design. The net present value (NPV) of incremental electric sector costs on the vertical axis of Figure 3-3 represents values above those incurred in the reference scenario (i.e., with business-as-usual policies and endogenous trade).[11] Costs include all operating, fuel, and new investment costs.

Compared to endogenous representations of cross-border electricity trade, simplified (fixed) trade can overstate total electric sector system costs across all three scenarios, as shown in Figure 3-3. Policy and market constraints like renewable mandates and high gas prices can amplify this difference, leading to almost a two-fold increase in percentage terms. For instance, the incremental cost of the 50% national RPS increases from $61 billion NPV to $96 billion. Restricting REC trading across regions more than doubles incremental compliance costs of the national RPS (increasing from $61 to $133 billion NPV). Note that the reference scenario NPV is approximately $2,400 billion.[12]

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[11] The cumulative metrics on both axes aggregate time profiles of costs and emissions to summarize total impacts across the model's planning horizon. Time-series outputs can be found in Appendix C.

High natural gas prices have a greater impact on electric sector costs than other scenarios, with incremental costs over $300 billion NPV. An implication for planning and modeling is that fuel cost uncertainty should be considered to understand potential upside and downside risks.

In plotting cumulative CO_2 emissions reductions against incremental costs, Figure 3-3 also traces an emissions reduction frontier with the scenarios considered in this analysis. There is generally a tradeoff between cost and emissions reductions, but some scenarios are dominated so that equal abatement can be achieved at lower cost (or greater mitigation at the same cost). For example, omitting endogenous electricity trade has relatively minor emissions impacts (increasing emissions in some cases) but substantially increases total costs. The greater emissions reductions under the high gas price scenarios come through greater wind and solar deployment in many regions, especially ones where natural gas pipeline constraints increase regional prices.

Table 3-2 summarizes cost and emissions differences across the trade scenarios.

Table 3-2
Implications of model specifications of electricity trade in US-REGEN. “Complex” scenarios assume endogenous inter-regional electricity trade, and “Simple” scenarios assume trade levels are constrained by their base year values. All values are relative to the reference model features under the reference scenario.

Metric	Units	Scenario	Complex (Trade)	Simple (Fixed)	Difference
Incremental Electric Sector Costs (NPV 2016–2050)	Billion $	Reference	0.0	60.3	60.3
		National RPS	61.2	156.4	95.2
		High Gas Prices	305.1	431.1	126.0
Cumulative CO_2 Reductions from Reference	Billion Metric Tons	Reference	0.0	-0.2	-0.2
		National RPS	10.1	11.7	1.6
		High Gas Prices	12.7	13.5	0.7

Finally, the national RPS without REC trade (triangle in Figure 3-3) exhibits higher emissions reductions due to higher marginal emissions intensities of displaced generation in regions that would otherwise import RECs. However, this mitigation comes at a cost, as total compliance costs with the federal RPS nearly double when limited REC trade distorts the cost-optimal spatial allocation of renewable deployment. Such scenarios emphasize how marginal emissions and cost impacts of incremental renewable installations, energy efficiency, and electric-vehicle deployment varies geographically and depends on trade assumptions.

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[12] Although incremental costs are a small fraction of the reference NPV, the split between capital and fuel costs change considerably across scenarios, increasing the importance of financing assumptions and the discount rate.

Discussion

Compared to a fully endogenous representation of electricity trade, simplified (e.g., fixed) trade can:

- Alter the economic competitiveness of dispatchable and variable renewable generators
- Increase total electric sector costs by eliminating the possibility of using trade with neighboring grids as a planning, compliance, or flexibility resource
- Have ambiguous impacts on emissions, which may increase or decrease depending on the policy and market context

Policy and market constraints (e.g., renewable mandates, high gas prices) can amplify cost impacts of restricted electricity trade, which leads to an almost two-fold increase in percentage terms over a BAU policy environment.

Restricting REC trade distorts the cost-minimizing allocation of renewables and increases compliance costs, especially under stringent wind and solar mandates. The availability of interstate REC trade materially alters investment decisions, though the degree and direction of impact depends on region-specific considerations.

A high-level takeaway is that trading – both of electricity and environmental compliance instruments – offers potentially important degrees of freedom in planning and policy compliance. Models that omit trade neglect potentially significant opportunities to lower costs and/or emissions.[13] Consequently, a best practice for modeling is to include endogenous trade and to replicate provisions associated with trade as faithfully as possible on a regional level to accurately evaluate electric sector investments and estimate costs. Shadow prices on market-clearing constraints provide useful information about economic impacts and trade opportunities. If endogeneity is not possible (e.g., for utility-scale models over a specific balancing area), then modelers should test over a wide range of possible prices to determine how imports or exports could impact conclusions. This second-best practice is easier for environmental compliance instruments with annual (e.g., REC prices) instead of hourly market-clearing constraints.

Simplified trade representations in models exhibit important differences across states, which requires explicit analysis to evaluate. These differences alter how such features may overstate or understate optimal deployment or costs depending on the circumstances of the region. A corollary is that, when policies omit trade, there may be considerable variation in the regional incidence of this restriction.

US-REGEN Spatial Aggregation Modeling Exercises

Scenario Overview

This section explores the effect of spatial aggregation on planning decisions by comparing results from a version of US-REGEN that aggregates the contiguous U.S. into 15 regions and another with all 48 Lower states, as shown in Table 3-3. Results in other sections use the 15-

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[13] Analysis of the Clean Power Plan indicates that regulatory costs are considerably higher when states opt to comply as “islands” without changing electricity trade or without participating in interstate allowance markets (Bistline, et al., 2017).

region model whose aggregation simplifies resources and operations at more granular state or substate levels (e.g., assuming no transmission constraints limiting electricity trade between states within a region).

Table 3-3
Modeling experiments to test spatial aggregation capability in US-REGEN. Spatial aggregation/granularity results are presented in Section 3.2.

Version of US-REGEN	RPS Specification	Gas Price Specification
Testing Model Spatial Granularity		
Simple (15 Regions)	**Reference** (Existing State RPS Only)	Reference
Complex (48 States)	**Reference** (Existing State RPS Only)	Reference
Simple (15 Regions)	**+ National RPS** (40% by 2040)	Reference
Complex (48 States)	**+ National RPS** (40% by 2040)	Reference
Simple (15 Regions)	Reference	**Reference** (AEO 2017 Ref)
Complex (48 States)	Reference	**Reference** (AEO 2017 Ref)
Simple (15 Regions)	Reference	**High Gas Prices** (AEO 2016 High)
Complex (48 States)	Reference	**High Gas Prices** (AEO 2016 High)

Results

When compared to finer resolution spatial modeling, geographical aggregation via regional modeling can overstate the need for wind and solar and understate the need for coal and gas, as shown in Figure C-11in Appendix C.

Figure 3-4 compares incremental RPS compliance costs with the 15-region model (left) and 48-state model (right). The 48-state resolution both with and without REC trading is significantly more expensive than the original RPS with 15 regions. The incremental cost of moving from 15 regions to 48 states is driven by:

1. The inability to pool the best-quality and lowest-cost wind and solar sites at regional level
2. More detailed transmission constraints impeding cross-state trade flows

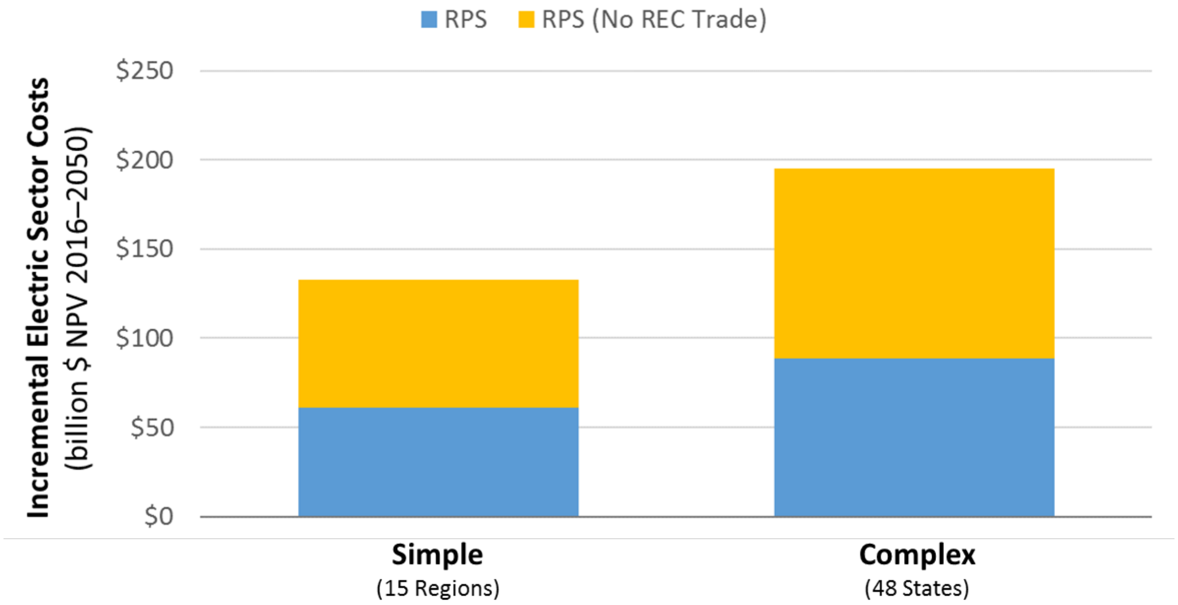


Figure 3-4
Incremental RPS compliance costs (billion $ NPV) with a simplified 15-region spatial resolution (left) and more detailed 48-state model (right). Costs are shown for the national RPS requiring 40% of 2040 generation come from wind and solar assuming full interregional REC trade (top of blue bar) and with restricting REC trade (top of yellow bar).

Table 3-4 summarizes cost and emissions differences across the spatial resolution scenarios.

Table 3-4
Implications of model specifications of spatial granularity in US-REGEN. All values are relative to the reference model features under the reference scenario.

Metric	Units	Scenario	Complex (48 States)	Simple (15 Regions)	Difference
Incremental Electric Sector Costs (NPV 2016–2050)	Billion $	Reference	6.1	0.0	-6.1
		National RPS	94.8	61.2	-33.6
		High Gas Prices	332.5	305.1	-27.4
Cumulative CO_2 Reductions from Reference	Billion Metric Tons	Reference	2.7	0.0	-2.7
		National RPS	-10.4	10.1	20.5
		High Gas Prices	6.1	0.0	-6.1

Discussion

Compared to finer-resolution, state-level modeling, geographical aggregation via regional modeling can:

- Overstate recommended variable renewable investments and understate the need for dispatchable generation
- Understate total electric sector costs, which are augmented by policy and market constraints

Spatial aggregation impacts capacity planning decisions for some technologies and regions more than others and affects model outputs most when these simplifications are jointly varied with alternate representations of trade and with market contexts that encourage higher variable renewable deployment.

Welfare improvements can arise from leveraging subnational comparative advantages in resources and technological costs like higher-quality renewable resource sites, especially when transaction costs are relatively small. However, restricting trade (e.g., of electricity or RECs) or modeling with an unsuitable level of spatial resolution can erode insights about the value of flexibility in policy design and of regional and sectoral technological specialization.

Summary of Insights

Given how power markets and associated markets for environmental compliance instruments are linked across broad geographical areas, considering spatial interactions between neighboring power systems and their policies is critical for understanding future system costs, planning needs, and renewable energy markets. Models that do not account for spatial dependence across neighboring geographical areas could omit essential information in assessing capacity planning decisions or the effectiveness of proposed policies, neglect potentially significant opportunities to lower costs and/or emissions.

Market fragmentation for electricity, RECs, and other goods increases costs nationally, though regional effects vary based on net trade positions in the absence of these constraints and other factors.

Ultimately, the appropriate level of geographical detail depends on the questions being asked for a given application by modelers and model consumers. Application- and policy-specific tradeoffs must be navigated to appropriately balance the degree of detail with computational tractability considerations. For instance, increased geographical detail can provide insight into regional distributional impacts of scenarios, which can vary significantly across scenarios even when national mix is similar. Some degree of trade and regional disaggregation is necessary in a modeling framework to evaluate the geographical incidence of policy, both in terms of benefits and costs. The degree of spatial disaggregation in a model should ideally be customizable to suit needs of specific analyses.

These results suggest that spatial resolution interacts strongly with trade assumptions, especially regarding the role of transmission as a resource. The spatial aggregation experiments in Section 3.2 suggest that adding detail and consequently more restrictions on trade flows with neighboring states can make renewable integration problems more challenging. Since US-REGEN currently omits intra-regional transmission, it be can be inferred that adding such detail (ceteris paribus) would increase these balancing challenges. Current results likely overstate the economic competitiveness of wind and solar in domains where deployment is driven primarily by markets alone, though the magnitude of this effect is left for future work. In scenarios and locations where variable renewable deployment is driven primarily by policy incentives, the omission of intra-regional transmission suggests that current results understate cycling challenges for in-region thermal generators (likely lowering their revenues) and understate economic competitiveness of balancing options (e.g., transmission, storage).

References

Bistline, J.E., Niemeyer, V., Young, D. (2017). Understanding Clean Power Plan Choices in Kansas: Options and Uncertainties, EPRI Technical Report #3002009492 (EPRI, Palo Alto, CA).

Bowen, E., Lacombe, D.J. (2017). "Spatial Dependence in State Renewable Policy: Effects of Renewable Portfolio Standards on Renewable Generation within NERC Regions," Energy Journal **38(3):177–193.**

Electric Power Research Institute (2017). US-REGEN Model Documentation, EPRI Technical Update #3002010956 (EPRI, Palo Alto, CA).

Heeter, J., Beiter, P., Flores-Espino, F., Hurlbut, D., Liu, C. (2015). Quantifying the Level of Cross-State Renewable Energy Transactions, NREL/PR-6A20-63458 (NREL, Golden, CO).

Mai, T., Drury E, Eurek, K., Bodington, N., Lopez, A., Perry, A. (2013). Resource Planning Model: An Integrated Resource Planning and Dispatch Tool for Regional Electric Systems, NREL/TP-6A20- 56723 (NREL, Golden, CO).

Shawhan, D., Taber, J., Shi, D., Zimmerman, R., Yan, J., Marquet, C., Qi, Y., Mao, B., Tylavsky, D., Schuler, R., W. Schulze (2014). "Does a Detailed Model of the Electricity Grid Matter? Estimating the Impacts of the Regional Greenhouse Gas Initiative," Resource and Energy Economics **36(1): 191–207.**

4

REPRESENTATION OF END USE

Along with load growth, which is generally easy to represent in long-run models, the most important aspect of representing electricity end use is the responsiveness of load to electricity prices. Basic economic theory provides a firm basis for expecting that increasing the electricity prices that electricity end users face will cause them to consume less, and that lowering the prices will cause them to consume more; furthermore, that end users' response to a given price change will increase over time as the need for equipment replacement gives them more opportunities to respond in the long run than in the short run. The results of empirical analyses are consistent with these expectations (Jorgensen, et al., 2012).

Not all end users face electricity prices that change frequently with rising or falling costs. Some end users face electricity prices that are set in a regulatory process, and some of them have experienced several consecutive years without a price change. However, in the long run, the prices faced by almost all U.S. and Canadian customers change due to changes in the costs of supplying electricity to those customers.

Not all models represent the responsiveness of load to changes in prices. For example, the default version of IPM, the main model used by the U.S. Environmental Protection Agency for benefit-cost analysis of policies that apply to power plant emissions, does not assume price-responsive load.

The E4ST simulations for this report use an elasticity of -0.4, a value that the meta-analysis in Jorgensen, et al. (2012) calculates as the approximate average long-run own-price elasticity of electricity demand estimated in empirical studies. The exception is the E4ST simulations that make the simplifying assumption that load is fixed.

E4ST End Use Modeling Exercises

Scenario Overview

Examining effects of the price responsiveness of load requires one scenario with it and one otherwise identical scenario without it. Examining the effects of the price responsiveness of load on the effects of a renewable portfolio standard requires four scenarios, which are identical to each other except that they have the four combinations of RPS or no RPS, and price-responsive load or fixed load. Table 4-1 shows these four scenarios.

Table 4-1
List of cases used to examine effects of price-response of load on effects of RPS, in E4ST simulations.

