The importance of temporal resolution in modeling deep decarbonization of the electric power sector

John E T Bistline

Electric Power Research Institute, 3420 Hillview Avenue, Palo Alto, CA 94304, United States of America
E-mail: jbistline@epri.com

Keywords: energy modeling, decarbonization, net-zero energy systems, renewables integration, power sector economics, macro-energy systems

Supplementary material for this article is available online

Abstract

Power sector decarbonization is a central pillar of economy-wide emissions reductions. However, model complexity, especially temporal resolution, can materially impact power sector decarbonization pathways. Using a detailed electric sector capacity planning and dispatch model, this analysis explores impacts of temporal resolution on electric sector investments and costs and how these outcomes vary under different policy and technology assumptions. Results show that approaches to simplify temporal variability used in many integrated assessment and energy system models may not replicate fundamental relationships for power sector decarbonization or may exhibit large quantitative deviations from more detailed modeling, including abatement costs rising nonlinearly at higher decarbonization levels; variable renewables and batteries being accompanied by additional low-/zero-/negative-emissions resources, especially approaching 100% decarbonization; and carbon removal technologies altering electric sector costs and investments. Representative day approaches can preserve many of these properties with large reductions in computational complexity. Simplified temporal aggregation approaches tend to underestimate the value of broader technological portfolios, firm low-emitting technologies, wind generation, and energy storage resources and can overstate the value of solar generation. Approximation accuracy also depends on assumptions about technological cost and availability: differences across approaches are smaller when carbon removal is available and when renewables costs are lower. The analysis indicates that higher temporal resolution is increasingly important for policy analysis, electric sector planning, and technology valuation in scenarios with deeper decarbonization and higher variable renewables.

1. Introduction

Power sector decarbonization is considered a central pillar of economy-wide emissions reductions through electrification and electricity-derived fuels (Edmonds et al 2006, Williams et al 2012, Barron et al 2018, EPRI 2018b). A growing number of studies investigates electric sector decarbonization strategies using a range of modeling frameworks, including detailed power sector capacity planning models, broader energy systems models, and global integrated assessment models (Kaufman et al 2020, Larson et al 2020, Phadke et al 2020, Blanford et al 2021, Orvis 2021). However, differences across studies beg questions about how model structure and complexity impact findings about decarbonization pathways.

In particular, temporal resolution—the degree of detail related to time periods within a year—is broadly recognized as being important to capture the joint variability of time-series variables (e.g. load and potential variable renewables output), chronological energy storage constraints, and power system operations (Cole et al 2017, DeCarolis et al 2017, Merrick and Weyant 2019). Temporal variability is typically aggregated in numerical models to reduce computational complexity and solve times. Models vary in their temporal resolutions, aggregation approaches, and other dimensions of model
complexity, including their sectoral coverage, spatial resolution, and technology detail, with context-dependent tradeoffs between the accuracy of the representation and model parsimony (Santen et al. 2017, Creutzig et al. 2019). Previous literature proposes different reduced-form approaches for simplifying temporal resolution in capacity planning models (Helistö et al. 2019, Hoffmann et al. 2020) and shows how aggregation approaches differ using simple models (Merrick 2016, Scott et al. 2019, Buchholz et al. 2020).

However, there are no studies in the extant literature that show how a range of common temporal aggregation approaches can materially impact power sector deep decarbonization pathways using a large-scale model and that systematically vary these approaches under a range of policy and technology assumptions.

This paper addresses these gaps by examining how model temporal aggregation approaches influence electric sector outcomes under deep decarbonization scenarios for the United States. The analysis compares generation mixes and costs across four common temporal resolution approaches using the Regional Economy, Greenhouse Gas, and Energy (REGEN) model, a detailed model of power sector investments and operations with hourly resolution (EPRI 2020). These comparisons highlight which technologies and resources could be misvalued with less accurate temporal aggregation approaches under different planning settings. Given uncertainty about technologies and policy, the paper also conducts sensitivity analysis to understand how model errors vary based on the stringency of the CO₂ reduction target and technological assumptions.

