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Best Practice Modeling to Achieve Low Carbon Grids

Why Today’s Grid Planning Tools Fall Short and How New Approaches Can Lower Electric Costs and Increase Reliability

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Executive Summary

Transitioning to a zero carbon electricity grid is likely to be a multi-trillion dollar undertaking[1]. Nearly one in three Americans currently have difficulty paying their energy bills,[2] underscoring the importance of making this transition at least cost and ensuring that electric utilities, regulators and grid operators have the best possible analytical tools available to plan future energy resource investments.

Utilities use a type of tool called a capacity expansion model to plan least-cost portfolios of energy resources (including generation, transmission and energy storage) to meet forecasted energy demand and clean energy goals. Many of the models in wide use today are ill-equipped to cost effectively guide the transition to a low-to-zero-carbon grid because they were not designed to account for the variability of renewable energy resources from hour to hour over a year, or across multiple years.

In this study, we articulate our view of best practices that modelers can use to plan cost effective and reliable low carbon grids. This view is backed by leading academics and practitioners. We highlight some key limitations of many of the commercially available tools today, summarize research underscoring the costs of these issues, and point to methods that modelers should use to plan lower carbon, lower cost, more reliable grids. Finally, we summarize a case study using Form Energy's capacity expansion tool and data from one of Form Energy's commercial partners[3], to demonstrate the measurable cost and reliability benefits that best-practice modeling methods can bring to utilities and their customers. The case study underscores many of the major findings from academia.

Limitations of incumbent capacity planning tools

The capacity expansion models in wide use today were designed around a planning mindset that assumed that thermal power plants are predictable and available when needed. Thus, if the electric grid had enough resources to meet peak demand, the grid would be capable of meeting demand at any other time. These tools were also built in an era that lacked the computational power and analytical methods available today. As a result, the tools include certain simplifications to save computational time and analytic complexity. Most notably, legacy capacity expansion models:

1. **Design resource portfolios based on limited time samples:** Rather than make investment decisions based on a model of at least one full year, incumbent models design resource portfolios using a small sample of hours or days, and assume that this trimmed down time series accurately captures the full intra-year variability of renewable resources and storage.
2. **Design portfolios using 'typical' operating conditions:** Incumbent models optimize portfolios for using 'typical' weather data, relying on reliability models to ensure the resulting portfolios are reliable across weather conditions. However, renewable generation and demand varies significantly from year-to-year, and portfolios designed for a single snapshot are less cost effective and reliable than a portfolio designed for diverse grid conditions.

1 One recent cost estimate comes from Chloe Holden, 2019. The Price of a Fully Renewable US Grid: $4.5 Trillion.
2 U.S. Energy Information Administration, 2018. One in three U.S. households faces a challenge in meeting energy needs.
3 The case study relies on sensitive data. We have anonymized the data and partner identification as a result.

Capacity expansion model capabilities needed

Academic and industry progress in building new capacity expansion models has led to an emerging set of best practices about how to plan low carbon grids that rely substantially on renewables and storage. Where possible, capacity expansion models should:

1. **Make investment decisions based on at least one full year of grid operations at hourly resolution**, including weather and load variability that reflects day-to-day, week-to-week, and season-to-season fluctuations.
2. **Make investment decisions based on multiple weather years and key future system conditions**, such as technological availability, commodity prices, or other variables.

Incorporating this level of granularity often requires modeling trade-offs, and the academic literature points to advanced modeling techniques that can avoid the need to capture multiple years of weather and system data at 8,760-hour granularity. Where these techniques are employed, it's critical that their efficacy is benchmarked against the full granularity model. Despite the impact of model simplifications on planning outcomes, few commercial models today use the advanced methods pursued in academia and none provide any guarantee of the performance of the model simplifications employed.

The benefits of modern capacity expansion modeling

Lower Costs: Models that represent hourly grid operations and can co-optimize portfolios across multiple scenarios produce lower cost portfolios than models that use time sampling and typical weather years. Our case study confirms existing research and finds that, for one particular utility, full year, hourly resolution modeling produces portfolios that are more than 10% cheaper than time sampled portfolios.

Accurate Technology Representation: Models that preserve the full time chronology of a year can accurately model technologies like long duration energy storage, which can produce energy continuously over days and can shift energy across seasons. By contrast, models that break apart the year's chronology often can't accurately model such technologies. Time sampling techniques overestimate baseload value, underestimate flexibility value, and often exclude long duration storage technologies altogether.

Increased reliability: Full year, hourly resolution modeling and co-optimization across scenarios of future system conditions produces portfolios that are more reliable than those produced by less capable models that consider single snapshots of the future.

Introduction

The U.S. spends roughly $200 billion each year[4] on electricity generation to meet growing electric demand and to replace old power plants. These investments translate to costs for customers, and, if insufficient, the electric grid's reliability can suffer. Further, investments in new fossil fueled power plants can lock utilities into producing high levels of greenhouse gas emissions and causing other environmental and health damages that last decades. It is essential that decision makers make the best, most informed investments possible.

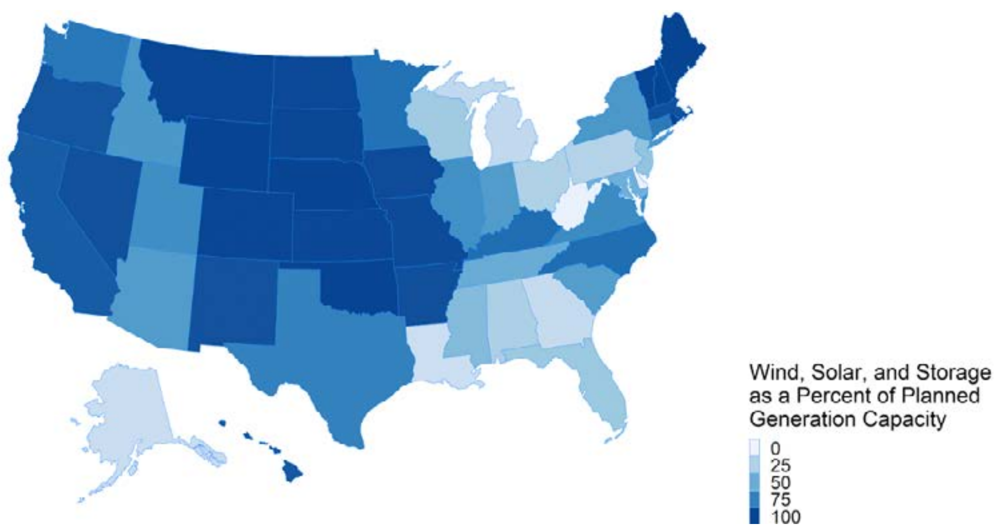
Electric utilities and their regulators rely on capacity expansion models — computer models that help utilities identify the least cost portfolio of power infrastructure investments needed to meet demand — as one of the primary tools to inform their investment decisions.[5] Unfortunately, the vast majority of the capacity expansion models used today were developed for electric grids with fossil fuel backbones and embed many assumptions that reflect this fact.