Version of E4ST	RPS Specification
Testing Effects of Representing Price-Responsiveness of Load on Effects of RPS	
Simple (Fixed Load)	**No RPS**
Complex (Price-Responsive Load)	**No RPS**
Simple (Fixed Load)	**National RPS** (40% by 2040)
Complex (Price-Responsive Load)	**National RPS** (40% by 2040)

Results

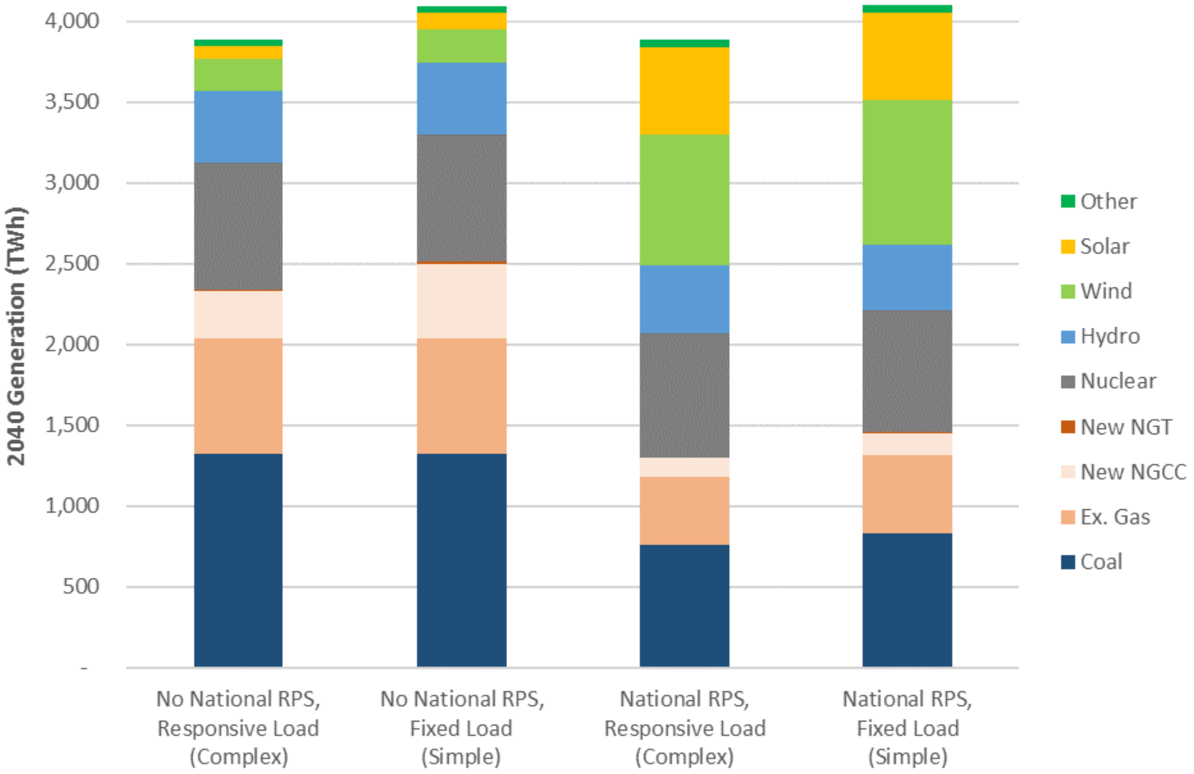


Figure 4-1
Generation (TWh) in 2040 by technology and scenario, in the E4ST Simulation of the Eastern Interconnection. "Responsive Load" scenarios model the long-run responsiveness of load to prices, and "Fixed Load" scenarios ignore it.

This section discusses the effects of assuming fixed load on the outcomes without a national RPS, on the outcomes with a national RPS, and on RPS-induced impacts.

All of the simulations assume that the price of natural gas will be higher in 2040 than it was in the base year of 2016, so real electricity prices are higher in 2040 than they were in 2016. As a result, the scenarios that ignore the price-responsiveness of load have higher load in 2040 than do the scenarios with price-responsive load. This is readily apparent in Figure 4-1. This simple difference causes all of the other differences described in the rest of this section, except where otherwise noted.

Both with and without a national RPS, the assumption that load is fixed (hence higher) instead of being price-responsive results in higher projections of the amounts of capacity of the three most cost-competitive buildable generation types: natural gas combined cycle, wind, and solar.

In the figures, "Ex. Gas" refers to gas-fueled generators built before 2017, and "Coal" refers to coal-fueled generators built before 2017, since the simulations assume that no coal-fueled capacity can be built after 2016. Together, these are referred to as "pre-existing coal and gas."

In the scenarios without a national RPS, the assumed regulatory and fuel price circumstances are such that almost all of the pre-existing coal and gas capacity that survives past 2020 survives through 2040, even with price-responsive load. In the scenario with fixed load, competition from the greater amounts of new NGCC, wind, and solar generators keeps the 2040 capacity factors from increasing substantially, such that the projected amount of generation from pre-existing coal and gas generators increases very little as a result of the fixed demand assumption.

However, with a national RPS, assuming fixed load does increase the projected survival of, and 2040 generation from, pre-existing coal and gas generators. It also increases the projected amounts of NGCC capacity and generation.

These effects on the outcomes without and with a national RPS in turn cause some effects on the projected consequences of a national RPS: Ignoring the price-responsiveness of load causes the model to understate the RPS-induced reductions in generation from pre-existing coal and gas generators by 70 and 60 TWh, respectively, in 2040. Together, these two understatement amounts equal 130 TWh, which is approximately one thirtieth of total system-wide projected 2040 generation. It equals the annual output of thirty 1-GW power plants with 50% capacity factors. Ignoring the price-responsiveness of load causes an offsetting reduction in NGCC generation (built after 2016) by 138 TWh. As a result, ignoring the price-responsiveness of load causes an understatement of the emission reductions that would result from the renewable portfolio standard, since coal and pre-existing gas generators tend to have higher emission rates than do new NGCC generators. Table 4-2 shows the magnitudes of the effects: ignoring the price-responsiveness of load causes an understatement of the RPS-induced reductions in SO_2 damage by 15%, in NO_X damage by 14%, and in CO_2 damage by 3%.

Ignoring the price-responsiveness of load also results in overstating the RPS-induced increase in 2040 wind generation by 81 TWh (13%) and understating the RPS-induced increase in 2040 solar generation by 32 TWh (7%). 81 TWh is the annual generation of approximately 7,700 modern three-MW utility-scale wind turbines, each one standing approximately 400 feet tall and able to meet the electricity needs of approximately 1,000 homes on average.

Table 4-2
Monetized net benefits of RPS with and without considering the price responsiveness of load.

	Net Present Value of Effects of RPS from 2018 through 2040		
Outcome	With Price Responsiveness of Load	Ignoring Price Responsiveness of Load	% Difference
	In billions of 2013 US $		
Total Production Cost	193	185	-4%
Constituents of Net Benefits (Social Surplus)			
Consumer Welfare (Net Consumer Surplus)	455		
CO2 Benefit (Damage Reduction from less CO2)	297	289	-3%
SO2 Benefit (from lives saved from less airborne sulfates)	210	177	-15%
NOX Benefit (from lives saved from less airborne nitrates)	73	62	-14%
Generators' Profits	-608	-779	28%
Government Net Revenue	-28	-29	6%
Congestion Revenue (Merchandising Surplus)	16	15	-8%
Total Social Surplus	414		

Discounted net present values are from the perspective of the middle of 2016, and are calculated using a real discount rate of 3%.

The effects of ignoring the price-responsiveness of load on the projected monetized effects of the RPS are discussed next. In Table 4-2, the first column of numbers is the same as in Table 2-4. The second column of numbers shows the effects projected if price responsiveness of load is ignored.

As predicted above, ignoring the price-responsiveness of load also results in underestimating the health and environmental benefits of the RPS, by $51 billion, or approximately 8%.

The effect of the RPS on consumer surplus cannot be calculated in the scenario that ignores the price responsiveness of load, because that simulation does not use a demand curve that enables the calculation of consumer surplus. Since consumer surplus is part of total surplus, total surplus too cannot be calculated in the scenario that ignores the price responsiveness of load.

As Table 4-2 shows, the largest effect of ignoring the price-responsiveness of load is that it results in overstating the negative effect of the RPS on producer profits by $170 billion, or 28%. This is not because it reduces the average electricity price in the presence of the RPS, but rather because it increases the average electricity price in the absence of the RPS. This illustrates that a simplification can affect the estimated effect of a policy not just by affecting the results of the policy case, but also by affecting the results of the no-policy case.

Summary of Insights

In this case study, gnoring the price-responsiveness of load affects the results mainly by increasing the projected load, which in turn increases the use of generation sources that are marginal in the long run. With the RPS, an appreciable portion of the potential generation from pre-existing coal and gas-fueled generators is marginal in the long run. Without the RPS, much less of it is, because most pre-existing coal- and gas-fueled capacity survives even if price responsiveness slows the load growth rate. As a result, the simulations without price-responsive load understate the retirements of old coal- and gas-fueled generators that would result from the RPS, and consequently understate the emission reductions that would result from the RPS. This is an example of a simplification interacting with a policy effect, to overstate or understate that effect.

Reference

Jorgensen, J., Joutz, F., Dahl, C. (2012). "A Meta-Analysis of U.S. Residential, Industrial, and Commercial Electricity Demand," 31st USAEE/IAEE North American Conference.

5

REPRESENTATION OF UNCERTAINTY

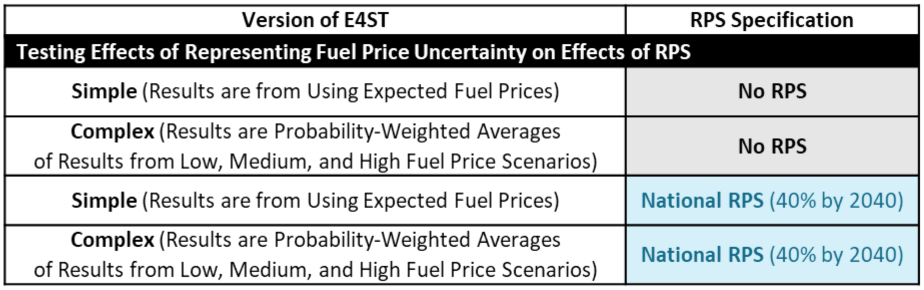
In this chapter, the effects of considering three fuel prices paths (the complex modeling option) are compared with the effects of assuming that the probability-weighted average fuel price path will occur (the simple modeling option).

E4ST Uncertainty Modeling Exercises

Scenario Overview

The results generated by E4ST are dependent on the assumed fuel prices. Three sets of fuel prices are used in high, medium, and low fossil fuel price scenarios. The probability-weighted averages of their outcomes are then compared with the outcomes that result from a simulation that uses as inputs the probability-weighted averages of the fuel prices.

Table 5-1
List of cases used to examine effects of uncertainty representation on simulated effects of RPS in E4ST.



Version of E4ST	RPS Specification
Testing Effects of Representing Fuel Price Uncertainty on Effects of RPS	
Simple (Results are from Using Expected Fuel Prices)	**No RPS**
Complex (Results are Probability-Weighted Averages of Results from Low, Medium, and High Fuel Price Scenarios)	**No RPS**
Simple (Results are from Using Expected Fuel Prices)	**National RPS** (40% by 2040)
Complex (Results are Probability-Weighted Averages of Results from Low, Medium, and High Fuel Price Scenarios)	**National RPS** (40% by 2040)

The prices are from the Annual Energy Outlook 2016 (EIA, 2016). The medium-price scenario is the “Reference case without Clean Power Plan.” The high-price scenario is the “Low oil and gas resource and technology” case. The low-price scenario is the “High oil and gas resource and technology” case, except that the prices in it are changed slightly so that the probability-weighted averages of the fuel prices equal the medium fuel prices. The prices from these three cases are shown in Figure 5-1. The prices are converted to 2013 dollars. An important fact about these price paths is that, while both natural gas and coal have high, medium, and low price paths, the differences between the paths are much larger for natural gas than for coal. As a result, it is reasonable to expect the high set of fossil fuel prices to reduce natural gas-fueled generation by more than it reduces coal-fueled generation (which it may not reduce at all in light of the reduced competitiveness of gas-fueled generators). It is also reasonable to expect the low set of fossil fuel prices to increase gas-fueled generation by more than it increases coal-fueled generation (which it may not increase at all in light of the increased competitiveness of gas-fueled generators).

Since the price paths of coal and oil differ from each other much less than do the price paths of natural gas, the text below will refer to changing from one price path to another as changing from one natural gas price path to another, though in fact that involves changing the coal and oil price paths as well.

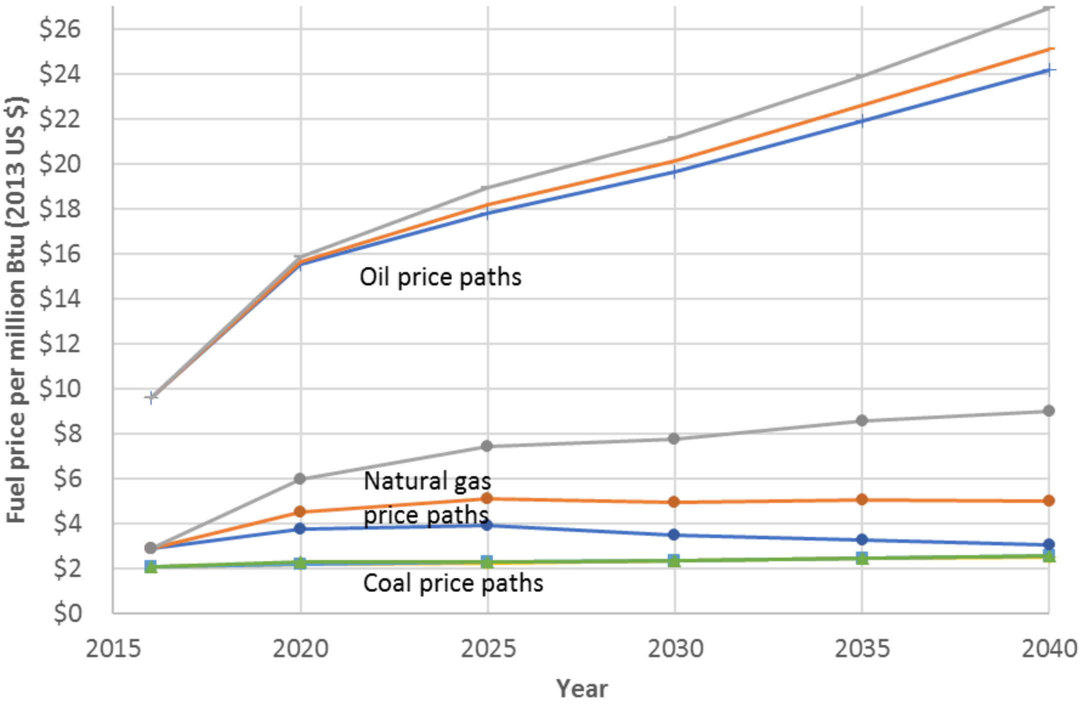


Figure 5-1
Fuel price trajectories.