Results suggest that model complexity strongly impacts evaluations of the cost and feasibility of electric sector decarbonization pathways. Approaches to simplify temporal variability in many integrated assessment and energy system models may not replicate fundamental relationships for power sector decarbonization, including nonlinear increases in abatement costs at higher levels, diminishing marginal returns for very high penetrations of variable renewables, and the value of broader technological choice sets and carbon removal. Across the range of sensitivities examined, errors from simplified temporal aggregation approaches increase with tighter CO₂ targets. Approximation accuracy also depends on assumptions about technological cost and availability: Differences across approaches are smaller when carbon removal is available and when renewables costs are lower. Simplified temporal aggregation approaches can distort costs by missing periods that are important to the valuation of low-carbon technologies as emissions decline and the deployment of renewables increases. These approaches can understate the value of broader technological portfolios, firm low-CO₂ technologies, wind, and energy storage. Models with low temporal resolution are not fit for purpose for assessing the relative competitiveness of electric sector technologies or rely heavily on side constraints that may not accurately reflect underlying dynamics.

2. Method

2.1. Electric sector capacity planning model

To investigate these questions, this analysis uses a power sector capacity planning and dispatch model with detailed technological, temporal, and spatial resolutions, which are critical in representing variable renewables, energy storage, and dispatchable low-carbon technologies (Cole et al. 2017, Collins et al. 2017, Santen et al. 2017, Blanford et al. 2018). The electric sector model, REGEN1, is fully documented in EPRI (2020), so only summaries of key features and assumptions are provided here and supplementary information appendix A (available online at stacks.iop.org/ERL/16/084005/mmedia). Under a given set of assumptions about policies, technologies, and markets, REGEN optimizes decisions about new generation investments, energy storage and carbon removal capacities, hourly system dispatch, and co-optimized transmission capacity and trade.

Although REGEN is frequently formulated as an intertemporal optimization across multiple decades, the variant used in this analysis is a single-year static equilibrium model with capacity investments and operations. In this quasi-greenfield mode, REGEN adds new capacity for the majority of the system and only includes existing capacity for hydropower, nuclear, and inter-regional transmission. The use of this single-year model is important in this analysis so that a full (non-aggregated) hourly model can be used as a benchmark to evaluate the performance of temporal aggregation approaches. Currently, it is intractable to include 8760 hourly resolution within a large-scale capacity planning model while maintaining an intertemporal optimization, though there are various approaches in the literature for addressing this difficulty including the temporal aggregation approaches evaluated here (Bistline et al. 2021)2. The insights from these experiments should be transferrable to the temporal aggregation approaches used in intertemporal (multi-period) optimization models.

1 The Regional Economy, Greenhouse Gas, and Energy (REGEN) framework is a detailed model of end-use technology adoption linked to a power sector capacity planning model. REGEN has been used extensively to explore energy system issues and potential policies. Full documentation and recent studies are available at: https://esca.epri.com/models.html.

2 Proposed approaches include using 8760 h for a single year or using a rolling horizon approach, keeping an intertemporal solve but using representative days to capture chronology, foregoing chronology altogether and adopting a more stylized representation of energy storage, using an intertemporal optimization with a system state approach, adopting non-chronological periods in the capacity planning and then soft-linking with a more detailed operational model, and using decomposition approaches (Wogrin et al. 2016, Bistline et al. 2020, Merrick et al. 2021).
Technological cost and performance assumptions come from EPRI's Integrated Technology Generation Options report (EPRI 2018a) with more recent updates for solar, wind, and battery costs. Capital costs are shown in figure 1. Although assumptions are based on 2050 projections, the analysis could be interpreted as an earlier year with accelerated technical change and/or policies. Demand projections and hourly electricity load profiles come from the REGEN end-use model, which characterizes technology adoption with heterogeneity across households, industries, and regions. The end-use model includes a $50/t-CO_2 carbon price beginning in 2020 to reflect the deep decarbonization context of these sensitivities. The national average power producer price of natural gas is assumed to be $4/MMBtu (in 2018$).

2.2. Temporal aggregation and deep decarbonization scenarios

The analysis considers four temporal aggregation approaches that are commonly used in electric sector capacity planning models, energy systems models, and integrated assessment models:

- **8760 hourly**: an hourly model without temporal aggregation provides a bounding case to assess the accuracy of the three simplified approaches. Hourly resolution may be too computationally costly for many tools, especially intertemporal optimization models that span multiple decades and have broad geographical coverage with many regions.

- **Representative day (RD)**: a RD approach selects two day types (a peak load day and average) per month for a total of 2 d types $\times 12$ months $\times 24$ h per day $= 576$ periods per year. The peak load day is based on the day with the highest hourly load within a month in a given region. The average load day is selected as the 24th day of each month, per the implementation of the SWITCH 2.0 model (Johnston et al 2019). Load and renewables availability come from hourly periods during these representative days and are weighted based on the number of days per month.