The power system is changing. In 2010, wind and solar contributed less than 2.4% of U.S. electricity generation capacity, but this quadrupled to 9.9% by 2019. Renewables and storage comprise the majority of planned power investments around the country, portending a continuation of these trends (see Figure 1). As the power sector transitions, the models utilities and developers use to guide their investment decisions need to adapt as well.

Study purpose

This study compares new, best-in-class capacity expansion modeling approaches with existing modeling tools to evaluate how their differences impact electric resource needs, portfolio costs and reliability in grids with high levels of renewables. The study reviews the current state of capacity expansion planning and highlights some of the primary shortcomings of these planning techniques. This paper then recommends capacity expansion modeling best practices drawn from academic and industry research. Finally, this paper summarizes a simple case study based on data from one of Form Energy's utility partners[6], to underscore the value of these recommendations.

Figure 1: Renewables and storage as a fraction of planned generation capacity by state



Data source: S&P Global Market Intelligence capacity in development

4 See Table 2.3 of the U.S. Energy Information Administration's Electricity Data for annual spend: https://www.eia.gov/electricity/annual/html/epa_02_03.html. See Table 8.3 for a breakdown of generation and other expense categories for Investor Owned Utilities: https://www.eia.gov/electricity/annual/html/epa_08_03.html

5 One of the first papers - if not the first paper - to apply computational optimization techniques to power system planning was published in 1957. Massé and Gibrat, 1957. Application of Linear Programming to Investments in the Electric Power Industry. Management Science. Vol. 3, No.2. https://doi.org/10.1287/mnsc.3.2.149

6 Form Energy has engaged in planning exercises with more than 100 utilities and asset owners and developers globally.

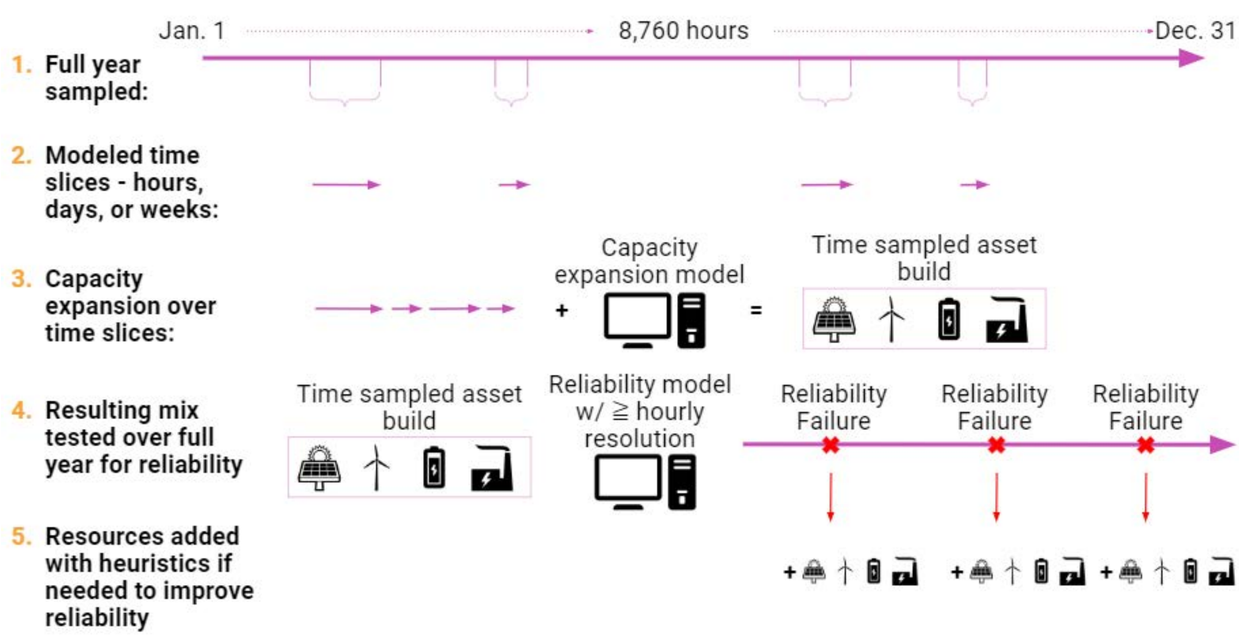
Incumbent Modeling Tools and Techniques

Historic Approach to Grid Modeling

The electric grid planning tools in wide use today were designed for an era when coal, natural gas, fuel oil and nuclear power plants were the grid's primary source of energy and the least-cost technologies available to meet growing electricity demand. Grid planning models were designed in service of a mindset that assumed that thermal power plants are predictable and available when needed, and thus if the electric grid had enough resources to meet the highest peak in demand, with an extra margin as an insurance policy, the grid would have enough capacity to meet energy demand in all other hours of the year. These tools were also built in an era that lacked the computational power and analytical methods available today. As a result, the tools were structured using certain simplifications to save computational time and analytic complexity.

The historical process for grid planning is summarized in Figure 2, and the key simplifications are described in the subsequent subsections. The process starts with reducing a single year or multiple years down to a few time slices and determining the least cost set of investments required to meet demand across these time samples (steps 1-3). The resulting portfolio is then run through a model with much higher time resolution and a larger number of weather and system conditions, often referred to as a production cost model, risk model, or reliability model. Models, or simple rules of thumb, are used to determine any new investments required to patch up any reliability failures encountered (steps 4-5).

Figure 2: The historical approach to grid planning



Investment Modeling Versus Operational Modeling

While production cost models are often run hourly, today's commercial planning models almost always perform the crucial capacity planning step — where the bulk of investment decisions are made — with only a small number of time slices. Our review of the literature and our case study will show the extreme impact that this discrepancy can have on the perceived value of renewable energy and energy storage.

The Need for Model Simplifications

Grid planning models need to include tens to hundreds of millions of variables to fully capture the electric grid's myriad uncertainties, such as future load levels, generation availability, commodities prices, transmission and distribution availability, and the detailed operational characteristics of grid assets. This means that grid modelers need to strike a balance between simplifications to reduce computational complexity and sufficient nuance to meaningfully inform utilities' electricity infrastructure investments.

Common Capacity Expansion Simplifications: Reduced Time and Typical Years

1) Few sample hours and days

Capacity expansion models tend to shy away from modeling the full complexity of a year: instead of modeling every hour of the year, they use only a few sample hours or days to represent an entire year of electric grid operations. Table 1 highlights some of the time sampling simplifications used in open source and proprietary commercial models. This simplification limits the models' ability to represent weather events that can span multiple days to weeks, the variability of renewable generation from day-to-day and season-to-season, and the services that technologies like energy storage can provide across time horizons.

Table 1: Time sampling methods in a selection of commonly-used capacity expansion models

Model	Time treatment
NREL ReEDS[7] [open source]	17 hours
EIA NEMS[8]	9 hours
BNL MARKAL[9]	9 hours
UC Berkeley SWITCH[10]	144 hours
ABB Capacity Expansion[11]	84 days
Energy Exemplar Aurora[12]	104 days, every-other-hour resolution

7 *See the method outlined in:* Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018.
8 *See the method outlined in:* The National Energy Modeling System: An Overview 2018.
9 *See the method outlined in:* Documentation for the MARKAL Family of Models.
10 *See the method outlined in:* Nelson et al., 2012. High-resolution modeling of the western North American power system demonstrates low-cost and low-carbon futures. Energy Policy.
11 *See the method outlined in:* Integrated Resource Plan of Southern California Edison Company. September 1, 2020.
12 *See the method outlined in:* San Jose Clean Energy 2020 Integrated Resource Plan. September 1, 2020.