Results

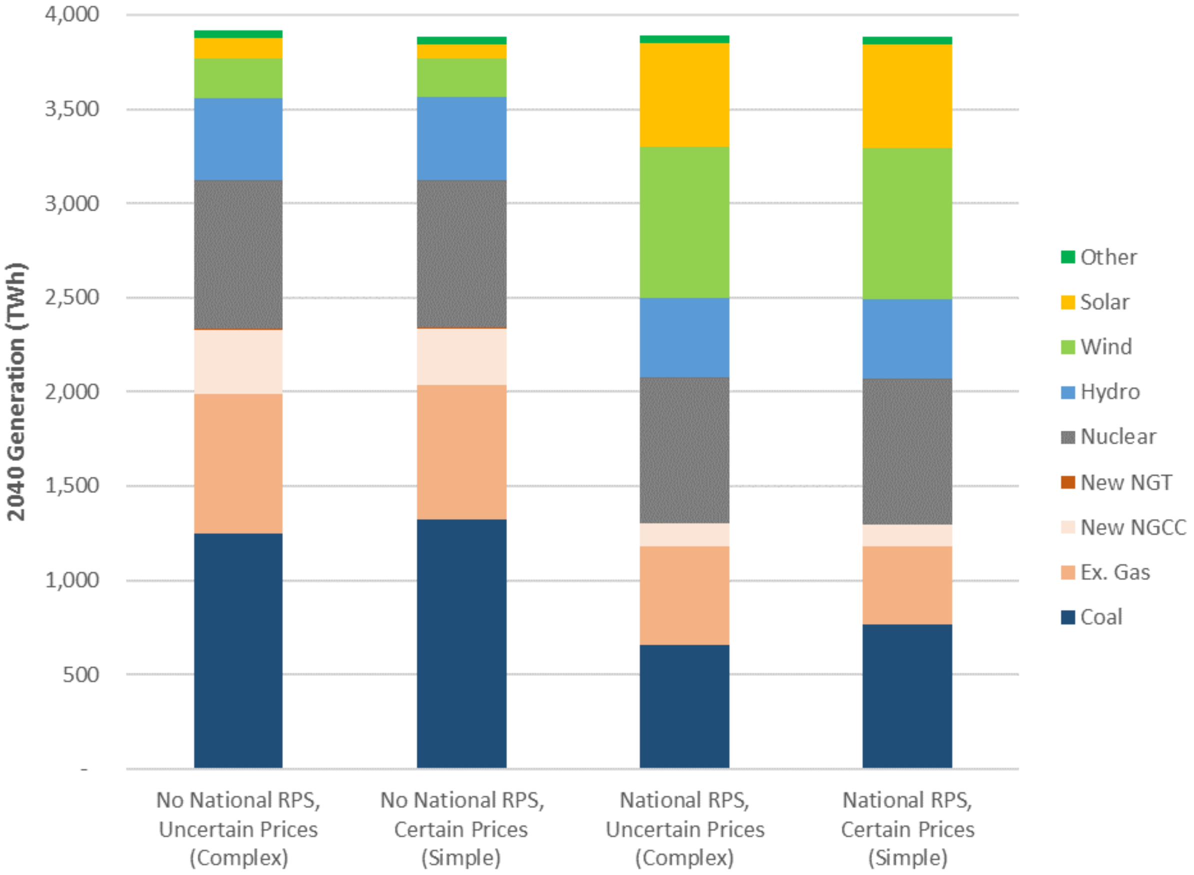


Figure 5-2
Generation (TWh) in 2040 by technology and scenario, in the E4ST Simulation of the Eastern Interconnection. The "Uncertain Prices" columns show the average of the generation shares resulting from the three fuel price scenarios. The "Certain Prices" columns show the generation shares only in the average fuel price scenario.

As in the previous chapters, the national RPS constrains the differences between the results in the two national RPS cases, and hence constrains the effects of the simplification. Many of the differences between the RPS effects in the complex and simple models are small as a result.

In spite of that, the results illustrate that changing a parameter can have highly non-linear effects. Changing the price of natural gas has two important non-linear effects. The first is visible in Figure 5-2. In that figure, the largest effect of ignoring the uncertainty about fuel prices is to overstate coal-fueled generation and to understate gas-fueled generation by approximately equal amounts. This occurs because of a major non-linearity: In these simulations, changing from the medium natural gas price path to the low one has much larger impacts on the coal and natural gas generation shares than does changing from the high natural gas price path to the medium one. The reason is that changing from the medium one to the low one causes many buildable and existing natural gas-fired generators to become less expensive than many coal-fired generators in their regions, while changing from the high path to the medium path does that for significantly fewer generators, per dollar of natural gas fuel price change.

Table 5-2
Monetized net benefits of RPS with and without considering uncertainty about fossil fuel prices.

	Net Present Value of Effects of RPS from 2018 through 2040		
Outcome	**Considering Fuel Price Uncertainty (Complex)**	**Ignoring Fuel Price Uncertainty (Simple)**	**% Difference**
	In billions of 2013 US $		
Total Production Cost	**194**	**193**	**0%**
Constituents of Net Benefits (Social Surplus)			
Consumer Welfare (Net Consumer Surplus)	**418**	**455**	**9%**
CO2 Benefit (Damage Reduction from less CO2)	**306**	**297**	**-3%**
SO2 Benefit (from lives saved from less airborne sulfates)	**207**	**210**	**2%**
NOX Benefit (from lives saved from less airborne nitrates)	**74**	**73**	**-2%**
Generators' Profits	**-566**	**-608**	**8%**
Government Net Revenue	**-31**	**-28**	**-10%**
Congestion Revenue (Merchandising Surplus)	**11**	**16**	**44%**
Total Social Surplus	**419**	**414**	**-1%**

Discounted net present values are from the perspective of the middle of 2016, and are calculated using a real discount rate of 3%.

Considering just one fuel price scenario instead of averaging the results from three fuel price scenarios reduces the expected downward effect of the RPS on the price of electricity. As a result, if price uncertainty is ignored, the projected consumer welfare benefit of the RPS is larger by $37 billion (9%) and the RPS' projected negative effect on producer profits is smaller by $43 billion (8%).

This results from the other major non-linear effect of changing the natural gas prices: Changing from the medium natural gas price path to the low one causes the RPS to reduce the price of electricity considerably less than does changing from the high to the medium natural gas price path. This is because natural gas is on the margin, and sets the price of electricity, less of the time when the natural gas price is low.

Summary of Insights

The first insight from this section applies when considering whether to simulate multiple levels of some important parameter, such as the price of natural gas, the cost to build solar generators, or the own-price elasticity of demand. One factor to consider is the non-linearity of the effects. In this chapter, changing the price of the marginal non-renewable fuel type, natural gas, had a non-linear effect on the RPS' impact on generation shares and the electricity price.

If more than two values are used, then the reader of the results can discern non-linearities that cause the expected value of a key result to differ from the result associated with the expected value of a parameter.

Reference

U.S. Energy Information Administration (2016). *Annual Energy Outlook 2016 with Projections to 2040* (EIA, Washington, DC).

6

CROSS-CUTTING CONCLUSIONS

This chapter is not intended to be a complete summary of the conclusions in the preceding chapters, as individual chapters have concluding summary sections. Although there is some overlap, this chapter articulates specifically cross-cutting solutions.

Analysts must balance levels of model detail with computational feasibility considerations. However, navigating these tradeoffs for model construction and interpretation is context-dependent, and modelers can learn from the best practices and experiences of others for how to better navigate them. The experiments in this report test and examine tradeoffs between appropriate levels of temporal, spatial, and technical complexity and suggest approaches for more consideration of model complexity.

On one hand, these analyses illustrate how simplifications of system features can lead to unrealistic evaluations of the effects of changes in technologies, polies, and markets. On the other hand, specific applications merit different tradeoffs and considerations in selecting an appropriate analysis framework, which depends on the application, modeler skill, computational resources, and data availability. There is no single “right way” to model anything, and these experiments do not unequivocally suggest appropriate degrees of model detail across general areas of analysis. This report offers insights to modelers assessing these tradeoffs and to consumers of model results as they evaluate outputs. The experiments in this report underscore how the effects of particular model simplifications can vary substantially based on regulatory and market conditions as well as other model simplifications.

Overall, these experiments illustrate how model representations of temporal resolution, spatial resolution, end-use detail, and uncertainty can materially influence long-run planning and investment decisions and policy analysis. However, which are the most critical features to include depends on the specific context, questions, and scenarios. For instance, Chapter 2 showed how temporal resolution and particular short-run operational details, costs, and constraints can impact the competitiveness of wind and solar. Therefore, if a study focuses on variable renewable energy (or its conclusions could be impacted by renewable penetration), then adequate temporal resolution should be prioritized in model selection or preparation.

Model Design and Selection

Potential interactions suggest that model features should be evaluated jointly. For instance, experiments in Chapter 3 indicated that model representations of trade and spatial resolution interact with each other, which can lead to superadditive or subadditive impacts. The experiments also underscore how alternative model features should be tested over a wide range of market, policy, and technology scenarios. For instance, the omission of temporal variability for time-series data matters more under a high-renewables future than one with lower wind and solar deployment (Chapter 3). Differences between simple and complex models can be amplified (or reduced) by regulatory and market conditions including renewable energy mandates and higher gas prices. Future work should conduct cross sensitivities to provide greater clarity on how simplified features impact each other and how impactful complexities can be in different contexts.

Another takeaway is that model developers should carefully consider possible unintended consequences of ad-hoc model simplifications and constraints. All modeling environments require simplifications of analysis features, which can be implemented in various ways such as cost adders or constraints to serve as reduced-form proxies of unmodeled (or partially modeled) features. Although the degree of appropriate simplification is content dependent, it is important to be aware of potential unintended consequences when formulating simplifications and when interpreting model results. Best practices for model development and application involve:

- Disclosing potential limitations resulting from model simplifications, especially ones that are likely to impact insights
- Periodically reassessing whether results are impacted as other model changes are made (e.g., changing the spatial resolution) and as new analysis areas are explored (e.g., assessing the impacts of dramatically lower solar and storage costs)
- Whenever possible, testing the robustness of conclusions with more detailed models
- Evaluating when to add complexity, use or build another model, omit technologies or policies from an analysis with proper qualification, or use non-model-based approaches
- Simulation of sensitivity cases that represent the range of probable values of potentially influential parameters, even though judging that range is a subjective matter

These practices are especially important over time as models are stretched into new analysis environments and further from their domains of calibration. For instance, less complex models of intra-annual temporal variability sufficed in former planning contexts (e.g., the “seasonal average” approach discussed in Chapter 2), but such simplifications become more problematic in worlds where higher deployment of variable renewable energy is expected.

Technology-Specific Modeling Insights

Given the rapid cost reductions and deployment of wind and solar in the power sector, it is important to represent unique features of these resources, which can require more temporal and spatial detail. These experiments in this report indicate that challenges associated with incorporating higher renewable shares into power systems should be incorporated into models to improve their capabilities, functionality, and relevance. Omissions in many widely used models can prevent analysis of technical and economic implications of wind and solar deployment and the evaluation of related policies. This finding is consistent with what Santen, et al. (2017) – the literature review that is another part of this project – uncovered about enhancing the spatial resolution and trade representation in models; namely, that these capabilities can result in meaningful differences in resulting capacity planning decisions.

For the features studied in this analysis, moving from simple to more complex models altered the economic level of variable renewable energy deployment. For example, replacing hour-specific, variable wind and solar availabilities with annual averages increased the value of wind and decreased the value of solar (Chapter 2.2). For two of the model capabilities (temporal resolution with “seasonal averages” and spatial resolution), the simplifications increased the value of wind and solar in the model and decreased the value of dispatchable generation. The opposite is true of trade, where not modeling the ability of neighboring markets to handle surpluses and shortfalls in renewables output reduced their market value.

If decision-makers anticipate that a high wind and/or solar state-of-the-world will obtain (regardless of the drivers), then this analysis suggests that modeling should account for:

- Hourly correlations between load, wind output, and solar output within and across regions (Chapter 2)
- Endogenous electricity trade across regional boundaries (Chapter 3)
- Flexibility provisions in policy design like renewable energy certificate markets for complying with renewable energy mandates (Chapter 3)
- The existing price responsiveness of load (Chapter 4)
- Relative costs of different generation resources (Chapter 5)

The analysis underscores how natural gas prices materially impact planning decisions, which increases the importance of related model considerations. Key factors include assumed fuel price trajectories over time and incorporation of uncertainty, location-specific delivered price differences and assumed changes over time (which intersects with infrastructure assumptions), and how temporal resolution impacts the economics of flexible resources like gas turbines, combined cycle units, and other technologies.

Policy Assessment

A key takeaway suggested across these analysis areas is that model selection for impact assessments should prioritize capabilities important for evaluating design elements of the proposed policy or regulation in question. Well-suited models should be capable of representing aspects of the system affected by a policy and of evaluating critical compromises between design elements. For instance, EPRI analysis of the Clean Power Plan illustrated the importance of endogenous trading of compliance instruments (allowances for states selecting mass-based pathways and emission rate credits for rate-based pathways) for state-level planning decisions (Bistline, et al., 2017).

Another cross-cutting conclusion is that the increased prevalence of layered regulations, policies, and incentives at state, regional, and federal levels will increase the importance of considering not just the marginal cost of technologies in evaluating investments but also their marginal system value. Marginal system value is affected by different functional attributes of technologies and products on specific grids (e.g., energy, capacity, and ancillary services); revenues and costs associated with regulatory compliance and out-of-market generation subsidies, incentives, and commodities (e.g., Renewable Energy Certificates, Zero Emissions Credits, Clean Power Plan compliance instruments); and revenues from participation in other markets (e.g., hydrogen sales). One challenge is that, although marginal cost evaluation requires improved scenario selection (and design of models capable of quick sensitivity analysis), marginal system value requires more detailed models capable of capturing these factors endogenously, which may require more work for modelers to construct and test additional model features and may challenge tractability. The comparisons in this report demonstrate the importance of accurate methods for estimating system costs and values and their dependence on scenario-specific assumptions and regional heterogeneity.

Given this planning context, a related takeaway is the importance of rigorously modeling provisions of complementary regulations. Evidence from ex-post policy evaluations and modeling exercises of prospective policies (in this analysis and elsewhere) show how such provisions can have less-than-obvious economic and environmental impacts (Shawhan, et al., 2014). When on-the-books regulations may substantially affect the research questions, it can be important to use modeling frameworks that capture detailed provisions and can quantitatively assess their potential significance. When model features and/or scope limit the representation of policy details, modelers should properly qualify their findings. A corollary is that, when performing prospective analysis for new or revised policies, analysis tools should be used that are capable of evaluating potential tradeoffs at the margin.

References

Bistline, J.E., Niemeyer, V., Young, D. (2017). Understanding Clean Power Plan Choices in Kansas: Options and Uncertainties, EPRI Technical Report #3002009492 (EPRI, Palo Alto, CA).

Santen, N., Bistline, J.E., Blanford, G., de la Chesnaye, F. (2017). Systems Analysis in Electric Power Sector Modeling: A Review of the Recent Literature and Capabilities of Selected Capacity Planning Tools, EPRI Technical Report #3002011102 (EPRI, Palo Alto, CA).

Shawhan, D., Taber, J., Shi, D., Zimmerman, R., Yan, J., Marquet, C., Qi, Y., Mao, B., Schuler, R., Schulze, W., Tylavsky, D. (2014). “Does a Detailed Model of the Electricity Grid Matter? Estimating the Impacts of the Regional Greenhouse Gas Initiative,” Resource and Energy Economics **36(1):191–207.**

Bistline, J.E. (2017). “Economic and Technical Challenges of Flexible Operations under Large-Scale Variable Renewable Deployment,” Energy Economics **64:363–372.**

A

DETAILED US-REGEN MODEL DESCRIPTION

This appendix provides additional detail about the US-REGEN model and scenario assumptions.

Model Description

The electric sector component of EPRI's U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model represents detailed capacity planning and dispatch decisions simultaneously with customizable state-based regions. Each customizable-length (typically five-year) time step includes capacity investment, retrofit, and retirement decisions as well as dispatch for installed capacity over representative intra-annual hours. The intertemporal optimization structure of US-REGEN determines investment and operational choices through 2050 while representing regional resource endowments, costs, interregional transmission, demand, and regulations. This appendix summarizes the primary features and assumptions of the model, especially those relating to the experiments in this report. Additional detail about the US-REGEN is provided in EPRI (2017).

US-REGEN typically aggregates U.S. states in the 15 regions shown in Figure A-1 (with states like California, Texas, New York, and Florida treated separately) but can be configured to consider any combinations of the continuous 48 states.