- **Seasonal average (SA)**: the SA approach is a commonly employed method in energy systems models that uses a few daily periods and seasons to capture the load duration curve (Blanford et al 2018). This approach assigns wind and solar capacity factors to each period based on average resource availability during the corresponding load period. The specific implementation is based on the U.S. Energy Information Administration’s NEMS model (U.S. EIA 2020). This approach has 3 seasons (winter, summer, and fall/spring) $\times 3$ daily periods (peak, shoulder, base) $= 9$ periods per year.

- **Levelized cost of electricity (LCOE)**: this approach relies on the levelized costs of different resources to evaluate their economic competitiveness. The implementation used here includes a peak load hour and an average for the remaining periods of the year. This average segment approach is implicit in an LCOE comparison and models where technologies are selected based on levelized costs.
such as many global integrated assessment models (Luderer et al. 2017).

There are many possible implementations of each approach, and the four chosen here replicate those from commonly used energy-economic models. Although there are many sophisticated aggregation approaches proposed in the literature (Hoffmann et al. 2020), commonly used models do not necessarily adopt these methods.

This analysis investigates a range of policy, market, and technology scenarios to understand how temporal aggregation approaches impact results in different settings:

- **CO₂ policy:** this analysis considers a national cap on CO₂ emissions relative to 2005 levels, spanning from 80% to 100%. Existing state and federal policies and incentives are excluded to explore least-cost portfolios without additional constraints.
- **Set of low-emitting technologies:** reference (i.e. all technologies included in figure 1) and renewables only.
- **Carbon dioxide removal (CDR) availability:** all scenarios are run with and without CDR technologies. REGEN includes direct air capture (DAC) and bioenergy with carbon capture and storage (BECCS). DAC and BECCS cost and performance assumptions are shown in Table 1 of appendix A.
- **Variable renewables and battery storage costs:** (figure 1): ‘Reference’ (i.e. best guess based on anticipated research and development); ‘Breakthrough’ (i.e. 5% probability outcome with very low capital costs).

2.3. Caveats

There are a number of caveats to bear in mind when interpreting the results. First, the analysis does not include side constraints and costs that some models employ in addition to their temporal aggregation approach in attempting to simulate missing dynamics and to correct for shortcomings of coarse temporal resolution (e.g. upper bounds on technology shares, outside-of-optimization calculations, fixed backup requirements and direct scaling assumptions, integration cost markups). These constraints may or may not replicate missing dynamics accurately, especially in settings farther from the model’s initial design space such as very high renewables and deep decarbonization scenarios. Second, implementation details for temporal aggregation approaches can vary considerably across models, which can impact the accuracy of individual model methods. Finally, the framework used here does not capture grid services, uncertainty, unit commitment costs/constraints, flexible demand, or sub-hourly/sub-state detail (Helistö et al. 2019).  

3. Results

3.1. Aggregation impacts on load and renewable resources

The accuracy of temporal aggregation approaches can be evaluated based on their ability to preserve key distributional characteristics of input data—namely, the 8760 hourly time-series data for regional load, potential wind output, and potential solar output. Figure 2 compares load and resource duration curves for California using 2015 meteorology.

The RD method successfully captures the shapes of the underlying load and solar data, whereas the SA and LCOE approaches underestimate variability, especially of wind and solar resources. The averaging in SA and LCOE methods omits maximum and minimum availability periods and their correlations with each other. Variability historically was only considered on the demand side when conventional capacity dominated the supply mix. Although the correlation between output and price matter most for resource valuation (Lamont 2008), correlations between generation and demand are proxies for this relationship. Figures 9 and 10 illustrate how simple temporal aggregation approaches do not appropriately reflect the distribution and co-variation of load and renewables output.

The accuracy of each approach can be evaluated using residual load duration curves, which are calculated as demand minus available renewables output and represent load that must be met with dispatchable resources. Figure 3 shows residual load in California with 60 GW solar (i.e. approximately peak load in 2015), sorted from low to high. The hourly values illustrate how solar has a limited capacity contribution (especially for higher electrification scenarios where peak residual demand occurs during winter early morning hours instead of summer midday or afternoon periods) and provides energy disproportionately at hours with low residual load. These characteristics contribute to declining marginal returns for increasing variable renewable deployment, which has been observed in actual markets and modeling studies (Hirth 2013, Mills et al. 2021, Millstein et al. 2021). However, the SA and LCOE approaches lead to contributions of solar to the peak being too high and to low-load hours being too low for the higher solar.