2) Limited representation of year-to-year weather and load variability ('typical' years)

Today's commercial capacity expansion models typically design least-cost resource portfolios to meet demand from a small time sample from a single year's weather characteristics and energy demand. For example, NREL's ReEDS model uses the 2012 weather year as the basis for all generation and load profiles.[13] Grid planners then use other methods (production cost models, for example) to ensure that a portfolio is reliable across a more diverse set of conditions. When these models encounter reliability failures resulting from weather or system conditions not captured in the capacity expansion model, they add capacity to improve reliability. The result is a portfolio that is far from least-cost for the full range of conditions that can and do occur. Utilities across the U.S. use combinations of capacity expansion and reliability models to inform the design of their portfolios.

These simplifications were reasonable when fossil-fueled generation was the primary source of existing and new capacity, but when used to plan for a future with high levels of variable renewable resources, they risk producing portfolios that are both higher cost and less reliable than expected.

This process can be improved by incorporating diverse weather years and grid conditions into the portfolio design (i.e. capacity expansion) stage, co-optimizing the resource portfolio across these diverse futures. It is computationally infeasible to incorporate all possible grid futures into a single model, but it is possible to design across a limited subset of factors that will drive the biggest changes in investment decisions. These factors include renewable generation profiles and technology cost, commodity costs, and demand levels. These more robust resource portfolios can then be more deeply analyzed in a reliability model, ideally resulting in fewer resources added with rules of thumb (Step 5 in Figure 2). This ultimately results in lower cost, more reliable systems than those designed based on single test years.

Effects of Model Simplifications

Academic and industry research has proven that it is necessary to model the grid with sufficient time granularity and system variability to achieve low cost, reliable portfolios with high levels of renewables and storage. As governments and utilities have set increasingly ambitious decarbonization targets, modelers have increasingly focused on how to appropriately plan investments to meet these targets. The following sections highlight the lessons learned about the pitfalls of incumbent modeling techniques from scholars in the field of deep decarbonization planning.

1) Limited Time Sampling Produces Inaccurate Resource Mixes in High-Renewables Grids

Time sampling a small fraction of the year changes the mix of assets — i.e. wind, solar, storage, etc. — that models select to minimize costs and meet reliability needs. Several studies have shown that limited time sampling overestimates the need for baseload generation, underestimates curtailment of renewables, and underestimates needs for flexibility options.[14] As a result, the resource portfolios that incumbent modeling tools select, and the investment signals they create, are unlikely to realistically meet renewable energy targets. Echoing these findings, a study from Lawrence Berkeley National Laboratory researchers found that time sampling methods underestimated total capacity needs, but overestimated baseload capacity needs.[15] Similarly, in an analysis of Chile's electricity system, scholars[16] found that high temporal resolution and inclusion of diverse system conditions in capacity expansion modeling increased the optimal installed capacity of storage by more than one order of magnitude and led to a lower cost, more reliable system.

13 See the method outlined in: Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018.

14 See: 1) Poncelet et al., 2016. Impact of the level of temporal and operational detail in energy-system planning models. Applied Energy, https://doi.org/10.1016/j.apenergy.2015.10.100. And 2) Gustavo Haydt et. al, The relevance of the energy resource dynamics in the mid/long-term energy planning models, Renewable Energy, 2011; 36:3068-3074, https://doi.org/10.1016/j.renene.2011.03.028. And Mallapragada et al., 2018. Impact of model resolution on scenario outcomes for electricity sector system expansion. Energy, https://doi.org/10.1016/j.energy.2018.08.015.

15 Nicolosi, M, The importance of high temporal resolution in modeling renewable energy penetration scenarios, 2011; 9th Conference on Applied Infrastructure Research, Berlin, https://escholarship.org/uc/item/9rh9v9t4

16 Diaz et al., 2019. The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies. Renewable and Sustainable Energy Reviews; 112: 797-812, https://doi.org/10.1016/j.rser.2019.06.002.

Historically, modelers have used limited time samples in order to more accurately capture other techno-economic details such as the ramp rates and starting and stopping conditions of generators. However, research published in the journal Applied Energy found that, when it comes to high renewables grids, using detailed time series is more important than accounting for potential variations in techno-economic assumptions.[17]

2) Limited Time Sampling Methods Fail to Accurately Model Long Duration Energy Storage

Multi-day and long duration storage are emerging technology categories that hold the promise of cost-effectively supporting the reliability of high renewable grids during days or weeks of low renewable energy output. However, many models use time sampling techniques that break time into independent chunks with no, or limited, inter-period connection, which underestimates system costs and artificially limits the perceived value of long duration energy storage technologies such as electrolytic hydrogen, pumped hydropower, and many others.[18] While some models use methods that attempt to make time sampling suitable for storage, a recent study published in Applied Energy found that all time sampling methods — whether using typical days (24 hours), three day periods (72 hours), or week-long periods (168 hours) — underestimated the optimal installed capacity of long duration storage. In fact, only the week-long time sampling method was able to capture any long duration storage value and include long duration storage in a least cost portfolio;[19] nonetheless, even week-long samples undervalued long duration storage relative to the full time series modeled system.

3) Modeling Limited Weather and System Variability Misrepresents Resource Needs and Costs

Multi-year weather variability can significantly impact the design and operation of renewable-heavy grids. Planning models that consider only one or a few years of weather data can produce substantially different estimates of the least cost mix of renewable energy. In a 2013 study of the United Kingdom (U.K.) power system, researchers found that optimization models based on different years of weather data could produce wildly different results, and that optimizing over multiple weather years was necessary to accurately capture the value of wind.[20]

The failure to capture multiple weather years also impacts perceived needs for flexible resources, even in grids with moderate levels of renewable resources. A recent study in Nature Energy[21] assessed the impact of modeling a single weather year versus multiple weather years on the design of the U.K. power system, and found that in a 50% renewable system, needs for energy storage capacity and other flexible generation varied by 40% depending on the weather year modeled. The authors found that using only one year of weather data can result in systems that frequently lack sufficient resources to meet energy demand over the course of multiple years. A recent study from scholars at the California Institute of Technology, Stanford, and the University of California at Irvine found that capacity expansion models using six years of weather and load data led to almost double the long duration storage in the least cost mix compared to models with only a single year.[22]

17 Poncelet, K et. al, 2016. Impact of the level of temporal and operational detail in energy-system planning models, Applied Energy;162: 631-643.
18 See Nahmmacher, Paul et. al, Carpe diem: A novel approach to select representative days for long-term power system modeling, Energy, 2016;112:430-442, https://doi.org/10.1016/j.energy.2016.06.081. And Modeling hourly electricity dynamics for policy making in long-term scenarios: https://doi.org/10.1016/j.enpol.2011.06.062
19 Kotzur et al. Time series aggregation for energy system design: Modeling seasonal storage. Applied Energy 2018;213: 123-135. https://doi.org/10.1016/j.apenergy.2018.01.023
20 Pfenninger. Dealing with multiple decades of hourly wind and PV time series in energy models: a comparison of methods to reduce time resolution and the planning implications of inter-annual variability. Applied Energy (2017);197:1–13. http://dx.doi.org/10.1016/j.apenergy.2017.03.051.
21 Zeyringer, M., Price, J., Fais, B. et al. 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 (2018). https://doi.org/10.1038/s41560-018-0128-x
22 Dowling et al., 2020. Role of Long-Duration Energy Storage in Variable Renewable Electricity Systems. Joule; 4: 1907-1928, https://doi.org/10.1016/j.joule.2020.07.007.