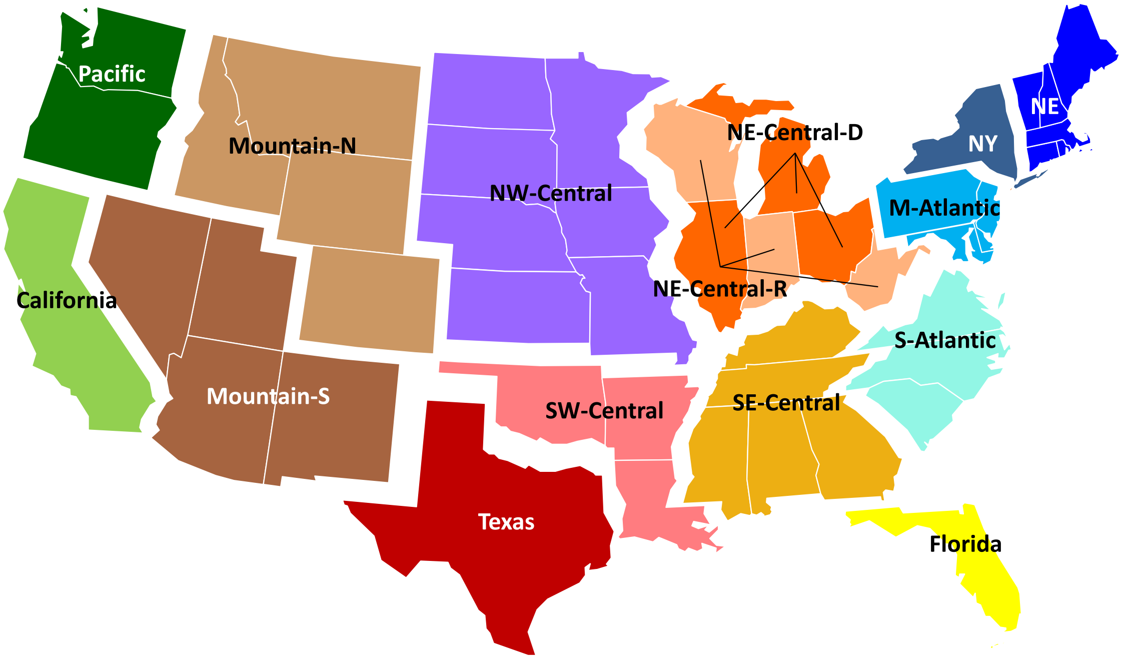


Figure A-1
Regional structure of the US-REGEN model. Lower 48 states are grouped into the 15 regions above unless otherwise specified.

US-REGEN uses a bottom-up representation of capacity grouped into technology blocks within a region based on heat rates and dispatches these blocks across a range of intra-annual time segments. Joint variation in load, wind, and solar across regions is captured through the selection of so-called “representative hours” using an approach described in Blanford, et al. (2016). This novel feature more accurately captures the spatial and temporal variability of power systems, which is critical for evaluating asset investments and operations especially under higher renewable deployment scenarios.

Many long-term capacity planning models have trade-based grid representations where segment-level cross-border transactions are bounded by installed transmission capacity (Santen, et al., 2017). US-REGEN adopts this approach to transmission capacity between regions (zonal) and allow for endogenous transmission investments. Like typical “pipe-and-bubble” representations of transmission, US-REGEN does not ensure that Kirchhoff’s voltage law is not violated, differentiate between AC and DC lines, or represent transmission constraints within regions explicitly. Existing transmission capacities come from aggregating data for inter-nodal capacity from the National Renewable Energy Laboratory’s Regional Energy Deployment System (ReEDS) model up to inter-state (or inter-regional) capacity.

Although the model includes endogenous investments in inter-regional transmission and segment-level electricity trade across regions, US-REGEN does not represent intra-regional transmission constraints. As described in Santen, et al. (2016), an important spatial modeling tension is between detail of “local” transmission constraints (common in utility-scale modeling) and cross-regional electricity and environmental commodity trade (common in national-level modeling). Omitting the former understates flexibility challenges, especially in scenarios with variable renewable build-outs constrained by transmission bottlenecks during high output periods. Omitting the latter understates role of trade and opportunities and challenges brought about by extending the system boundary (e.g., by linking neighboring grids).

Important caveats to bear in mind when interpreting US-REGEN results include:

- **Economic and electricity demand growth:** US-REGEN’s initial equilibrium is based on 2015 calibration and is combined with exogenously specified demand growth projections from EIA’s Annual Energy Outlook (AEO) 2017 reference scenario without the Clean Power Plan. Electricity demand grows at about 0.8 per year on average, while real GDP increases at roughly 2.2%. As with all model assumptions, these assumptions can be modified to evaluate the impact of alternatives. The macroeconomic and end-use submodules of US-REGEN can also be linked to the electric sector model for endogenous feedbacks.
- **Fuel prices:** Reference coal, natural gas, and petroleum prices over time are based on AEO 2017 trajectories, as discussed in the next section.
- **Discount rate:** US-REGEN typically assumes a 5% discount rate in real terms.
- **Electricity market formulation:** Regions in US-REGEN are characterized as cost-of-service or competitive, which impacts how retail electricity prices are formulated. Details are discussed in EPRI (2017).
- **No new storage investment:** Although the static version of US-REGEN (with 8,760 hours and capacity investment and dispatch for a single year) includes a variety of existing and new

storage technologies, the lack of chronology in the dynamic electric sector model precludes accurate modeling of new storage investment and operations.

- **No unit commitment costs and constraints:** The US-REGEN electric sector model incorporates a simple model of dispatch that excludes several operational costs, constraints, and unit-level detail due to the high computational cost of including such features in a multidecadal, intertemporal optimization model. To better understand the short-run costs and technical challenges of operating different capacity mixes from the dynamic model, a standalone unit commitment version of US-REGEN was developed (EPRI, 2015).

Recent applications of US-REGEN investigate a range of power sector and energy questions (e.g., Bistline, 2017; Bistline, et al., 2017; James, et al., 2015; Blanford, et al., 2014).

Scenario Assumptions

The "reference" configuration of the US-REGEN model assumes:

- Endogenous inter-regional electricity trade subject to transmission constraints
- 15 U.S. regions (regional definitions are shown in Figure A-1)
- Natural gas prices from the Energy Information Administration's 2017 *Annual Energy Outlook* reference case without the Clean Power Plan
- Existing state-level RPSs only, including on-the-books trading and compliance provisions

All runs assume no upper bounds on national investments by specific technologies between time periods. To facilitate *ceteris paribus* comparisons, all scenarios exclude energy efficiency investments and demand response.

Technological cost and performance assumptions come from EPRI's Integrated Generation Technology Options report with more frequent updates for technologies like solar and wind. Default capital cost assumptions are shown in Figure A-2.

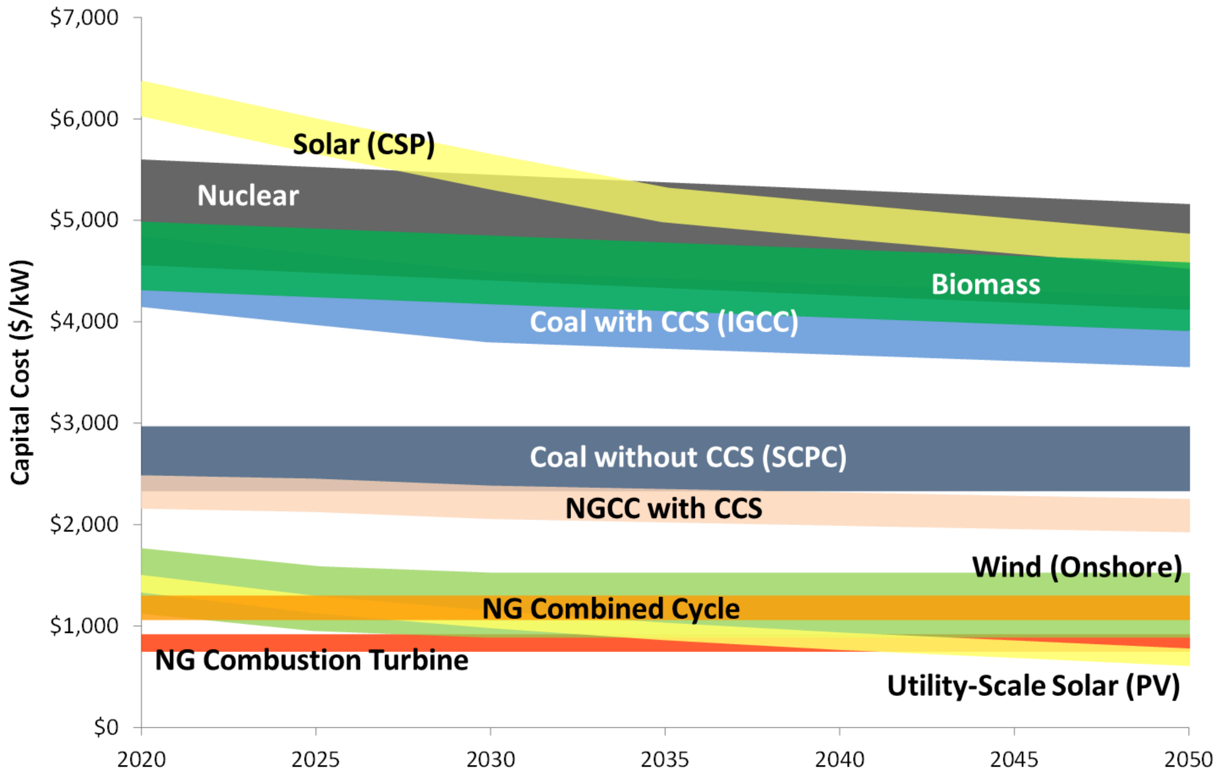
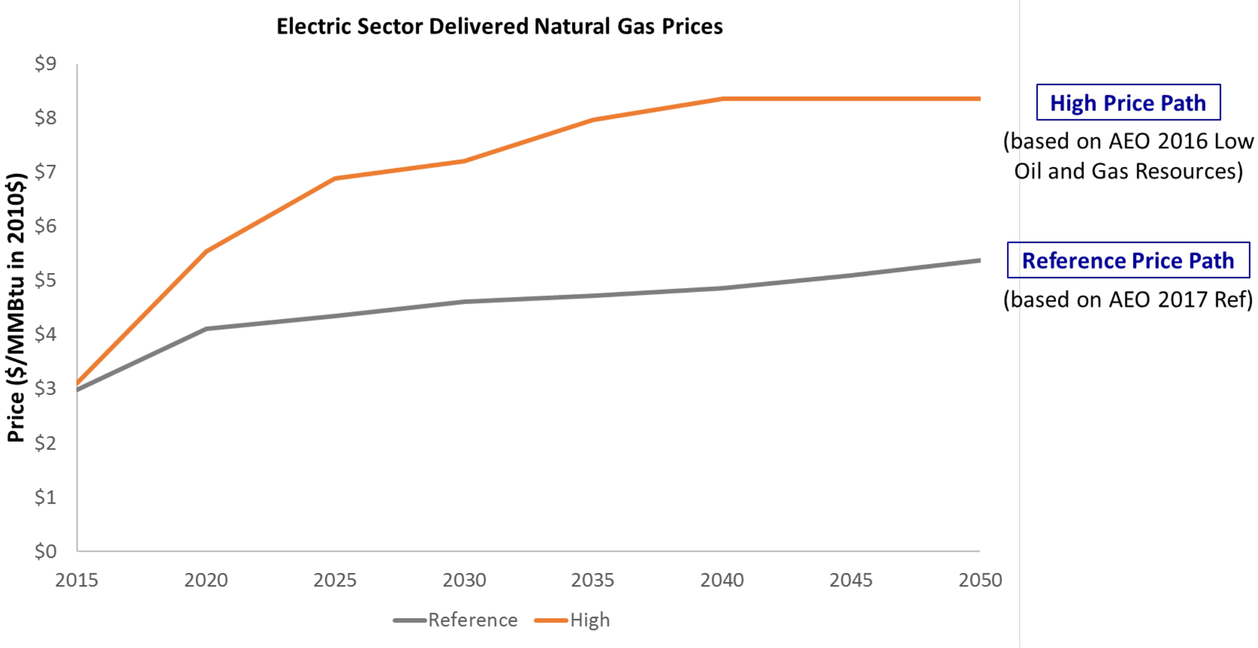


Figure A-2
Assumed capital cost trajectories in US-REGEN by technology. Ranges represent region-specific differences in cost.

Fuel price trajectories come from the AEO 2017 reference scenario without the Clean Power Plan. Fuel prices are not responsive to changes in demand for these runs, though such feedbacks are possible using the integrated version of US-REGEN. Figure A-3 shows the average national electric sector gas prices, including the reference price path (based on the AEO 2017 reference scenario) and the high price path (based on the AEO 2016 Low Oil and Gas Resource scenario). Delivered gas prices in the model include region-specific adders, which are calibrated to observed 2016 values and assumed to decline over time.



High Price Path

(based on AEO 2016 Low Oil and Gas Resources)

Reference Price Path

(based on AEO 2017 Ref)

Figure A-3
Natural gas price trajectories used in sensitivity analysis. Values represent average electric sector delivered prices.

All national RPS sensitivities assume that wind and solar technologies are the only eligible resources and that the federal regulation is layered with existing state-level mandates.[14] For the national RPS scenario, variable renewable energy targets linearly ramp from current levels to 35% by 2035 and then increase linearly in stringency to 50% by 2050, as shown in Figure A-4. The denominator in the national RPS compliance equation is generation, which means that regions could hypothetically comply by lowering in-region generation if permitted in a given scenario.

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[14] The analysis assumes that the national targets do not preempt existing state RPS regimes, which may have more ambitious near-term commitments that they are unlikely to abandon and have separate provisions to promote related state objectives.

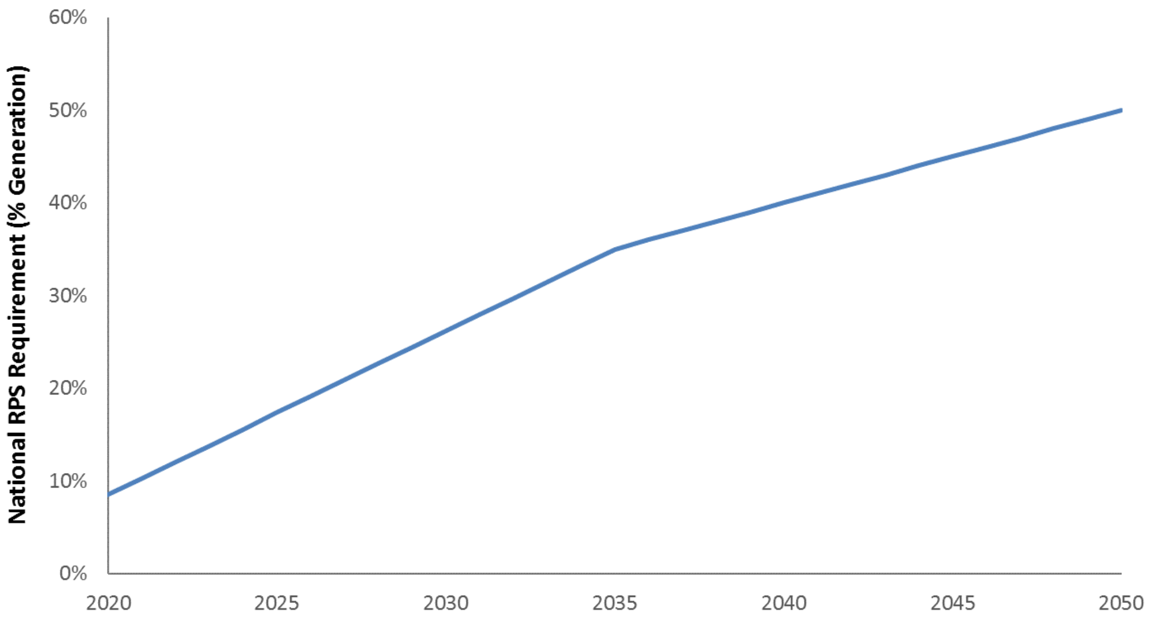

Figure A-4
National RPS scenario targets (i.e., minimum qualifying generation as a fraction of total in-region generation) over time. Wind and solar are assumed to be the only eligible resources for the national RPS.

Transmission between regions can be endogenously added with an assumed cost of $3.85 million per mile for a notional high-voltage line to transfer 6,400 MW of capacity. Note how, due to changes in flows across regions (with associated transmission losses) and different levels of new transmission investments, total national generation may vary across scenarios.

The cost metric most commonly used in this report is the net present value (NPV) of total electric sector costs across the modeling horizon (i.e., between 2016 and 2050). These cost comparisons include the following discounted electric-sector cost categories:

- Capital costs associated with new investments
- Fixed and variable operation and maintenance costs
- Fuel costs
- Cost of new transmission plus maintenance, which are assumed to be split equally across connected regions
- Regulatory costs (e.g., alternative compliance payments for renewable portfolio standards)

These costs are typically expressed as *incremental costs* relative to the reference scenario.

References

Bistline, J.E. (2017). “Economic and Technical Challenges of Flexible Operations under Large-Scale Variable Renewable Deployment,” Energy Economics **64:363–372.**

Bistline, J.E., Niemeyer, V., Young, D. (2017). Understanding Clean Power Plan Choices in Kansas: Options and Uncertainties, EPRI Technical Report #3002009492 (EPRI, Palo Alto, CA).