3 Unit commitment problems are computationally complex due to the need for integer variables to represent startups, minimum load levels, and other dynamics that are difficult to model in a linear programming setting. These challenges have led to simple economic dispatch being used in most large-scale capacity planning models, while more detailed unit commitment is used in operational models (Collins et al. 2017). These two types of tools are sometimes soft-linked (Deane et al. 2012, Bistline 2017).
penetration case, which underestimates peak capacity needs and curtailments.

These traits and their impacts on electric sector outcomes will be illustrated in subsequent sections. Ultimately, the accuracy of aggregation approaches can only be evaluated ex post after running full numerical simulations and comparing with the solution of the full, non-aggregated (i.e. 8760 hourly) model in hand, but these duration curves provide intuition for why certain approaches perform better or worse than others.

3.2. Impacts of temporal aggregation on generation and cost without carbon removal

For a full hourly model (i.e. without temporal aggregation), cost-minimizing pathways to reach 80% decarbonization continue current trends of expanding variable renewables and battery storage while maintaining hydro, nuclear, and gas capacity (figure 11 in appendix B.2). For deeper decarbonization, firm very-low-CO₂ options such as new nuclear and hydrogen play important roles, though wind and solar dominate generation in many regions.

Temporal aggregation alters generation mixes, but the impacts vary by approach and by policy stringency, as shown in figure 4. Simple aggregation (e.g. the SA and LCOE methods) can overestimate the capacity contribution and value of resources (especially variable renewables) and can undervalue dispatchability. Higher temporal resolution more appropriately characterizes energy and capacity contributions of resources, especially under deep decarbonization scenarios. New nuclear, hydrogen, and battery storage comprise 24% of the generation...
mix for the 8760 model under the 100% CO$_2$ cap scenario but only 3% and 1% for the SA and LCOE approaches, respectively\(^4\). Simplified aggregation also distorts the value of solar vis-à-vis wind with the LCOE approach having a higher solar share and 8760 model a higher wind share for the reference and 100% cap scenarios. Figure 14 in appendix B.2 shows changes in the capacity mix and demonstrates that simple aggregation approaches underinvest in firm\(^5\) capacity relative to hourly models, which capture the system value of technologies that can meet periods

---

\(^4\) Note that generation is higher with the 8760 and representative day approaches due to the higher deployment and utilization of energy storage technologies, especially as CO$_2$ reductions approach 100%, as shown in figure 8 in appendix A.

\(^5\) Here, firm resources refer to technologies ‘that can be counted on to meet demand when needed in all seasons and over long durations (e.g. weeks or longer)’ (Sepulveda et al 2018). There are varying degrees of firmness in practice, but resources filling this role can include existing and new nuclear, fossil capacity, biomass, geothermal, zero-carbon gas-fueled capacity (e.g. hydrogen), and long-duration energy storage.
with sustained energy deficits when wind and solar output are low.

Temporal aggregation approaches alter the size and composition of energy storage technologies (figure 15 in appendix B.2). Deeper decarbonization targets and lower costs increase the economic competitiveness of different energy storage options. Longer-duration energy storage technologies such as power-gas-power hydrogen increase rapidly near 100% decarbonization, though deployment is lower when CDR technologies are available. Battery storage is extensive across all scenarios, and total deployment and composition of battery technologies are sensitive to cost assumptions (figure 12 in appendix B.2). Simplified temporal aggregation lowers the deployment of energy storage, as the SA and LCOE methods dampen the variability of system operations and prices, which consequently lower incentives for energy storage deployment. Figure 16 in appendix B.2 illustrates how alternate assumptions about transmission expansion impact generation shares and policy costs across temporal aggregation approaches.

Overall, higher temporal resolution better captures the value of portfolio diversity, as simple aggregation approaches lead to the dominance of single technologies within a region. From an economic perspective, individual hours are unique electricity goods, and the number of electricity goods increases significantly as the competitiveness of variable renewables increases, making more sophisticated temporal aggregation approaches increasingly relevant for deeper decarbonization targets (Merrick 2016).

Without temporal aggregation, electric sector abatement costs sharply increase near 100%, even with significant cost reductions in renewables and energy storage, as shown in figure 5. Breakthrough renewables and battery costs can shift the curve downward but do not avoid the cost asymptote, including in marginal abatement cost terms (figure 17 in appendix B.2). Simplified temporal aggregation can distort costs by omitting periods that are important to the valuation of low-carbon technologies as emissions decline and the deployment of renewables increases. Aggregation errors for the SA and LCOE approaches increase at higher decarbonization levels, and these methods do not capture the trends or magnitudes in abatement costs, understating values by an order of magnitude in many instances. By contrast, the RD approach captures cost trends as mitigation increases, and costs are within 7% of the values with the 8760 model.