Failing to optimize resource portfolios across multiple weather years can lead to a failure to reach imposed decarbonization targets and can underestimate the cost of reaching those targets. Researchers from University College Cork, ETH Zurich, and Imperial College London[23] found that generation portfolios designed with individual weather years led to higher costs of meeting decarbonization targets than portfolios designed by accounting for diverse weather conditions.

Because storage acts as a hedge against future uncertainties, optimizing across uncertainties can uncover greater storage value. In an analysis of Chile's electricity system, scholars[24] found that optimizing across uncertain fuel prices lead to greater renewables and storage, and note that "failing to appropriately upgrade [capacity expansion] models may lead to a significant underestimation of [renewable] integration costs and risks, misleading relevant decisions in policy, regulation, market design."

23 Seán Collins et al., 2018. Impacts of Inter-annual Wind and Solar Variations on the European Power System, Joule; 2: 2076-2090, https://doi.org/10.1016/j.joule.2018.06.020.

24 Diaz et al., 2019. The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies. Renewable and Sustainable Energy Reviews; 112: 797-812, https://doi.org/10.1016/j.rser.2019.06.002

New Modeling Capabilities Needed to Achieve Low Carbon Electric Grids

Fortunately, academics and businesses have made progress in building new models to better accommodate new clean energy resources, and a set of best practices is emerging about how to plan for low carbon grids that rely heavily on intermittent renewables and storage: grid planning models must be able to capture the variability of renewable resources, demand, and grid conditions—and the impacts that this variability has on system operations and design—over days, weeks, and even years.

Capabilities Needed: Detailed Chronology and System Variability

1) Full Year Representation at Hourly Resolution

Capacity expansion models should ideally capture the hour by hour dynamics of renewable generation, load, and storage for at least one year. Full hourly granularity can require other modeling tradeoffs, such as lower technological or spatial detail. Where these details are critical, it may be valuable to explore high quality methods to reduce temporal granularity. There are advanced methods that can substitute for full year, hourly resolution, but it is critical these methods are robustly tested to guarantee they can capture all necessary grid dynamics.[25] This testing is not common for today's commercial tools.

In a simple case study below, we show that modeling the grid with full year, hourly resolution results in resource portfolios that are lower cost and more reliable than portfolios that emerge from reduced form models, underscoring the findings of the academic community.

2) Co-optimization Across Diverse Weather and System Conditions

Models should be able to identify the least-cost resource portfolio that satisfies grid reliability requirements under a wide range of potential scenarios. The most critical uncertainties are weather-driven renewable resource availability and load events, but other critical uncertainties may include technology cost and availability, and fuel cost and availability. This differs from the typical approach of developing a resource portfolio based on 'typical' weather and load conditions. In a renewable energy-centric electric system in which energy demand and energy supply are both highly sensitive to weather variability across seasons and years, and where future technology costs remain uncertain, co-optimization is a powerful technique to help grid planners build resource portfolios that are likely to meet their cost and reliability goals under a range of future grid conditions.

The combined capability to perform co-optimization and model full year hourly grid operations can significantly improve the overall cost and operational effectiveness of planned power systems. However, outside of a small group of models, these methods are not widely adopted in commercial planning models today. Unless incumbent models evolve or utilities switch to using models better suited for grids with high levels of renewable energy and energy storage, there's a risk that outdated models will guide utilities to invest in a suboptimal mix of assets, increasing costs by tens to hundreds of millions of dollars, jeopardizing reliability, and excluding key emerging technologies like long duration storage.

25 See, e.g., Kotzur et al., 2018, footnote 11.

Table 2: Next-generation capacity expansion models capable of full year, hourly resolution and/or co-optimization

Model	Time treatment	Scenario Co-Optimization
Vibrant Clean Energy WIS:dom	Proprietary, configurable to full year, hourly resolution or greater	Proprietary, but captures diverse weather conditions
University of Hawaii Switch 2.0 [open source]	Configurable to full year, hourly resolution or greater	Configurable to capture diverse weather & system conditions
MIT/ Princeton GenX [soon to be open source]	Configurable to full year, hourly resolution or greater	Configurable to capture diverse weather & system conditions
Form Energy Formware™	Configurable to full year, hourly resolution or greater	Configurable to capture diverse weather & system conditions

Case Study: Advanced Modeling Techniques in Practice

To evaluate how the modeling best practices we highlight above may impact utility portfolio planning in practice, we designed a set of case studies to quantify the benefits of grid planning using full year, hourly resolution modeling and co-optimization compared to conventional modeling approaches. These case studies build upon our review of capacity expansion modeling best practices and our experience working with utilities and project developers across the power sector. We sourced data and select assumptions from one of Form Energy's utility partners. We've normalized and anonymized aspects of the data in light of its sensitivity. We then used Formware™ — Form Energy's proprietary capacity expansion modeling tool — to design least cost portfolios of generation and storage resources under a variety of futures.

The cases analyzed do not represent our partner's exact planning assumptions; rather, the cases represent realistic planning assumptions with real-world data while exploring the impact of common modeling assumptions. These case studies are simplified and modified versions of the scenarios we analyze with our partners.

Our results confirm the findings of academic and industry literature. First, capacity expansion models with full year, hourly granularity lead to lower cost systems than models that are less granular. Second, models that don't capture the full degree of system variability run the risk of excluding certain technologies from the chosen asset mix based purely on modeling assumptions, rather than on system needs. Third, our results underscore the fact that including diverse weather and system conditions into the design of resource portfolios lowers system costs and increases reliability relative to test year designs.

Study Design

Like many U.S. utilities, our partner's portfolio today consists of coal and gas generation with a significant and growing share of renewable resources. When we began working together, our partner's portfolio was majority thermal resources (a mix of coal and gas), complemented by roughly 30% wind power (as a fraction of peak demand). The technology options we evaluated include short duration storage, long duration storage, and wind. The resource costs and other attributes considered are depicted in Table 3.[26]

Table 3: Technologies modeled and their attributes

Attribute	Lithium ion		Long Duration Energy Storage (LODES)		Wind	
	Low	High	Low	High	Low	High
Energy Capex [$/kWh]	$85	$155	$3.75	$11.50	NA	NA
Power Capex [$/kW]	$280	$515	$330	$1,275	$1,125	$1,125
Design Duration[27] [hours]	1-100	1-100	100-200	12-48	NA	NA
Round Trip Efficiency [%]	85%	85%	45%	49%	NA	NA
OpEx [$/kW-yr]	$5	$20	$30	$42.50	$34	$34
Lifetime [years]	25	25	25	25	25	25

26 See the Methodology section for more details on cost derivations. These costs are not intended to represent Form Energy's technology.