Blanford, G.J., Merrick, J.H., Bistline, J.E., Young, D. (2016). Simulating Annual Variation in Load, Wind, and Solar by Representative Hour Selection, EPRI Technical Update #3002008653 (EPRI, Palo Alto, CA).

Blanford, G.J., Merrick, J.H., Young, D. (2014). “A Clean Energy Standard Analysis with the US-REGEN Model,” The Energy Journal **35(1):137–164.**

Collins, S., Deane, J.P., Poncelet, K., Panos, E., Pietzcker, R.C., Delarue, E., Gallachóir, B.P. (2017). “Integrating Short Term Variations of the Power System into Integrated Energy System Models: A methodological review,” Renewable and Sustainable Energy Reviews **76:839–856.**

Electric Power Research Institute (2017). US-REGEN Model Documentation, EPRI Technical Update #3002010956 (EPRI, Palo Alto, CA).

Electric Power Research Institute (2015). US-REGEN Unit Commitment Model Documentation, EPRI Technical Update #3002004748 (EPRI, Palo Alto, CA).

James, R., Hesler, S., Bistline, J.E. (2015). Fossil Fleet Transition with Fuel Changes and Large Scale Variable Renewable Integration, EPRI Technical Report #3002006517 (EPRI, Palo Alto, CA).

Santen, N., Bistline, J.E., Blanford, G., de la Chesnaye, F. (2017). Systems Analysis in Electric Power Sector Modeling: A Review of the Recent Literature and Capabilities of Selected Capacity Planning Tools, EPRI Technical Report #3002011102 (EPRI, Palo Alto, CA).

B

DETAILED E4ST MODEL DESCRIPTION

This appendix provides additional detail about the E4ST model and scenario assumptions.

Model Description

This appendix documents the Engineering, Economic, and Environmental Simulation Tool (E4ST), a detailed model of the U.S. electricity system.[15] E4ST is designed to simulate optimal generation, investment, and retirement across the electricity generation sector in response to incentives or regulations, while maintaining reliability of the electricity system. The documentation of methods presented here shows how E4ST is designed as an optimization problem, including the objective function as well as constraints. The model combines characteristics of a conventional analytical model with important physical details of the power grid. The specification of the model is similar to that developed by economists specializing in electricity markets who have long recognized the importance of line constraints (e.g., Kirschen and Strbac, 2004; Hogan, 1992; Joskow and Tirole, 2000). E4ST adds generator entry and retirement to the prior specification.

The model includes nodal demand, generator output, and locational marginal prices. Costs of fuel, operation, and construction are exogenous, as is the demand function at each node. In each time period, the model endogenously determines usage and emissions of each generator, total cost, and change in producer plus consumer surplus relative to the base case. In addition, it endogenously determines the following at each node: price and quantity demanded in each representative hour, and generator entry and retirement (except in year 0). The model takes the following form for each year modeled:

$$\max_{p_{ijk}, I_{ij}, R_{ij}} \left\{ \sum_i \sum_j \left[\begin{array}{c} \left(\sum_k H_k \left(B_{jk} - \left(c_i^F + a_{jk} e_i \right) p_{ijk} \right) \right) \\ - \left(c_i^T \left(p_{ij}^0 + I_{ij} - R_{ij} \right) + c_i^I I_{ij} \right) \end{array} \right] \right\}$$

subject to

$$p_{ij}^0 + I_{ij} - R_{ij} \geq p_{ijk}$$

$$p_{ijk} \geq \alpha_i^{\min} (p_{ij}^0 + I_{ij} - R_{ij})$$

$$K_{ij} > I_{ij}$$

$$\sum_i p_{ijk} - L_{jk} + \sum_{j'} S_{jj'} (\Theta_{jk} - \Theta_{j'k}) \geq 0$$

$$F_{jj'} > \left| S_{jj'} (\Theta_{jk} - \Theta_{j'k}) \right|$$

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[15] The description of E4ST presented in this appendix is based on Shawhan, et al. (2014) and Mao et al. (2016).

where the following notation is used:

i	Generator index
j	Node index
k	Representative hour index
p_{ijk}	Aggregate real power output from generator *i* at node *j* during representative hour *k* (price-responsive demand is modeled as negative generation)
p^0_{ij}	Capacity of generator type *i* at node *j* already existing at the beginning of the year
R_{ij}	Capacity of generator type *i* retired at node *j* during the year
I_{ij}	Capacity of generator type *i* at node *j* newly built during the year
c^F_i	Variable cost per megawatt-hour of generator *i*, including cost of fuel and variable operations and maintenance costs
c^T_i	Annual fixed costs per megawatt, including taxes, insurance, and fixed operating and maintenance costs
c^I_i	Levelized per-year cost per megawatt of new investment in generator type *i* if its total investment cost is amortized over ten years
H_k	Hours per year represented by representative hour *k*
e_i	Carbon dioxide emission rate for generator *i*, tons/megawatt-hour
a_{jk}	Carbon dioxide emission price at node *j* in hour *k*, $/ton
α_i^{min}	Minimum generation fraction of capacity for type *i*
K_{ij}	Maximum megawatts of new generation capacity of fuel type *i* that can be built at node *j*
B_{jk}	Piecewise linear consumer surplus function associated with non-fixed portion of demand.
L_{jk}	Quantity demanded (also called "load") at node *j* in representative hour *k*
$F_{jj'}$	Flow limit on line from node *j* to node *j'*
$-S_{jj'}$	Susceptance of the line from node *j* to node *j'*
Θ_{jk}	Phase angle of node *j* in hour *k* (the difference in phase angles between two nodes drives flow)

The model maximizes annual gross consumer surplus minus the sum of variable operating, fixed operating, and annualized investment costs. The control variables are the output of each generator in each hour, the quantity demanded at each node, the construction of new generators, and the retirement of existing generators. The constraints, in the order shown, require the following:

- Generation cannot exceed the pre-existing capacity plus the amount of new generation capacity minus the amount of newly retired capacity.
- Each generator that is online must produce at least its minimum output, which is zero for all units except coal generators, to allow generators to effectively be turned off during some or all representative hours of the year. Coal units cannot be operated below 15% of their maximum generation during the year unless they retire, in which case their output is constrained to be zero throughout the year.
- Total new entry by a particular generator type can be no greater than the specified limit on feasible construction of that type in the decade.
- Generation minus quantity demanded at each node equals the net flow across all line segments that touch that node. The shadow price on this constraint determines the nodal price of electricity.
- The electricity flow on each line cannot exceed the line's flow limit. This is where the lines' transmission limits come into play.

The resulting optimization problem is large. For the Eastern Interconnection, it has millions of optimization variables and millions of constraints. For the western and Texas grids, it has hundreds of thousands of each. Gurobi solver software has worked well for solving this large optimization problem quickly.

The criterion for retirement implicit in the model's optimization is that each generator's annual revenue, if it remains in service, is less than the sum of its annual variable operating and fixed operating costs. Note that existing generators do not have to cover investment costs in order to continue to exist. The criterion for entry is that the revenues in the first twenty years of the generator's existence must exceed or equal the variable and fixed operating costs in those twenty years plus the unit's total investment cost. This calculation assumes that the revenues and costs in those twenty years will be the same as in the representative year in which the generator first exists. Investment cost includes a 5.44% real annual cost of capital on any portion of first cost not yet recovered.

To reduce the complexity of E4ST's optimization calculations, the model includes a 5,000-node representation of the eastern transmission system that is a simplification or "reduction" of a 62,000-node model of the Eastern Interconnection from Energy Visuals, Inc. (2012). This reduction of the transmission system was achieved based on the approach in Shi, et al. (2012), which developed and used a modified Ward reduction method to combine clusters of the original 62,000 network into aggregated nodes. In Shawhan, et al. (2014), the performance and accuracy of three reduced models with 5000 nodes, 300 nodes and one node respectively are compared. The 5,000 nodes model has been shown to closely replicate the behavior of the original 62,000 nodes model while the results from 300 nodes and one node models are significantly different from those of 5000 nodes. Figure B-1 shows the original 62,000-node network, while Figure B-2 shows the "reduced" 5,000-node network.

Similar to its representation of the Eastern Interconnection, E4ST includes simplified representations of the Western Electricity Coordination Council (WECC) grid and the Texas (ERCOT) grid.

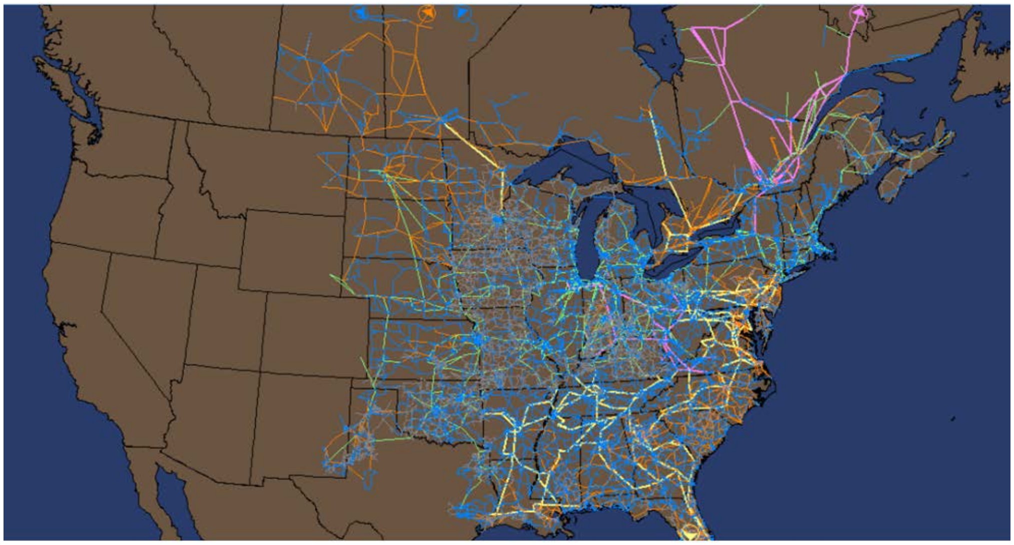

Figure B-1
The original Eastern Interconnection network.

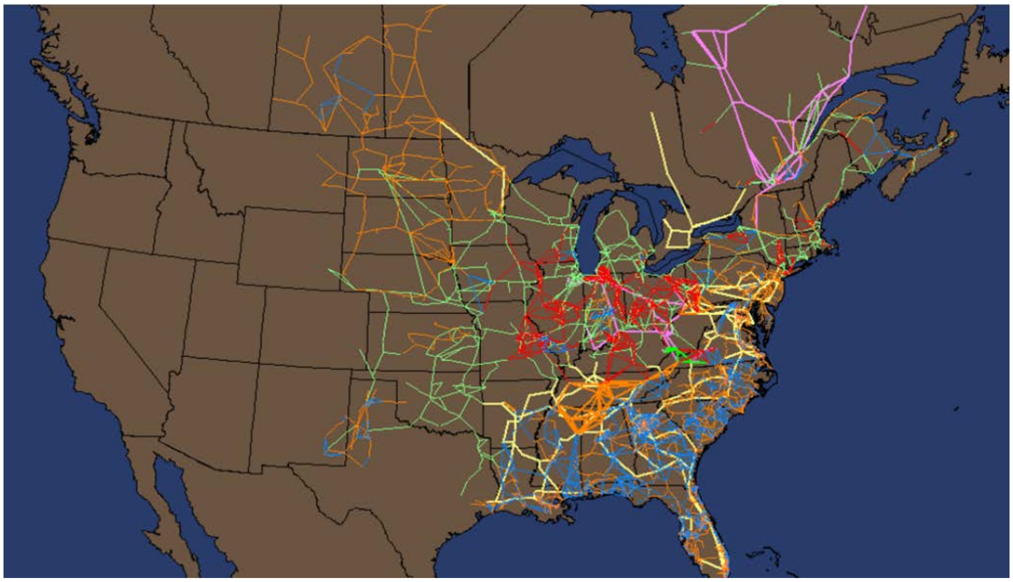

Figure B-2
The reduced Eastern Interconnection network.

Generator Data

The generator data in E4ST includes generator capacities, variable operating and maintenance costs, fixed operating and maintenance costs, tax and insurance, fuel types, emission rates, heat rates, and geographic locations. For newly built generators, the dataset includes annualized investment costs.

The generator dataset in E4ST includes those generators existing at the end of 2015, according to EIA Form 860 data for December 31, 2015.[16] The generator dataset was created by combining several EIA Form 860 datasets with one EPA dataset[17] and the Energy Visuals Transmission Atlas and FirstRate datasets. Mao, et al. (2016) describe the process used to match these datasets. This process involved the combination of similar generators and the placement of generators on the corresponding transmission network model.

The five generator types that are buildable in E4ST are shown in Table B-1. For newly built natural gas and nuclear fueled generators, E4ST uses capital cost, annual fixed cost, and heat rate estimates from EIA (2013). For newly built wind and solar generators, the model uses capital cost and annual fixed cost estimates from the National Renewable Energy Laboratory (2016) *Annual Technology Baseline*. For all other generators, the model applies fixed annual cost per MW from EIA (2013), except that it assumes annual fixed cost of zero for hydro- and refuse-powered generators so that they do not shut down, since they provide another service in addition to power generation. For all types of newly built generators, E4ST uses capital taxation and financing assumptions, and cost reduction assumptions through 2050, from the National Renewable Energy Laboratory (2016). In addition, the model assumes non-income tax and insurance rates calculated from data reported by power plant owners on Federal Energy Regulatory Commission Form 1.

New nuclear generators can be built only at model nodes (aggregated buses) where a nuclear generator or coal generators with a capacity over 800 MW existed at the end of 2011. There are 20 such buses in the western interconnection, 176 in the Eastern Interconnection, and 10 in the Texas grid.

The assumed costs for individual newly built generators, and the assumed annual fixed costs for pre-existing generators of five types, are shown in Table B-1 The capital costs in the table are total cost per megawatt for newly built generators although these costs are typically amortized across a number of years. The variable costs for NGCC and NGCT depend on the natural gas price (P_{ng}).

Table B-1
Costs of newly built generators in E4ST.

Fuel Type	Capital Cost ($/MW)	Annual Fixed Costs ($/MW/Year)	Variable Cost ($/MWh)
Natural gas combined cycle	1,293,084	10,451	$3.32 + 6.6 \times P_{ng}$
Natural gas combustion turbine	898,307	6,459	$10.17 + 9.8 \times P_{ng}$
Nuclear	9,094,045	95,290	9.16
Wind	2,027,770	50,020	2
Solar	2,099,292	14,892	2

---

[16] Additional information on the EIA 860 dataset is available at https://www.eia.gov/electricity/data/eia860/.

[17] U.S. EPA, Air Program Markets Data, https://ampd.epa.gov/ampd.

Representative Hours, Varying Demand, and Varying Generator Availability

Currently, E4ST uses 38 representative hours to represent the year in the Eastern Interconnection and similar numbers in the western interconnection. Each representative hour represents between 4 and 412 real hours. Weights are assigned to each hour such that the frequency distribution of energy demand, wind, and solar generation for the 38 selected hours is almost the same as that of the original 8,760 hours.

Each generator has an "availability factor" in each hour. For wind farms and solar generators, the availability factor measures the proportion of its maximum possible hourly output in MW that it can generate in that particular hour, given the wind or sunlight available to it in that particular hour. For each of the thousands of buildable wind farms in the model, that availability factor comes from the hourly, site-by-site generation estimates produced for the Eastern Wind Integration and Transmission Study (Corbus, et al., 2010). For each of the thousands of buildable solar generators in the model, that availability calculation comes from the nearest high-quality solar measurement station, assuming a fixed-tilt solar array. For other generators, the availability factor represents the estimated average capacity of that generator in that hour, as a proportion of that generator's rated maximum summertime generation capability in MW. For each generator fuel type, E4ST uses an affine, strictly increasing function of the hourly demand function multiplier to calculate the availability factor of generators with that fuel type. Specifically, the model uses the affine function that sets the availability factor equal in the highest-load hour equal to the forced outage rate of that fuel type, and sets the average availability factor equal to the average forced and unforced outage rate of that fuel type, according to outage rate data from the North American Electric Reliability Corporation (2012).