Costs across scenarios are broken out by category in figure 13 in appendix B.2. This decomposition illustrates how generation investment costs are the primary driver of increases at higher abatement levels with contributions from energy storage and transmission, which are partially offset by lower fuel costs. Simplified temporal aggregation underestimates the extent of generation capacity, energy storage, and transmission required to ensure hourly supply and balancing in each region, which means that costs are underestimated across the range of CO₂ reductions (figure 5).

3.3. Sensitivity to alternate net-zero definitions

Target definitions for reaching (net-)zero emissions in the power sector can materially impact costs and generation portfolios. Figure 6 shows three common definitions: A 'Net Zero' case (where negative emissions technologies such as BECCS and DAC allow a positive emissions component to remain), a 'Carbon Free' case (where only non-emitting resources are eligible, as illustrated in the results in the previous section), and a '100% Renewables' case (where only renewables and energy storage resources are eligible).
Results with the 8760 hourly model underscore how policy stringency and design strongly impact electric sector generation mixes. Figure 6 illustrates the impact of target definitions, including how CDR technologies lower generation from new nuclear and long-duration energy storage and increase gas generation. In contrast, simplified temporal aggregation can miss insights on the value of full portfolios by suggesting that the generation mixes look relatively similar across the target definitions.

CDR lowers the costs of achieving policy goals by placing a ceiling on marginal abatement costs, hence lowering total costs for higher stringency scenarios (figure 5). Differences in policy costs between the 8760 hourly model and simpler temporal aggregation approaches are smaller when CDR options are available and the decarbonization goal is framed as a ‘Net Zero’ target. The RD approach more closely resembles the generation mixes and costs from the 8760 model across the zero emissions definitions, including the ‘Net Zero’ target with CDR technologies.

4. Discussion

This analysis demonstrates how model complexity impacts evaluations of the cost and feasibility of electric sector decarbonization pathways. It provides quantitative evidence in support of claims in the literature on the importance of temporal resolution in capacity planning models (Pfenninger et al 2014, Hamilton et al 2015, DeCarolis et al 2017).

Approaches to simplify temporal variability used in many integrated assessment and energy system models may not replicate fundamental relationships for power sector decarbonization or exhibit large quantitative deviations from more detailed modeling, including:

- Total electric sector abatement costs increase nonlinearly for CO₂ reductions around 80%, especially when carbon removal technologies are not available (figure 5). Simplified temporal resolution approaches capture marginal abatement rising sharply near 100% (figure 17 in appendix B.2), but total and marginal abatement costs approaching these levels are systematically lower than the non-aggregated values. These conclusions are supported by other studies in the literature (Mileva et al 2016, Sepulveda et al 2018, Jayadev et al 2020, Blanford et al 2021, Neumann and Brown 2021).
- Solar and wind become the largest generation resources across all scenarios, though shares are less than 100% unless the portfolio of eligible technologies is constrained (figures 4 and 6). This finding is shared across a range of different studies with different input assumptions, model structures, and geographies (Bistline et al 2018, Jenkins et al 2018, Bistline and Young 2019).
- Broader CO₂ target definitions (i.e. the eligible choice set of technologies under a decarbonization policy) bring on additional low-/zero-/negative-emissions resources, and in particular, CDR availability impacts policy costs (figure 5) and the generation mix (figure 6), especially as decarbonization targets approach 100%. Although costs and generation shares change between the ‘Net Zero,’ ‘Carbon Free,’ and ‘100% Renewables’ scenarios with simplified temporal resolution approaches, these changes are dampened relative to higher resolution approaches. Lower temporal resolution can miss more nuanced interactions between system resources, including how the degree of substitutability across different classes of technologies can be scenario- and context-dependent. Other studies also have concluded that the presence of CDR can materially impact power sector outcomes (Dagbash and Mac Dowell 2019, Bistline and Blanford 2021a).
- Targets beyond 80% CO₂ reductions from 2005 levels entail emerging low-/zero/
negative-CO$_2$ technologies (figures 4 and 6) such as long-duration energy storage (e.g. power-gas-power electrolytic hydrogen), new nuclear, carbon-capture-equipped capacity, and CDR technologies. This findings is qualitatively similar to other studies in the extant literature, though the decarbonization levels where such emerging technologies begin to deploy depend on regional factors, technology assumptions, and policies (Jenkins et al 2018, Sepulveda et al 2018, Bistline and Blanford 2020, Bistline and Blanford 2021b).