27 Design durations reflect the durations that Formware is able to select in the least-cost mix. The range of design durations reflects the fact that certain costs and performance attributes scale as a battery's duration scales, while others do not. As a result, the cost and performance parameters for a 24-hour battery can differ from a 100-hour battery. A 100 hour minimum design duration makes the technological costs in the low cost scenario possible.

The Benefits of Full Year, Hourly Resolution Modeling Compared to Limited Time Sampling

We designed three cases to highlight the potential impact of time sampling methods compared to modeling grid operations over a full year of 8,760-hour operations:[28]

- 8760 Case: Designs generation and storage portfolios using full hourly resolution of forecasted load and renewable generation (using 2030 load and simulated 2011 wind data).[29] Does not use any time sampling.
- Time Sampled Case: Modeled: Uses a time sampling technique based on a method developed by the National Renewable Energy Laboratory (NREL), which estimates resource needs and costs over a subset of five days meant to represent the average winter, spring, summer, and fall day, as well as the peak day, for a total of 120 hours, and scales those results to reflect annual demand. This time sampling method closely mimics NREL's Regional Energy Deployment System (ReEDS) model, and is covered in more detail in the technical appendix.
- Time Sampled Case: Achieved: Extracts the resource portfolio of wind and storage from the Time Sampled Case: Modeled, and operates these assets over the entire year with hourly resolution. This case reflects the true cost of the Time Sampled Case.

Time sampling predicts low costs but results in higher actual costs than full year, hourly resolution modeling

Figure 4 shows the levelized costs for each of the three cases, with cost ranges reflecting the low and high technology cost estimates from Table 1. The time-sampling method results in a resource portfolio that appears to have low levelized system costs (Time Sampled Case: Modeled). However, when this resource portfolio is operated over a full year, the portfolio's true costs far exceed the modeled costs (see Time Sampled Case: Achieved).

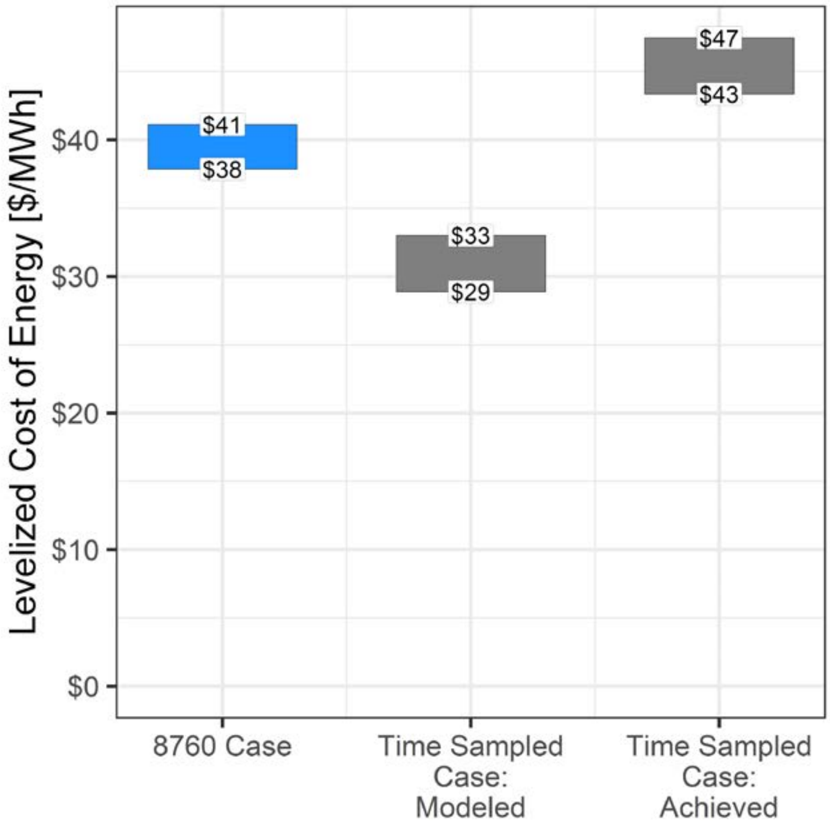
There are two main drivers of these higher costs. First, in the Achieved case, fossil fuel plants run more frequently than the Modeled case predicts, as wind and short duration storage resources are less firm than expected. Second, there is a small amount of lost load (representing 0.01% of demand). Third, the Time Sampled cases install a significant amount of wind and short duration capacity, which is ultimately under-utilized. The result is that the time sampling model predicts low operational costs, but achieves relatively high operational costs. The results show that a portfolio designed using a full year's 8,760-hour time horizon from the outset (the 8760 Case) results in lower levelized costs in practice.

Small differences in levelized costs translate into huge costs to customers. **The $5/MWh difference in levelized costs between the 8760 Case and the Time Sampled Case: Achieved (as shown in Figure 4) results in $27 million in savings per gigawatt of peak demand per year.**

28 See further details in the Methods section.

29 2011 was the most typical wind year between 2000 and 2018 in the region we analyzed. We explore multiple wind years in the following sections.

Figure 4: Levelized cost by scenario



Time sampling undervalues technologies that can shift energy over long time periods

It is intuitive that modeling techniques that consider only a subset of days or hours of a year and that do not capture the grid's continuous operations over long sequential periods will fail to accurately consider needs for technologies, like long duration energy storage, that have the ability to shift energy or demand over long time periods. The case study below quantifies this dynamic. It shows how the choice of modeling approach — full year, hourly resolution modeling compared to time sampling — significantly affects the mix of resources models select as part of a least-cost portfolio. We focus on long duration energy storage in this case study, but time sampling broadly undervalues resources that provide flexibility, as the academic literature highlighted in this paper shows.