There is a demand function at each bus that has customers. The Eastern model has six demand regions, and the Western model has one demand region. Each demand region has a different load multiplier in each hour, based on the historical electricity consumption in that region in that hour. These load multipliers are used as demand function multipliers. As a result, each demand region has a different demand function multiplier in each hour.

To represent the responsiveness of load to price, E4ST assumes that the load at each bus in each representative hour has an own-price elasticity of -0.4 based on the elasticity meta-analysis presented in Jorgensen, et al. (2012), and that the end-user price is $60 per MWh higher than the wholesale price, to account for distribution charges and taxes.

Demand is assumed to grow at a constant rate in each demand region. E4ST uses the assumed 2015-2040 annual load growth rates from the U.S. Energy Information Administration's 2016 *Annual Energy Outlook* Reference Case Without Clean Power Plan (EIA, 2016), converted to demand multipliers by assuming that the own-price elasticity of demand is -0.4, applied to the end-user price. A demand multiplier equals the load growth rate if the price in real terms did not change. Where the EIA regions are smaller than those in E4ST, the model uses the average of the corresponding EIA regions, weighted by 2030 load.

Demand Elasticity

Under the representation of price-responsive load used for this report, if a policy change or other change of circumstance increases the real (inflation-adjusted) price of electricity in a given representative hour (relative to the price in that same representative hour in the base year of

2010), it will reduce the load in that hour. If change A increases the average price more than does change B, then change A will reduce the load more than will change B. Circumstances that decrease the price have the opposite effect. To accomplish this, at each of the thousands of load nodes in the model, a ten-step demand function is used that closely approximates a smooth demand function with an elasticity of -0.4. As a result of needing to use a step function, some price changes, such as some small ones, will not change the load, but the annual load changes nonetheless closely approximate an elasticity of -0.4.

Additional Information about E4ST

Readers interested in more information about E4ST may wish to see Mao et al. (2016), Shawhan et al. (2014), and/or E4ST.org. E4ST has been built by the several authors of those two papers as well as Zamiyad Dar and Andrew Kindle, upon code originally written by Carlos Murillo-Sánchez for an operations context (Murillo-Sánchez et al. 2013), and upon MATPOWER (Zimmerman et al 2011). E4ST is currently improved and maintained primarily by researchers at Resources for the Future. Some of the other important members of the E4ST team are at Cornell University and Arizona State University.

E4ST has been built with funding from the U.S. Department of Energy, the Consortium for Electric Reliability Technology Solutions, the New York Independent System Operator, the Power Systems Engineering Research Center, and the National Science Foundation. Energy Visuals, Inc. provided its Transmission Atlas and FirstRate transmission system and generator data.

Scenario Assumptions

The renewable portfolio standard is implemented as a requirement that wind and solar generation in the U.S. and Canadian parts of the Eastern Interconnection must equal or exceed the following percentages of U.S. electricity consumption in the Eastern Interconnection: 8% in 2020, 17% in 2025, 26% in 2030, 35% in 2035, and 40% in 2040. This embodies the assumption that Canadian wind and solar generation will be allowed to help to satisfy U.S. renewable energy requirements, which is a cost-reducing feature in some U.S. state renewable portfolio standards. Also, in the specification of this standard in the simulations, U.S. electricity consumption includes transmission and distribution losses in the U.S.

The tax credits received by wind farms and solar generators in E4ST depend on when they are built. Wind generators that will be built in 2020 receive a tax credit of $18 per MWh. Solar generators built in 2020 receive a tax credit that equals to 30% of the cost to build them, while solar generators built in 2025 receive a tax credit that equals to 10% of the cost to build them.

References

Corbus, D., King, J., Mousseau, T., Zavadil, R., Heath, B., Hecker, L., Lawhorn, J., Osborn, D., Smit, J., Hunt, R. (2010). Eastern Wind Integration and Transmission Study, CP-550-46505 (NREL, Golden, CO). Available at: http://www.nrel.gov/docs/fy09osti/46505.pdf.

Energy Visuals (2012). Transmission Atlas file ss11SUM107152010. www.energyvisuals.com.

Hogan, W. (1992). Contract networks for electric power transmission. Journal of Regulatory Economics **4(3):211–242.**

Jorgensen, J., Joutz, F., Dahl, C. (2012) A Meta-Analysis of U.S. Residential, Industrial, and Commercial Electricity Demand. 31st USAEE/IAEE North American Conference.

Joskow, P., Tirole, J. (2000). Transmission rights and market power on electric power networks. The RAND Journal of Economics **31(3):450–487.**

Kirschen, D., Strbac, G. (2004). Fundamentals of Power System Economics, Wiley (West Sussex, England).

Mao, B., Shawhan, D., Zimmerman, R., Yan, J., Zhu, Y., Schulze, W., Schuler, R., Tylavsky, D. (2016) The Engineering, Economic and Environmental Electricity Simulation Tool (E4ST): Description and an Illustration of its Capability and Use as a Planning/Policy Analysis Tool. Proceedings of the 49th Hawaii International Conference on System Sciences, **2317–2325.** Available at: https://doi.org/10.1109/HICSS.2016.290.

Murillo-Sanchez, C. E. Zimmerman, R. D., Anderson, C. L., and Thomas, R. J., “A Stochastic, Contingency-Based Security-Constrained Optimal Power Flow for the Procurement of Energy and Distributed Reserve”, Decision Support Systems, Volume 56, December 2013, Pages 1-10, ISSN 0167-9236. DOI: 10.1016/j.dss.2013.04.006

National Renewable Energy Laboratory (2016). 2016 Standard Scenarios Report: A U.S. Electricity Sector Outlook, NREL/TP-6A20-66939 (NREL, Golden, CO).

North American Electric Reliability Corporation (2016). Energy Supply and Demand. Available at: http://www.nerc.com/pa/RAPA/ESD/Pages/default.aspx.

Shawhan, D., Taber, J., Shi, D., Zimmerman, R., Yan, J., Marquet, C., Qi, Y., Mao, B., Schuler, R., Schulze, W., Tylavsky, D. (2014). “Does a Detailed Model of the Electricity Grid Matter? Estimating the Impacts of the Regional Greenhouse Gas Initiative,” Resource and Energy Economics **36(1):191–207.**

Shi, D., Shawhan, D., Li, N., Tylavsky, D., Taber, J., Zimmerman, R. (2012). Optimal Generation Investment Planning: Part 1: Network Equivalents. North American Power Symposium.

U.S. Energy Information Administration (2016). Annual Energy Outlook 2016 with Projections to 2040 (EIA, Washington, DC).

U.S. Energy Information Administration (2013). Capital Cost Estimates for Utility Scale Electricity Generating Plants (EIA, Washington, DC).

Zimmerman, R. D., Murillo-Sanchez, C. E., and Thomas, R. J., “MATPOWER: Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education,” Power Systems, IEEE Transactions on, vol. 26, no. 1, pp. 12-19, Feb. 2011. DOI: 10.1109/TPWRS.2010.2051168

C
ADDITIONAL US-REGEN RESULTS

This appendix presents additional US-REGEN model results.

Temporal Resolution

Section 2.2 describes experiments to compare the representative hour and seasonal average approaches to representing intra-annual variation. The representative hour approach more accurately captures the joint variation in time-series data like load, wind output, and solar output across regions (Blanford, et al., 2016) compared with the simplified seasonal average approach, which focuses on capturing the load duration curve.

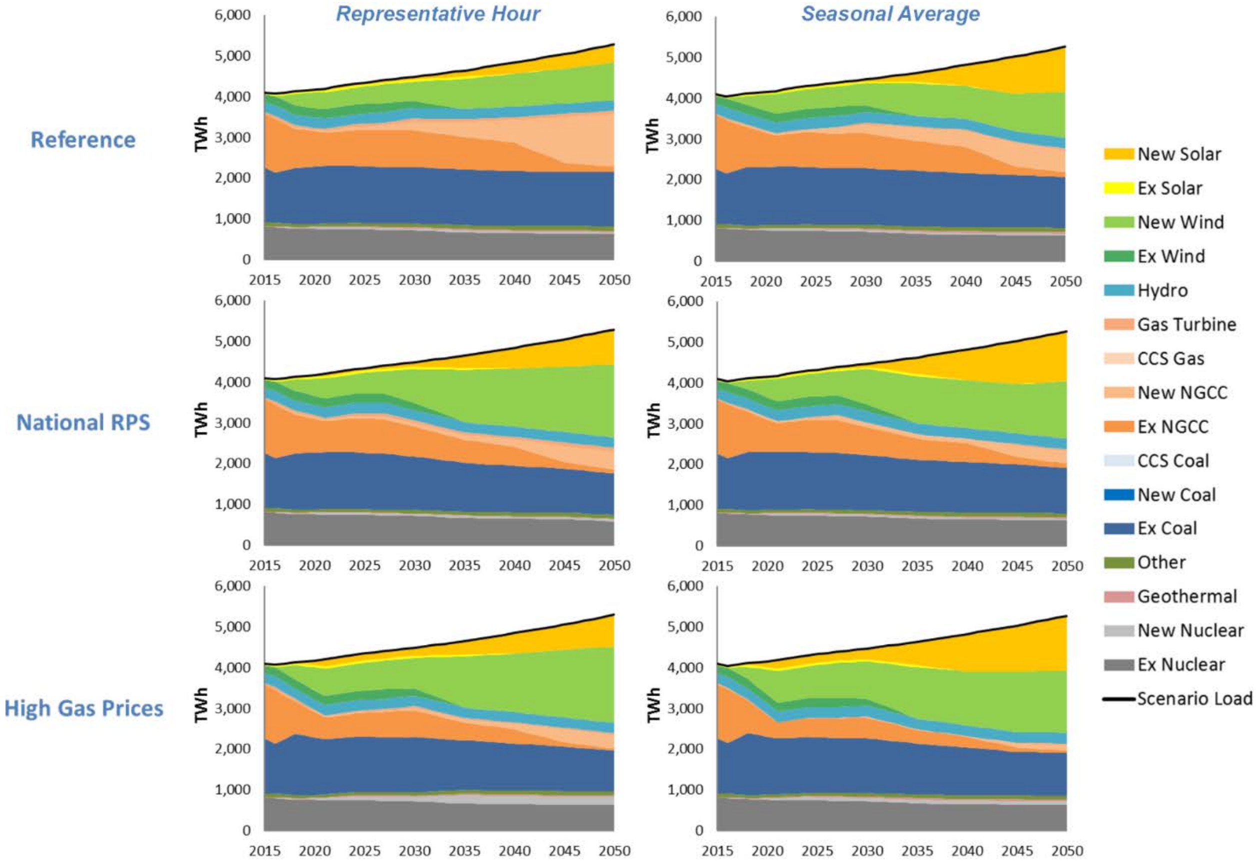

Figure C-1
National electricity generation (TWh) over time by scenario (rows) and model approach for representing intra-annual variability (columns) from US-REGEN model results. Scenario assumptions are described in Section 2.2.

Figure C-1 provides national electricity generation by technology over time for each of the three scenarios (reference policies, national RPS with REC trading, and higher natural gas prices) along with the two specifications for modeling intra-annual variability. These figures illustrate how the 2040 snapshot in Figure 2-2 is broadly representative of impacts across different years, though differences between the representative hour and seasonal average approaches tend to increase over time as existing units are replaced (and marginal additions in many regions depend critically on the representation of intra-annual variability).

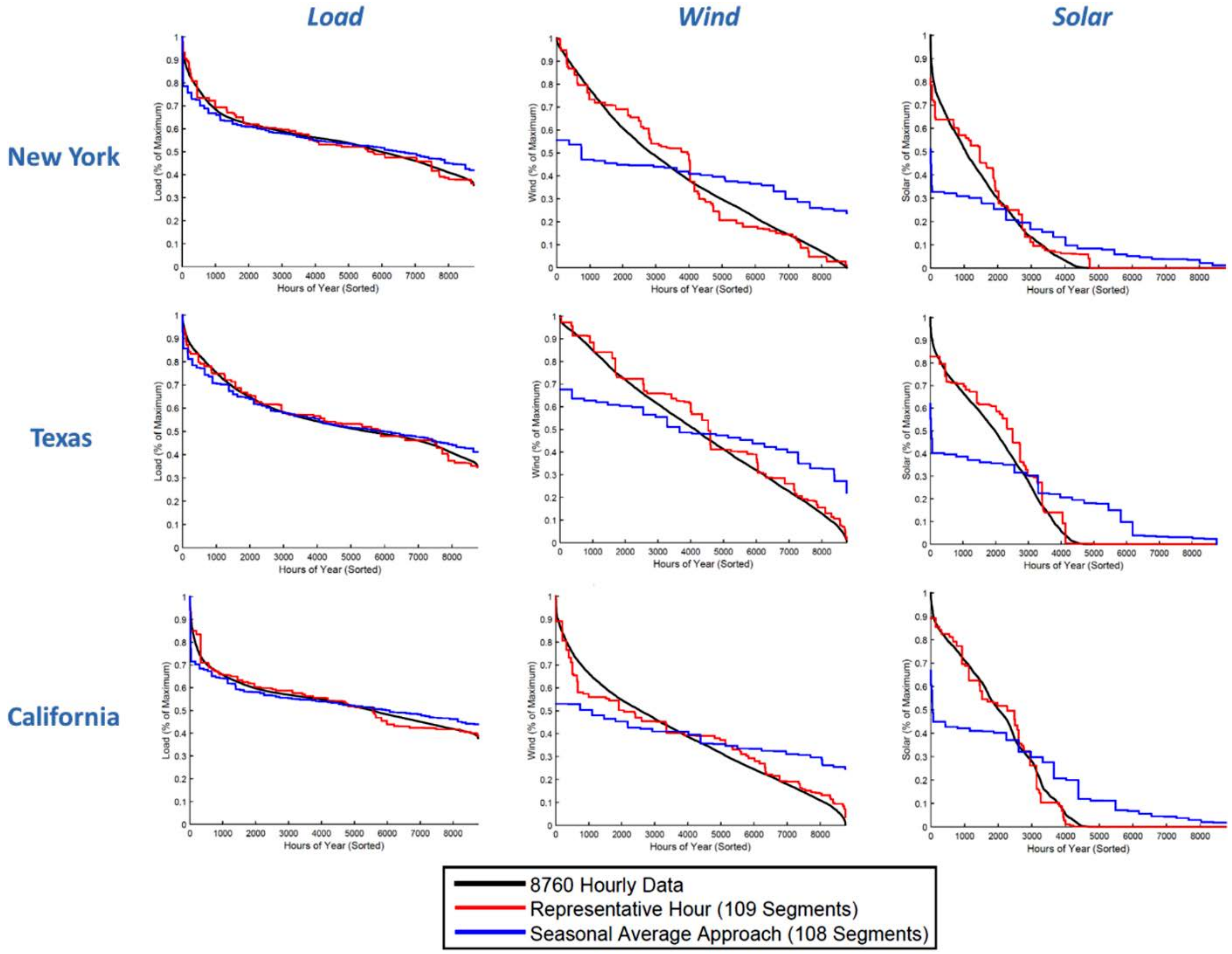

Figure C-2
Sorted duration curves for load (left column), wind (middle), and solar (right) for three regions (rows). Load and wind are normalized as a fraction of their respective maximum annual values. Curves represent the complete hourly data (black), representative hour approach for capturing intra-annual temporal variability (red), and simplified seasonal average approach (blue).

Likewise, Figure C-2 reinforces the conclusions in Section 2 across a greater range of technologies and regions.