An important function of models is not only to provide decision support but to train mental models. Reduced-form temporal resolution models are shown here to exhibit potentially misleading relationships, which can suggest or reinforce inaccurate mental models about power systems decarbonization. These results highlight the need for corrections when simpler approaches are used and how much weight these side constraints and costs carry in terms of influencing model outcomes. Unlike other studies have suggested (Victoria et al 2021), it is prima facie unclear whether these corrections lead to over- or under-estimations of the economic potential of variable renewables and other resources, especially since the magnitudes and directions of change depend on model parametrizations (Merrick 2016).

SA and LCOE approaches do not capture renewable resource availability or correlations with load, and RD approaches perform better (though still may miss important features of the 8760 hourly distribution). Other aggregation approaches combine features of these methods (e.g. selecting subsets of periods in representative days), and although such simplifications should be explicitly evaluated using experiments similar to those in this paper, expected performance likely falls somewhere between the SA and RD approaches. Simplified methods miss intra-annual extremes that are important for resource valuation such as periods where load is high but wind and solar are low. This result aligns with analyses demonstrating how static capacity contributions for variable renewables (i.e. assuming that the fraction of available capacity during the peak residual load period does not vary based on the system composition or level of deployment) tend to build more wind and solar and less clean firm capacity (Baik et al 2021).

Simplified temporal aggregation approaches can understate the value of broader technological portfolios, firm low-CO$_2$ technologies, wind, and energy storage and can overstate the value of solar. There is a well-documented history of overstating costs and understating deployment of solar (Creutzig et al 2017, Nemet 2019, Victoria et al 2021). Given this historical track record, the finding in this analysis that low temporal resolution models overestimate solar’s value suggests that it will be challenging moving forward to determine whether a particular study is an overestimate or an underestimate of solar’s likely role. It will be particularly difficult to diagnose given that solar will likely be the lowest levelized cost resource for the foreseeable future, making long-run energy systems models especially important for assessing changes in value as the system composition changes.$^6$

Across the range of sensitivities examined here, errors from simplified temporal aggregation approaches increase with more stringent CO$_2$ targets, as very deep decarbonization heightens the importance of structural features in models to capture temporally resolved system operations and chronology across periods. An implication is that model differences that mattered less in the past for planning are increasingly influential as variable renewables, energy storage, and deep decarbonization become more important. Approximation accuracy also depends on assumptions about technological cost and availability: Differences across approaches are smaller when carbon removal is available and when renewables costs are lower. Variations across policy stringency levels and technology assumptions suggest that the accuracy of specific approaches is not guaranteed across all possible sets of input assumptions, which indicates that proposed methods should be compared under a range of scenarios.

5. Conclusion

Electric sector and energy systems models can be used to systematically assess decarbonization pathways, inform company strategy, conduct policy analysis, evaluate technology choices, and explore decisions under future uncertainties. This research investigates the impacts of common approaches to temporal aggregation on potential insights from such models under different assumptions about policies and technologies. Since temporal variability impacts the economics of power sector resources, inappropriate simplifications can generate errors in outputs of interest (e.g. investments, costs) and distort economic insights. This research highlights how model structure can matter as much as input assumptions for key planning decisions (Mai et al 2018, Jaxa-Rozen and Trutnevyte 2021).

These results help consumers of model outputs to interpret (and contextualize) findings and guide model developers in selecting a temporal aggregation approach. Net-zero policies and company goals make

$^6$ Conversely, global integrated assessment models have been criticized for their use of carbon removal technologies (Anderson and Peters 2016, Carton 2020). However, in light of the low temporal resolution of many of these models, the results in this analysis imply that some integrated assessment models could be underestimating carbon removal demand at least in the electric sector to address ‘last ton’ problems.
modeling these deep decarbonization strategies and high renewables systems increasingly important. Improving temporal resolution in long-term planning models can more appropriately value system resources, facilitate rapid decarbonization, and enable a more affordable and reliable electricity system.

Ultimately, acceptable levels of aggregation error and model complexity vary by analysis type, motivating question, system characteristics, and available resources for development and analysis (Merrick and Weyant 2019, Saltelli 2019). Differences may be critically important in some decision contexts or within acceptable tolerances for others. However, given the large expected roles of variable renewables and decarbonization in planning, many modelers should likely prioritize temporal resolution in model development. Although full hourly modeling is infeasible in many settings, these results indicate that RD approaches can preserve key features of higher resolution models with an order-of-magnitude reduction in dimensionality. More sophisticated selection methods and decomposition approaches are promising ways to accommodate additional levels of detail while remaining tractable (Scott et al. 2019, Merrick et al. 2021).