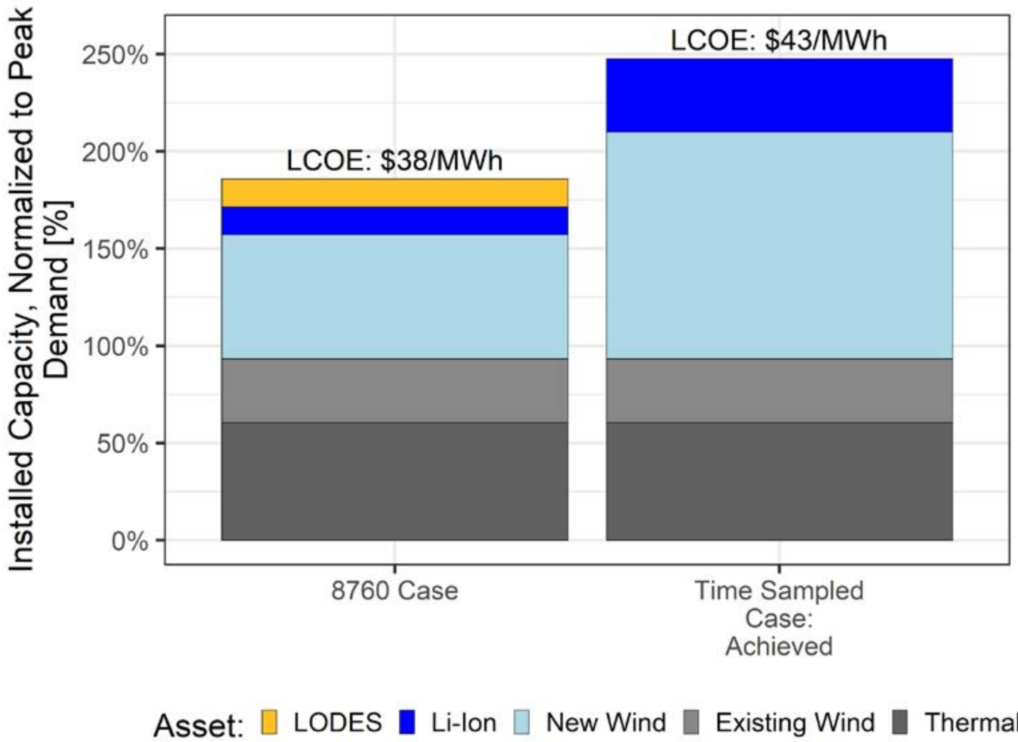
Figure 5 illustrates how time representation in models affects the resource portfolios models select.[30] **The time sampled cases completely exclude long duration storage, whereas the 8760 Case selects a significant amount of long duration storage (nearly 20% of peak load), a difference attributable entirely to modeling techniques rather than resource value.** This is due to the fact that the Time Sampled cases break the chronology between modeled days, finding little value in storage that stores energy over many days.

Likewise, the Time Sampled Case: Modeled selects twice the wind capacity as the 8760 Case, an outcome that in practice can have significant secondary effects on perceived land use impacts and needs for new transmission infrastructure to support excess renewable capacity. The over reliance on wind and short duration storage in the Time Sampled cases is due in part to the fact that the time sampling method creates average daily profiles of renewable energy production.[31] Profile averaging makes the wind energy

30 The Time Sampled: Modeled and Time Sampled: Achieved cases have the same asset builds by design.
31 This mimics the method in NREL's Regional Energy Deployment System (ReEDS) model, although ReEDS employs other methods to address excessive reliance on renewables. For example, ReEDS uses heuristics to estimate the "capacity value" (an estimate of the reliability of the asset) of renewables and other resources, and sets constraints requiring the model to procure resources that sum to a sufficient level of capacity value.

appear firm and masks real-world events when wind output may be low over periods longer than a day. As a result, the Time Sampled model finds significant opportunity to charge shorter duration batteries with what appears to be low cost, always available energy within the day. In fact, when the full year is examined at hourly resolution, we see several multi-day low wind stretches occur that render short duration storage insufficient (see, for example, Figure 6).

Figure 5: Resource portfolio by scenario (low cost case)[32]



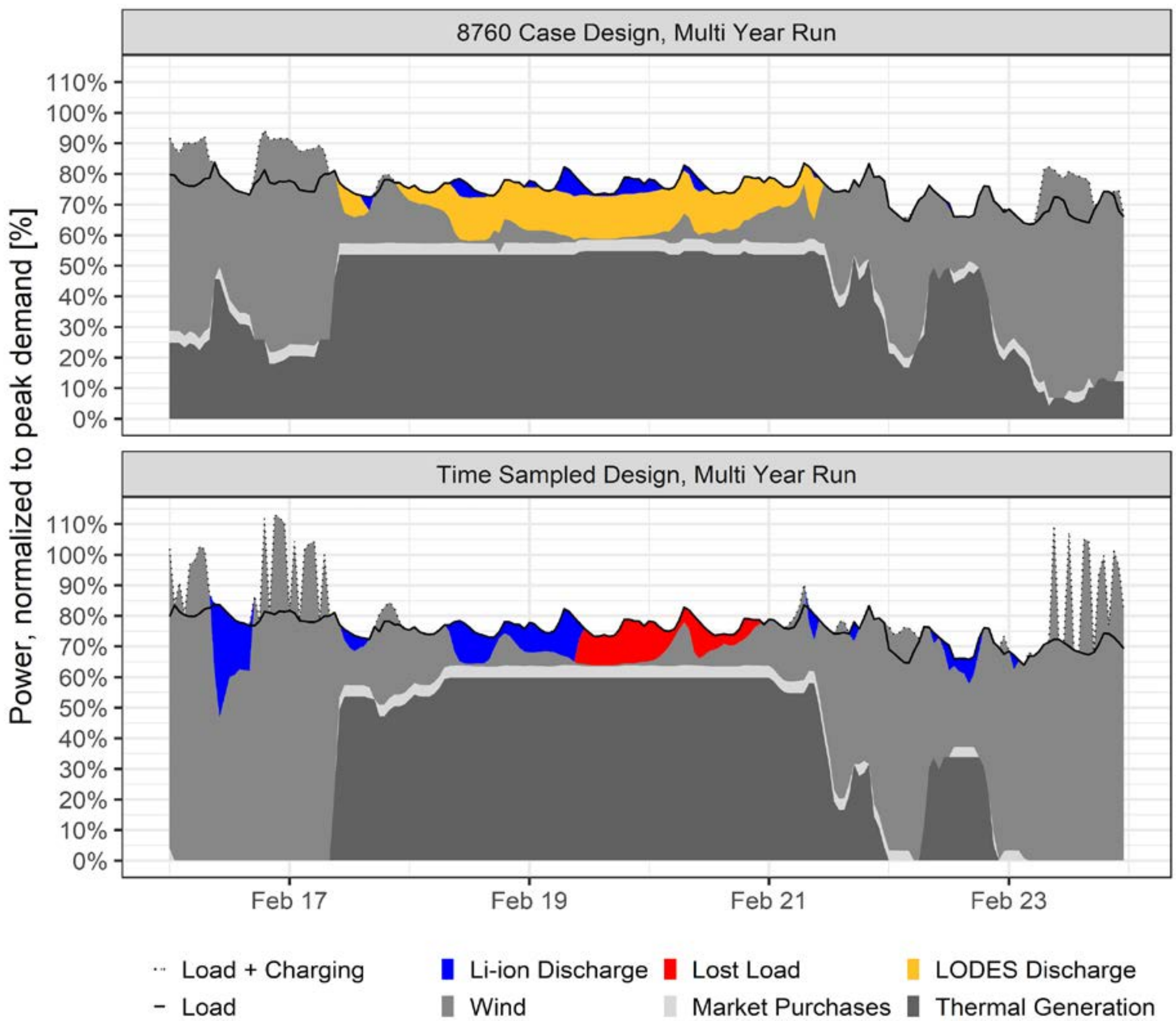
Time sampling produces portfolios that are less reliable than expected

Time Sampled portfolios are often less reliable than expected when exposed to the diverse system conditions that can occur over a full year. To test the reliability of a Time Sampled portfolio we simulated the operations of the resource portfolios from the 8760 Case and the Time Sampled Case over three weather years: 2010, 2011, and 2014. In the geography analyzed, 2010 was a relatively low average wind production year among the 2000 to 2018 period examined; 2011 had typical wind patterns; and 2014 had relatively high production wind patterns.