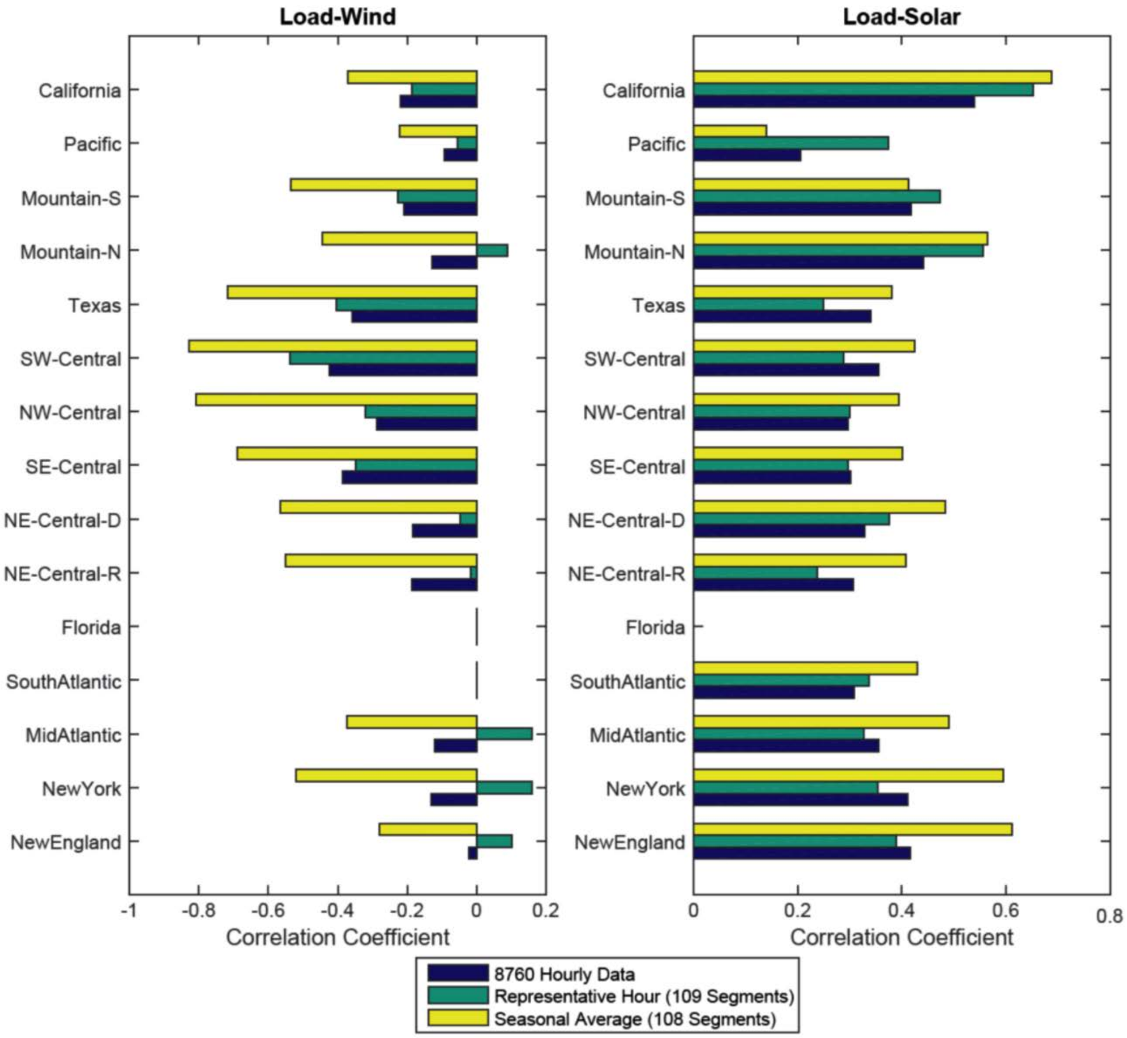

Figure C-3
Correlation coefficient comparison for load and wind (left panel) and load and solar (right panel) by region. Values are shown for the complete hourly data (blue), representative hour approach for capturing intra-annual temporal variability (green), and simplified seasonal average approach (yellow).

Figure C-3 demonstrates how the representative hour approach captures correlations between load and renewable output well. However, the seasonal average approach does not sufficient represent these characteristics. Additionally, time-series correlations across regions are an important dynamic to capture for trade outcomes and system balancing. Figure C-4 illustrates how the representative hour approach outperforms the seasonal average approach in this dimension as well.

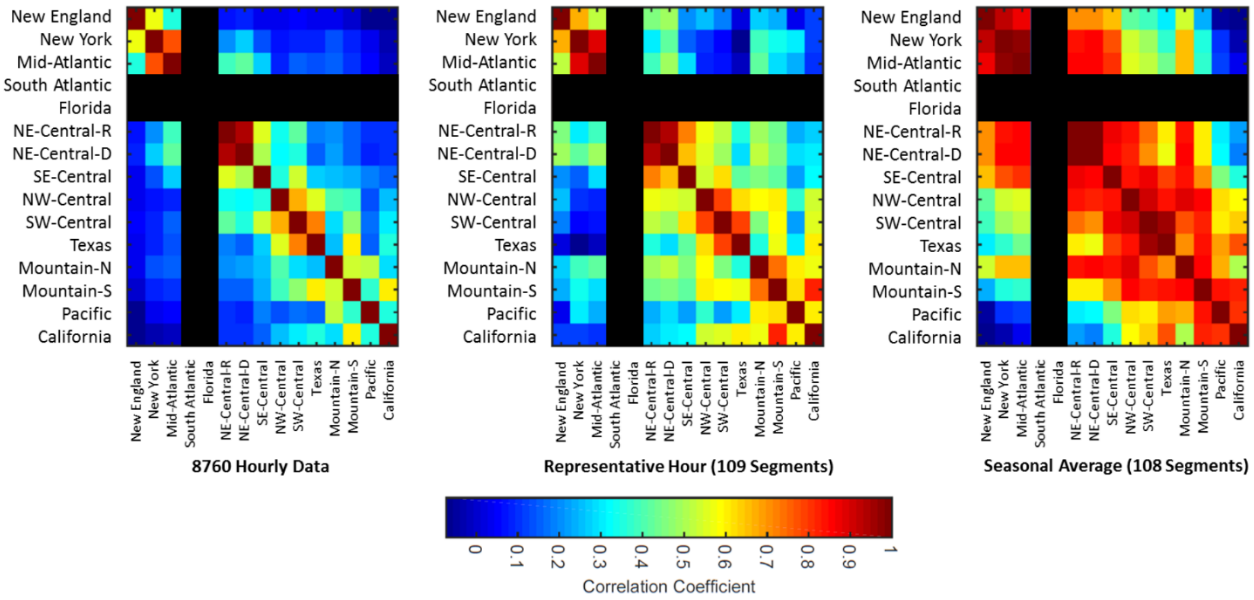

Figure C-4
Interregional correlation coefficient comparison for existing wind output. Values are shown for the complete hourly data (left panel), representative hour approach for capturing intra-annual temporal variability (middle panel), and simplified seasonal average approach (right panel).

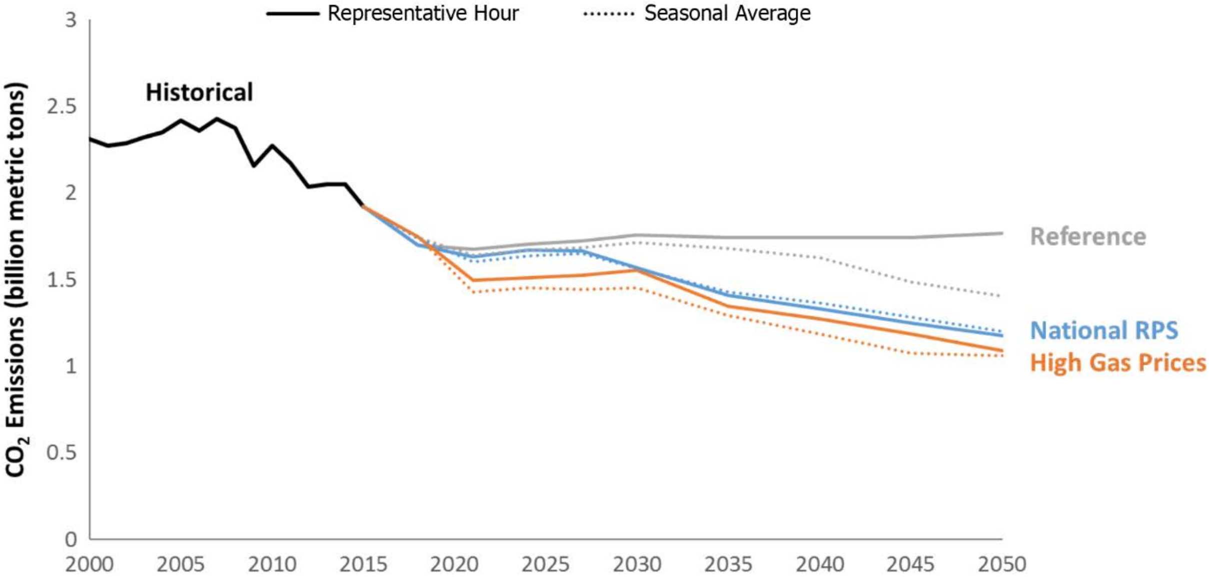

Figure C-5
National electric sector CO_2 emissions (billion metric tons), including historical and modeled time series. Values are shown for the three scenarios and two model approaches for representing intra-annual variability.

Figure 3-3 aggregated emissions impacts over time to provide a convenient summary statistic for comparing environmental outcomes across a range of scenarios. Figure C-5 provides time-series data for emissions trajectories across the temporal resolution scenarios.

Trade

Chapter 3.1 describes experiments to evaluate the impacts of alternate trade assumptions, contrasting US-REGEN's fully endogenous inter-regional trading capability with co-optimized transmission investment ("Trade") with a simplified approach that assumes that trade levels are constrained by their base year values ("Fixed").

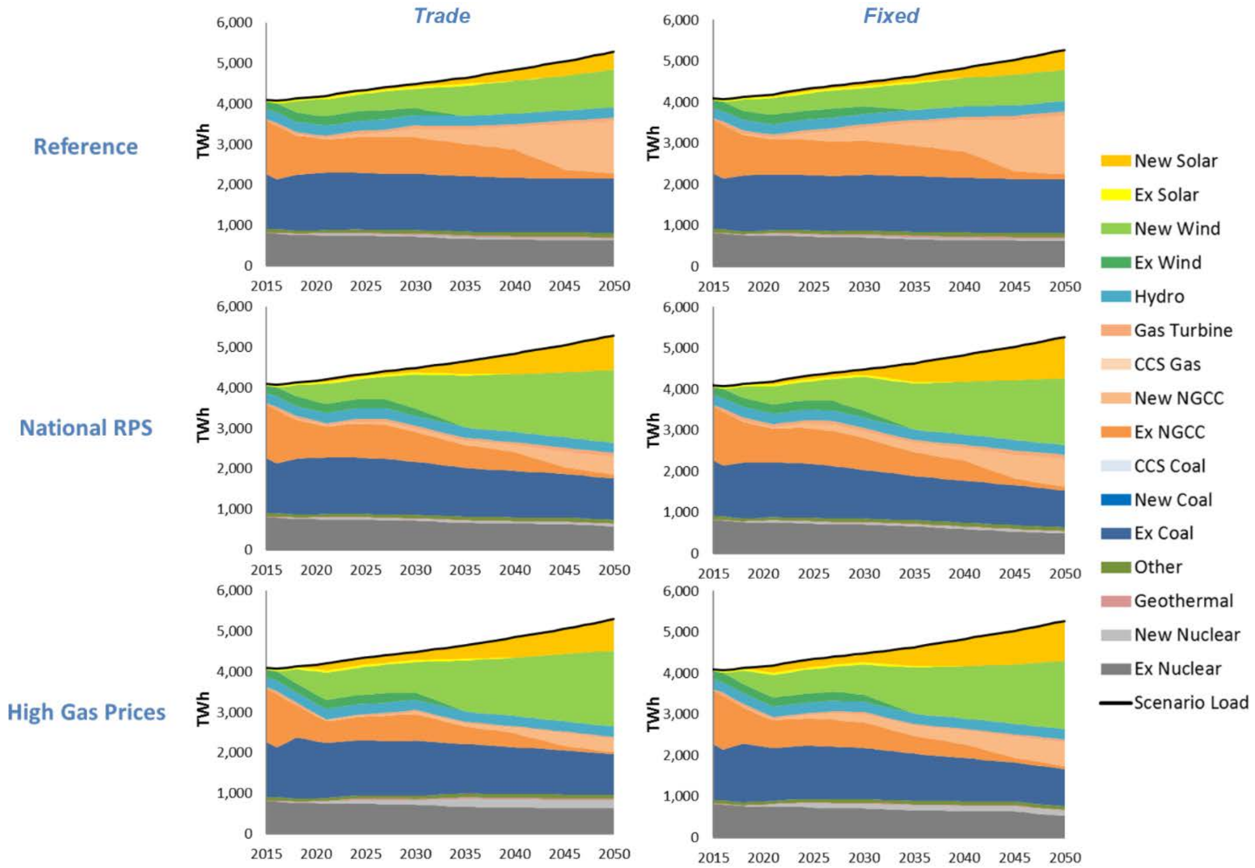

Figure C-6
National electricity generation (TWh) over time by scenario (rows) and model approach for modeling trade (columns) from US-REGEN model results. Scenario assumptions are described in Chapter 3.1.

As described in Section 3.1, the regional outputs across these scenarios in Figure C-6 differ more than their national counterparts in Figure C-7.

Additional US-REGEN Results

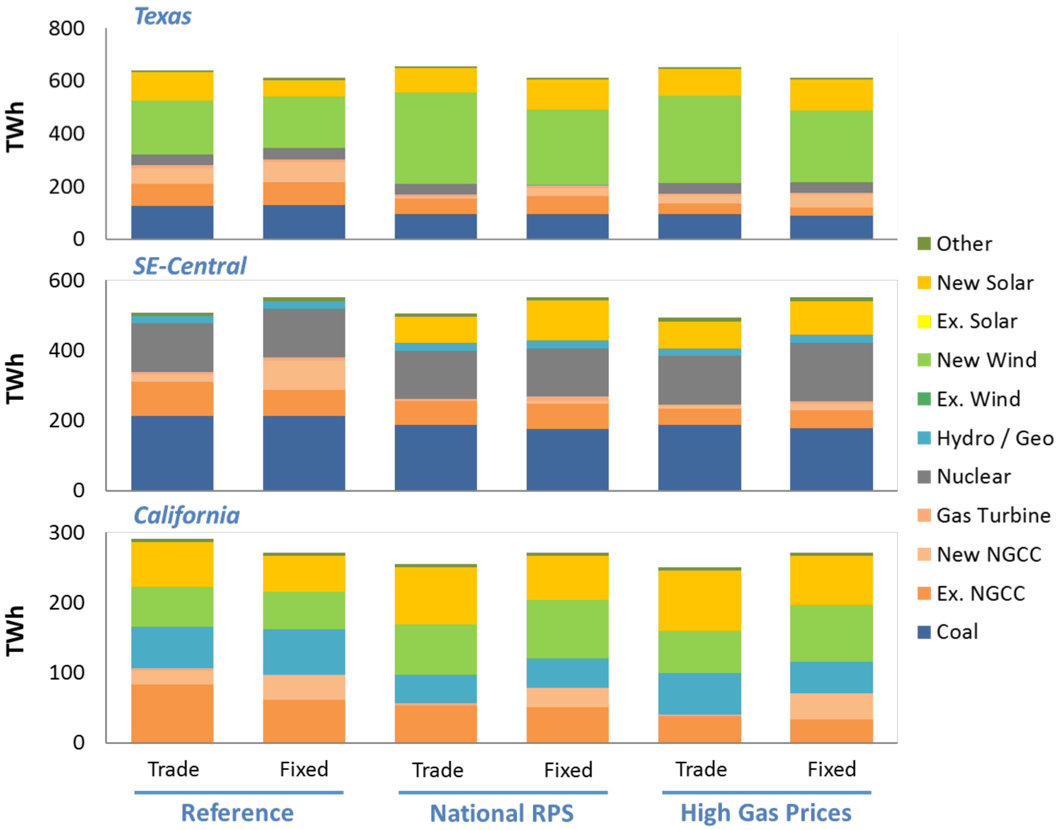

Figure C-7
Regional generation (TWh) in 2040 by technology and scenario from US-REGEN model results. "Trade" scenarios assume endogenous inter-regional electricity trade, and "Fixed" scenarios assume trade levels are constrained by their base year values.

Another output of interest is changes in inter-regional electricity imports and exports across time and across scenarios. Figure C-8 provides a 2040 snapshot of the net trade position (i.e., the difference between the sum of domestic and international exports minus imports) by region and scenario. Comparing the reference and national RPS trade outputs suggests that adding renewable mandates across the country not only has the potential to switch the direction of a state or region's net trade position (e.g., switching from a net exporter to an importer) but more significantly can alter the magnitude of this trade position. For instance, the Northwest Central region exports 8 TWh in 2040 under the reference scenario but almost 91 TWh in the national RPS with REC trading, largely due to its higher-quality wind resources. California increases its annual net imports from 26 TWh under the reference scenario to 62 TWh with the national RPS.