This analysis suggests a few opportunities for additional research. First, many models with simplified temporal aggregation recognize limitations of these approaches and add side constraints and costs. Future work should explicitly evaluate different types of corrections to determine which are most effective in different environments for replicating missing dynamics. Second, temporal resolution is only one dimension of model complexity in long-term planning tools, and modeling teams must constantly balance conflicting goals of maximizing the accuracy of information produced while minimizing model detail (Merrick and Weyant 2019). Future work should examine impacts of other important dimensions of model complexity (e.g. spatial resolution, uncertainty, sectoral coverage) and how design choices interact with temporal aggregation (Frew and Jacobson 2016). Third, subhourly resolution, inter-annual resource variability, and extreme events are increasingly important for characterizing resource adequacy but introduce computational challenges that require additional research to overcome (Zeyringer et al. 2018, Bistline 2021). Finally, unilateral technological portfolios are fragile given uncertainty in the planning environment not captured here, and future research should examine how parametric and structural uncertainties may impact planning (Bistline 2015, Yue et al. 2018).

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

The author would like to thank Geoff Blanford, Nils Johnson, and anonymous reviewers for their helpful comments. The author wishes to recognize the many subject matter experts who provided input to the analysis and assumptions, including John Larsen, Whitney Herndon, Erin Minear, Marcus Alexander, Robin Bedilion, Neil Kern, and Joseph Swisher. The views expressed in this paper do not necessarily reflect those of EPRI or its members.

Author contributions

J E T B conceived the study, developed the model, designed scenarios, and wrote the article.

Conflict of interest

The author has no financial or non-financial interests associated with the material in this manuscript.