Figure 6 shows how the portfolios from the 8760 Case and the Time Sampled Cases perform during a roughly 5-day period with low wind output in February 2010. Due to its inclusion of long duration energy storage, the 8760 Case portfolio is able to meet load and maintain grid reliability across the entire period of low wind output. However, the Time Sampled cases experience nearly two days of lost load. **This demonstrates the risk of relying on models that perform time sampling: they are incapable of accurately capturing the links between days, and thus the operational challenge of meeting load over successive days of low renewable energy output.** As a result, they have a structural bias: they undervalue needs for firm, flexible, dispatchable resources that can deliver energy over successive days, and they discount the risk of having insufficient renewable generation to recharge daily-cycling lithium-ion storage from one day to the next.

32 The high cost results follow a very similar pattern, and are shown in the Appendix.

Figure 6: Asset operations over a select one week period, low cost case



To prevent these multi-day outages from occurring, grid planners typically pair legacy capacity expansion tools with separate reliability models that can simulate system operations across full 8,760-hour annual grid operations over multiple weather years. When the traditional two-step capacity expansion plus reliability assessment process identifies that portfolios have an unacceptable risk of lost load, the reliability model will add additional assets outside of the least-system-cost framework until the modeled system reaches the desired reliability target. Because these assets are added without least-cost optimization, the result is a higher cost system than what would arise if least-cost optimization were conducted while modeling full 8,760-hour grid operations. By incorporating diverse weather conditions into the optimal resource portfolio design step, more advanced capacity expansion tools such as Formware can dramatically reduce the need for reliability models to add capacity with heuristics, rather than optimization.

The value of co-optimization

Power system planners face many uncertainties beyond the availability of renewable generation: future commodity prices, electricity demand, technology costs, transmission availability, and other factors can impact the mix of resources that capacity expansion models select in a least-cost optimization. To account for these uncertainties, incumbent capacity expansion models take one of two approaches: 1) ignore uncertainties and design a system around a single set of assumptions (referred to as a “test year”); or 2) perform sensitivity analyses to examine the effects of uncertainties, and then rely on judgment to choose which uncertainties to incorporate in reliability models.

Ideally, grid planners should have access to a third and better option: modeling tools with the ability to develop a single portfolio that is co-optimized across a range of uncertain future scenarios. This approach has the potential to result in a portfolio that is least-cost across a range of future grid conditions and uncertainties and is therefore less likely to result in stranded costs and avoidable reliability risks.

Co-optimization comes at a cost: it is more computationally intensive and complex than single-scenario optimization. It is infeasible to incorporate all possible future conditions and their probabilities of occuring into the portfolio design step. However, co-optimization is feasible when applied to a subset of scenarios that are likely to have major impacts on grid reliability and cost.

To demonstrate the potential value of co-optimization relative to a typical "test-year" approach, we designed a simple case study that co-optimized the utility's resource portfolio across different weather years and future system conditions. Specifically, we considered the following conditions:

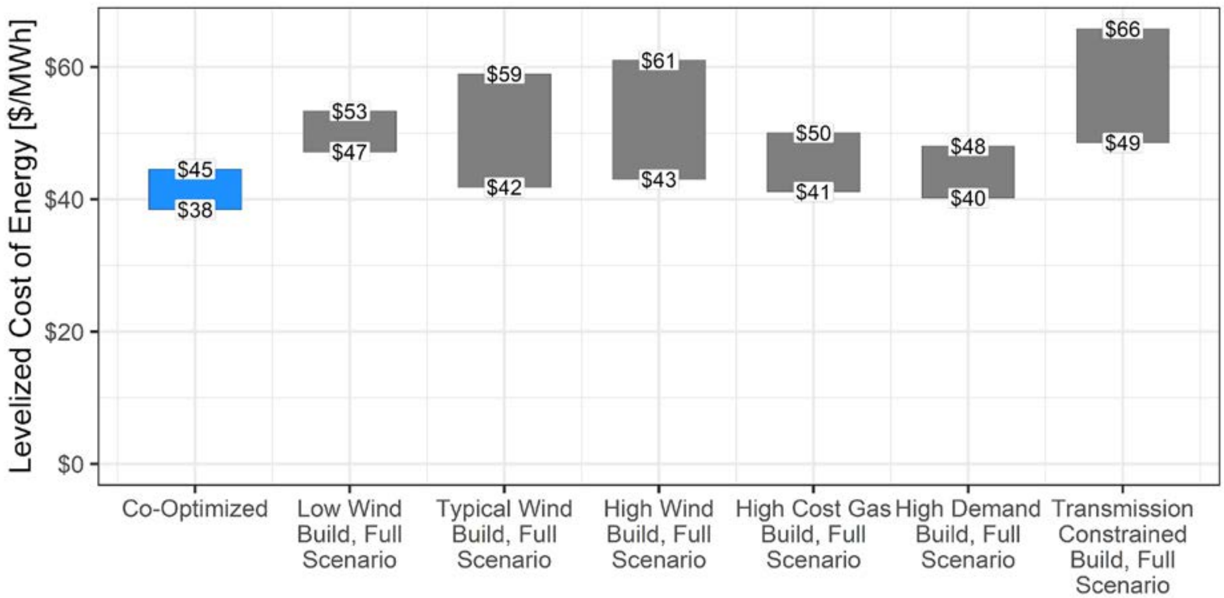
- Weather years:
  - Low wind (2010 wind data)
  - Typical wind (2011 wind data)
  - High wind (2014 wind data)
- System uncertainties:
  - High gas prices ($5/MMBtu in 2030, compared to the $3/MMBtu base forecast)
  - High demand (a 25% increase in annual demand over the 2030 base case)
  - Limited transmission availability (transmission can only deliver additional wind equivalent to 30% of the utility's peak load)

We first developed a case in which we co-optimize the resource portfolio across the six conditions described above.[33] We then developed optimal resource portfolios for each of the above system conditions individually, and operated each of these single-scenario-designed portfolios across all of the scenarios to arrive at their true levelized cost of energy. We did not use any time sampling in these model runs; each portfolio was developed using a full 8,760-hour time series of load and generation.

Figure 7 shows the levelized costs from these model runs, which demonstrate that co-optimization results not only in the least-cost system, when considering all possible futures, but it also results in the lowest spread across high and low cost resource scenarios.

33 For simplicity, we assumed equal probabilities of these futures rather than expected probabilities. In practice, the expected probabilities of different weather years and events can easily be incorporated, as well as more subjective probabilities such as the likelihood that a new industrial facility (i.e. large incremental load) or transmission line will be built.