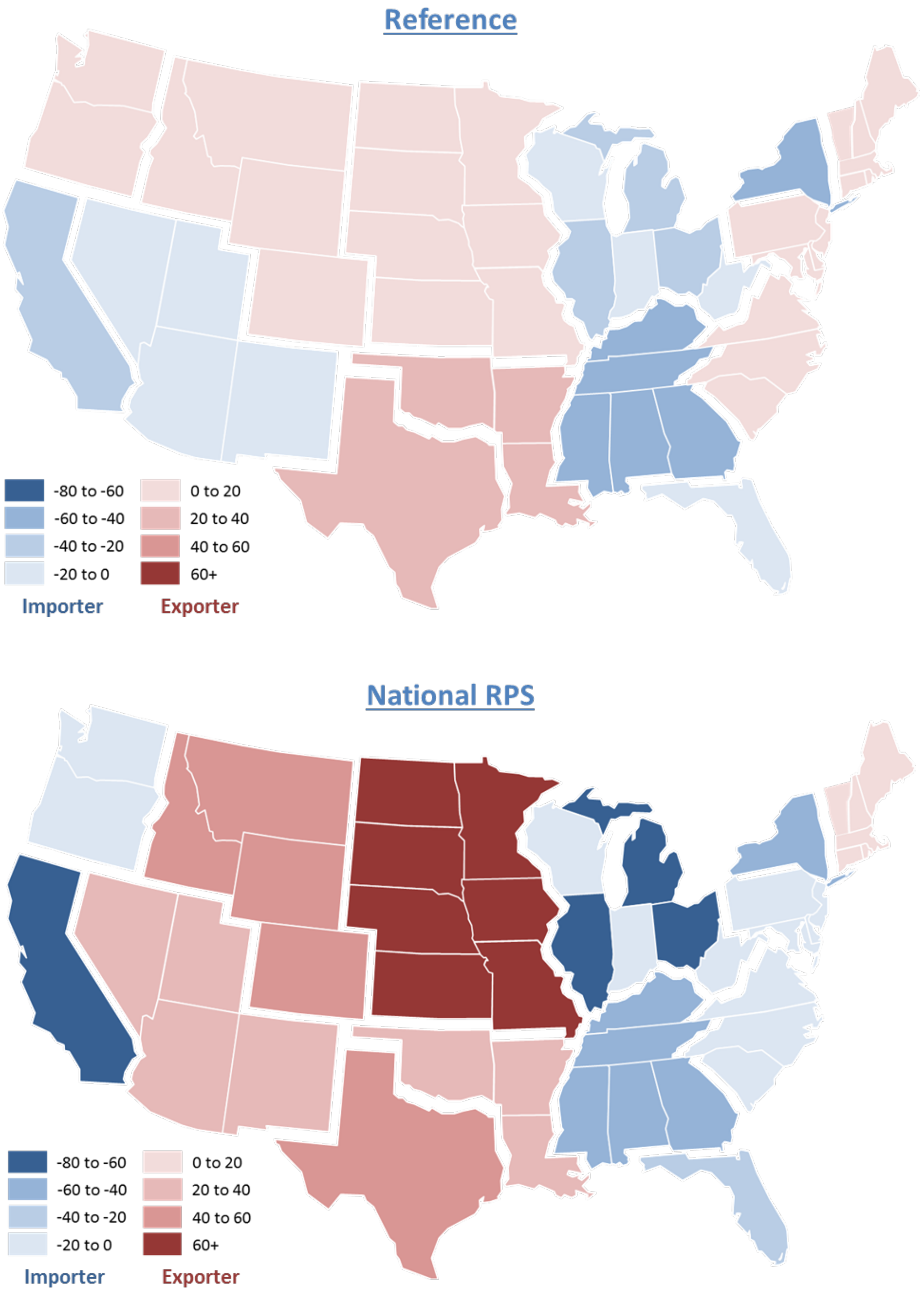
Reference
-80 to -60
-60 to -40
-40 to -20
-20 to 0
0 to 20
20 to 40
40 to 60
60+
Importer
Exporter
National RPS
-80 to -60
-60 to -40
-40 to -20
-20 to 0
0 to 20
20 to 40
40 to 60
60+
Importer
Exporter

Figure C-8
2040 net trade position (TWh) by region and scenario. Annual sum of domestic and international exports minus imports (i.e., negative values indicate a region is a net importer).

These changes in electricity trade are also accompanied by extensive REC trade under the national RPS. Figure C-9 shows the 2040 net REC exports by region. Texas is the biggest REC exporter (177 TWh), while the Southeast Central region is the biggest REC importer (128 TWh).

This geographical heterogeneity reflects differences in wind and solar resource quality and region-specific costs (and marginal value) associated with additional deployment.

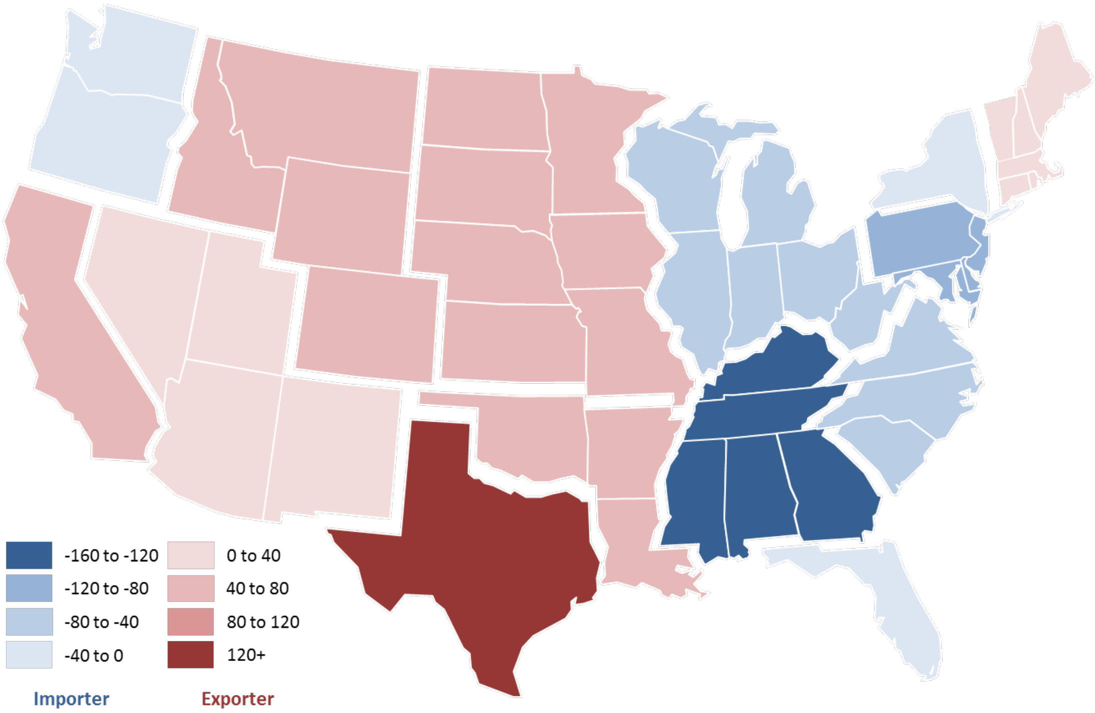
-160 to -120
-120 to -80
-80 to -40
-40 to 0
0 to 40
40 to 80
80 to 120
120+
Importer
Exporter

Figure C-9
2040 net REC exports (TWh) by region. Values shown for the national RPS scenario.

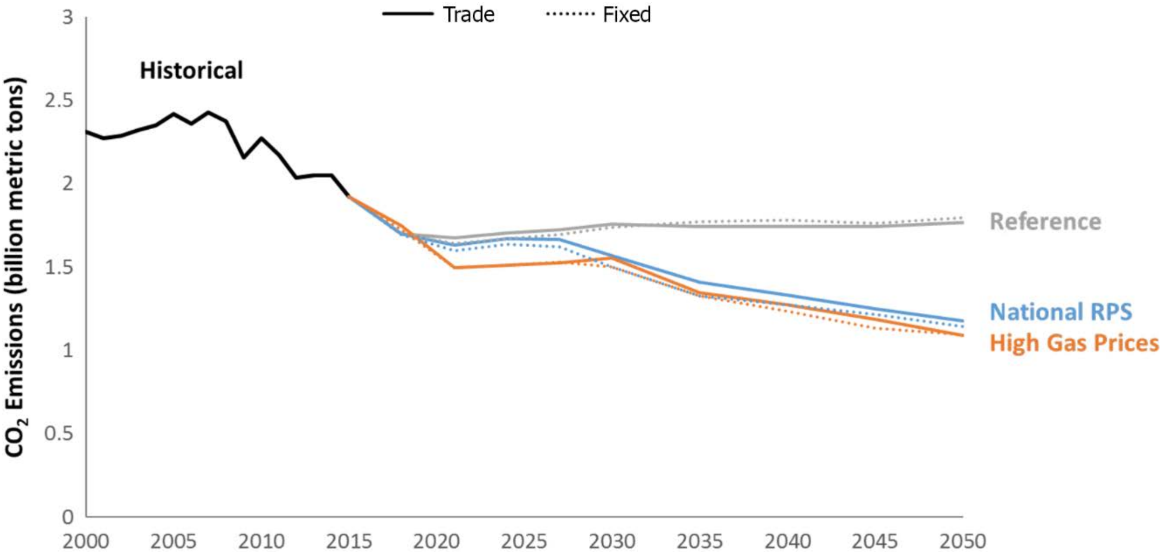

Figure C-10
National electric sector CO$_2$ emissions (billion metric tons), including historical and modeled time series. Values are shown for the three scenarios and two model approaches for representing electricity trade.

Figure C-10 illustrates emissions across the alternate trade scenarios, which exhibit less variation than the temporal resolution cases.

Spatial Aggregation

Section 3.2 describes experiments to evaluate the impacts of alternate spatial aggregation, comparing the 15-region version of US-REGEN and one with 48 states.

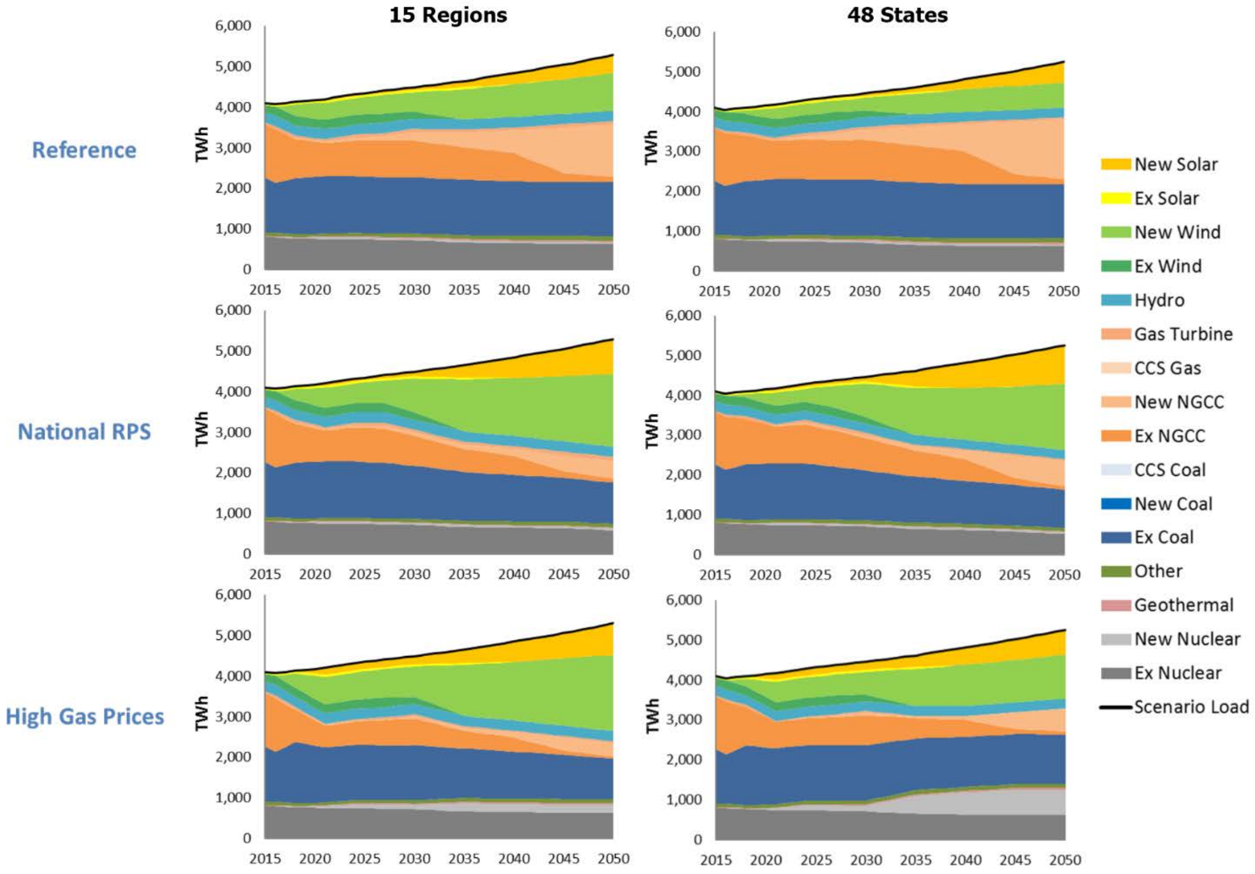

Figure C-11
National electricity generation (TWh) over time by scenario (rows) and spatial aggregation (columns) from US-REGEN model results. Scenario assumptions are described in Section 3.2.

Figure C-11 provides national electricity generation by technology over time for each of the three scenarios and two specifications of spatial aggregation.

Additional US-REGEN Results

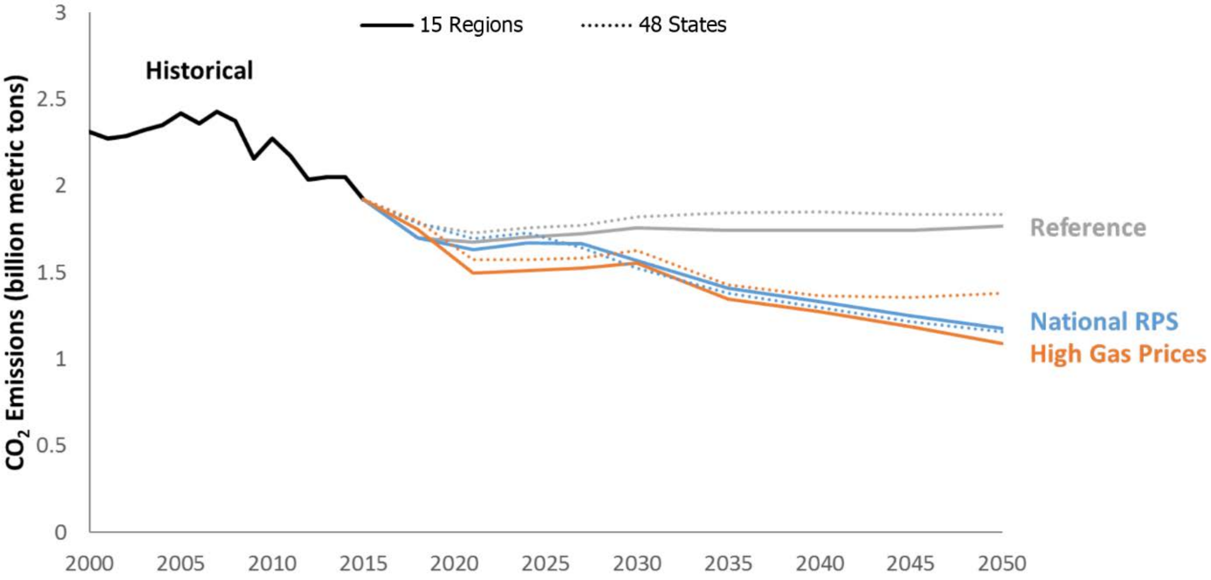

Figure C-12
National electric sector CO_2 emissions (billion metric tons), including historical and modeled time series. Values are shown for the three scenarios and two model approaches for representing spatial aggregation.

Figure C-12 illustrates emissions across the alternate spatial aggregation scenarios.

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