ORCID iD

John E T Bistline @ https://orcid.org/0000-0003-4816-5739

References

Anderson K and Peters G 2016 The trouble with negative emissions Science 354 182–3
Baik E, Chawla K, Jenkins J, Kolster C, Patanakar N, Olson A and Long J 2021 What is different about different net-zero carbon electricity systems? Energy Clim. Change
Barron A, Fawcett A, Hafstead M, McFarland J and Morris A 2018 Policy insights from the EMF 32 study on U.S. carbon tax scenarios Clim. Change Econ. 9 1840003
Bistline J 2015 Electric sector capacity planning under uncertainty: climate policy and natural gas in the U.S Energy Econ. 51 236–51
Bistline J 2017 Economic and technical challenges of flexible operations under large-scale variable renewable deployment Energy Econ. 64 363–72
Bistline J 2021 Variability in deeply decarbonized electricity systems Environ. Sci. Technol. 55 5629–35
Bistline J and Blanford G 2020 Value of technology in the U.S. electric power sector: impacts of full portfolios and technological change on the costs of meeting decarbonization goals Energy Econ. 86 104694
Bistline J and Blanford G 2021a Impact of carbon dioxide removal technologies on deep decarbonization of the electric power sector Nat. Commun. 12 3732
Bistline J and Blanford G 2021b The role of the power sector in net-zero energy systems Energy Clim. Change 100045
Bistline J, Blanford G, Mai T and Merrick J 2021 Modeling variable renewable energy and storage in the power sector Energy Policy 156 112424
Bistline J, Cole W, Damato G, DeCarolis J, Frazier W, Linga V and Young D 2020 Energy storage in long-term system models: a review of considerations, best practices, and research needs Prog. Energy 032001
Bistline J, Hodson E, Rossmann C, Creason J, Murray B and Barron A 2018 Electric sector policy, technological change, and U.S. emissions reductions goals: results from the EMF...
Jayadev G, Leibowicz B and Kutanoglu E 2020 US electricity infrastructure of the future: generation and transmission pathways through 2050 Appl. Energy 260 114267
Jenkins J, Lake M and Thernstrom S 2018 Getting to zero carbon emissions in the electric power sector Joule 2 1248–510
Johnston J, Henriquez-Auba R, Maluenda B and Fripp M 2019 Switch 2.0: a modern platform for planning high-renewable power systems SoftwareX 10 100251
Kaufman N, Barron A, Krawczyk W, Marrs P and McJeon H 2020 A near-term to net zero alternative to the social cost of carbon for setting carbon prices Nat. Clim. Change 10 1010–4
Lamont A 2008 Assessing the long-term system value of intermittent electric generation technologies Energy Econ. 30 1208–31
Larson E, Greig C, Jenkins J, Mayfield E, Pascale A, Zhang C and Socolow R 2020 Net-Zero America: Potential Pathways, Infrastructure, and Impacts (Princeton, NJ: Princeton University)
Luderer G, Pietzcker R, Carrafa S, De Boer H, Fujimori S, Johnson N and Arent D 2017 Assessment of wind and solar power in global low-carbon energy scenarios: an introduction Energy Econ. 64 542–51
Mai T, Blanford J, Sun Y, Cole W, Marcy C, Namovica C and Young D 2018 The role of input assumptions and model structures in projections of variable renewable energy: a multi-model perspective of the U.S. electricity system Energy Econ. 76 313–24
Merrick J 2016 On representation of temporal variability in electricity capacity planning models Energy Econ. 59 261–74
Merrick J, Blanford J and Blanford G 2021 On representation of energy storage in electricity planning models (arXiv)
Merrick J and Weyant J 2019 On choosing the resolution of normative models Eur. J. Oper. Res. 279 511–23
Mileva A, Johnston J, Nelson J and Kammern D 2016 Power system balancing for deep decarbonization of the electricity sector Appl. Energy 162 1001–9
Mills A, Seel J, Millstein D, Kim J, Bolinger M, Gorman W and Wiser R 2021 Solar-to-Grid: Trends in System Impacts, Reliability, and Market Value in the United States with Data through 2019 (Berkeley, CA: LBNL)
Millstein D, Wiser R, Mills A D, Bolinger M, Seel J and Jeong S 2021 Solar and wind grid system value in the United States: The effect of transmission congestion, generation profiles, and curtailment Joule (https://doi.org/10.1016/j.joule.2021.05.009)
Nemet G 2019 How Solar Energy Became Cheap: A Model for Low-Carbon Innovation (London: Routledge)
Neumann F and Brown T 2021 The near-optimal feasible space of a renewable power system model Electr. Power Syst. Res. 190 106699
NREL 2020 2020 Electricity Annual Technology Baseline (ATB) (Golden, CO: NREL) (available at: https://atb.nrel.gov/electricity/2020/data.php) (Accessed 1 January 2021)
Orvis R 2021 A 1.5 Celsius Pathway to Climate Leadership for the United States (San Francisco, CA: Energy Innovation)
Pfenninger S, Hawkes A and Keirstead J 2014 Energy systems modelling for twenty-first century energy challenges Renew. Sustain. Energy Rev. 33 74–86
Phadke A, Paliwal U, Abhyankar N, McNair T, Paulos B, Wooley D and O’Connell R 2020 2035: Plummeting Solar, Wind, and Battery Costs Can Accelerate Our Clean Electricity Future (Berkeley, CA: Goldman School of Public Policy, University of California Berkeley)
Saltelli A 2019 A short comment on statistical versus mathematical model uncertainty Nat. Commun. 10 1–3
Santen N, Blanford J, Blanford G and DeLa Chesnay F 2017 Systems Analysis in Electric Power Sector Modeling: A Review of the Recent Literature and Capabilities of Selected Capacity Planning Tools (Palo Alto, CA: EPRI)
Scott I, Carvalho P, Botterud A and Silva C 2019 Clustering representative days for power systems generation expansion
planning: capturing the effects of variable renewables and energy storage Appl. Energy 253 113603
Sepulveda N, Jenkins J, De Sisternes F and Lester R 2018 The role of firm low-carbon electricity resources in deep decarbonization of power generation Joule 2 2403–20
U.S. EIA 2020 The Electricity Market Module of the National Energy Modeling System: Model Documentation 2020 (Washington, DC: U.S. Energy Information Administration)
Victoria M et al 2021 Solar photovoltaics is ready to power a sustainable future Joule 5 1041–56
Williams J, DeBenedictis A, Ghanadan R, Mahone A, Moore J, Morrow W and Torn M 2012 The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity Science 335 53–9
Wogrin S, Gallbally D and Reneses J 2016 Optimizing storage operations in medium- and long-term power system model IEEE Trans. Power Syst. 4 3129–38
Yue X, Pye S, DeCarolis J, Li F, Rogan F and Gallachoir B 2018 A review of approaches to uncertainty assessment in energy system optimization models Energy Strategy Res. 21 204–17
Zeyringer M, Price J, Fais B, Li P and Sharp E 2018 Designing low-carbon power systems for great britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather Nat. Energy 3 395–403