Figure 7: Levelized cost by scenario: comparing co-optimization with a test year approach



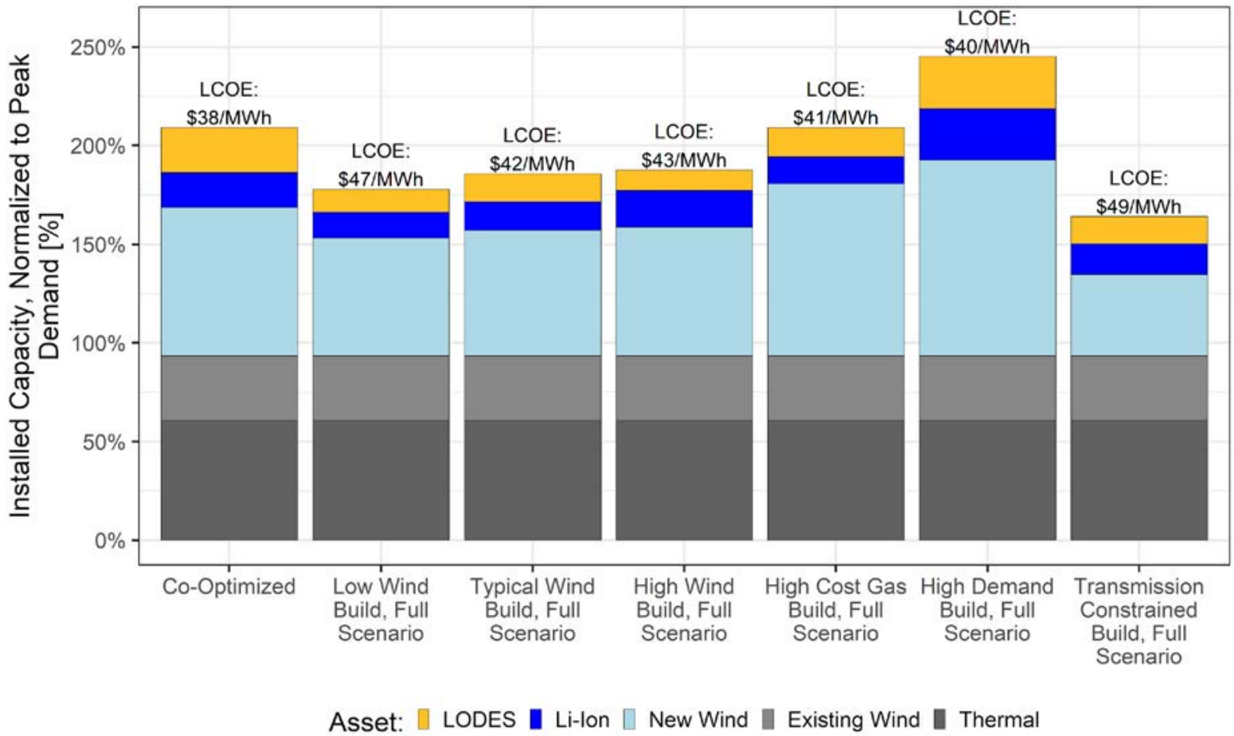
Similar to the time sampling cases shown above, small changes in levelized costs result in tens of millions of dollars in additional costs to consumers. The asset builds from the six scenarios plus co-optimization across these scenarios are shown in Figure 8. Co-optimization finds there is higher value in technologies like long duration storage that provide flexibility, as these technologies act as a hedge against diverse futures. This result echoes the academic literature, which highlights the risk mitigation value of long duration storage.[34]

There are two key drivers of higher costs in the non-co-optimized cases. First, smaller zero carbon resource portfolios lead to heavier reliance on the utility's existing fleet of thermal resources, including in some cases heavy reliance peakers that are costly, relative to the remainder of the utility's fleet. Second, smaller resource portfolios lead to less reliable operations during periods of low wind or high demand; as modeled, reliability failures come at a cost of $9,000/MWh[35], meaning that a few MWh of lost load can add up in cost quickly. This also explains why the portfolio that is closest in cost to the co-optimized portfolio is built to handle the high demand scenario.

34 In particular, see: Diaz et al., 2019. The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies. Renewable and Sustainable Energy Reviews; 112: 797-812, https://doi.org/10.1016/j.rser.2019.06.002.

35 See the Appendix for context on this number.

Figure 8: Resource portfolio by scenario (low cost case)36



36 The high cost results follow a very similar pattern, and are shown in the Appendix.

Recommendations

Given the current pace and scale of the electric grid's transformation, we encourage utility regulators, utilities, and independent system operators to act swiftly to adopt best-in-class modeling approaches. This single action is likely to lower system costs and lower reliability risks as renewable and zero-carbon resources increasingly replace existing fossil-fueled resources. We suggest minimum modeling capabilities grid planners should adopt, steps grid planners can take to smoothly transition to using new modeling approaches, and broader investments in modeling tools and studies that are needed to build industry consensus about best-in-class approaches to modeling low-carbon electric grids.

Best Practice Modeling Capabilities

We recommend that grid planners ensure that the capacity expansion modeling tools they use have certain minimum capabilities:

- **Full Year, Hourly Resolution:** Models should be able to represent at least one full year of hourly grid operations (an 8,760-hour time horizon) to accurately capture the effects that varying demand and renewable generation have on future resource needs and reliability. Increasing temporal granularity can require some modeling tradeoffs. Where making these tradeoffs is unacceptable, some advanced time sampling methods can be used, if the model can demonstrate that the resource portfolios produced reasonably match the resource portfolios from a full time series model.[37]
- **Co-Optimization Across Diverse Weather and System Conditions:** Models must have the ability to develop a single portfolio that reflects the least-cost resource mix across multiple scenarios of future grid conditions - most critically, across weather futures that account for real but atypical weather conditions. Without this capability, capacity expansion models are unlikely to result in portfolios that remain least-cost as weather, technology costs, energy costs, and energy demand evolve in uncertain ways.

Process to Transition to New Modeling Capabilities

Grid planners should invest in a transparent step-wise process to examine existing modeling practices, compare these practices against new modeling capabilities, and transition to adopting new modeling approaches where needed.

Step 1: Evaluate

Examine current modeling practices and whether they meet minimum recommended standards by asking the following questions:

1. How do existing models represent the hourly chronology of energy demand and renewable energy generation?
2. How do existing models represent the operational challenge of serving load over multi-day weather events and during atypical weather years, if at all?
3. Are existing models capable of accurately representing technologies like long duration storage that, depending on the duration, can deliver energy over sequential days without recharging or can move energy over weeks and seasons?

37 Note that it is not enough to prove that the time sample input into the model closely matches the full time series. This approach - attempting to match the input time series - does not always provide reliable results (see, for example: Pfenninger. Dealing with multiple decades of hourly wind and PV time series in energy models: a comparison of methods to reduce time resolution and the planning implications of inter-annual variability. Applied Energy (2017);197:1–13. http://dx.doi.org/10.1016/j.apenergy.2017.03.051.)

Step 2: Benchmark

Test current models against those that can represent time over a full 8,760-hour annual time period and that can develop a least-cost resource portfolio that is co-optimized against multiple scenarios. These benchmarking tests should examine the following questions:

1. What are the effects of current time-sampling practices compared to full year, hourly resolution modeling?
2. How does co-optimization change the least-cost resource mix compared to existing models?
3. How well do portfolios from current models versus best-in-class models maintain reliability over multi-day weather events and atypical weather years?
4. For each benchmarking test, examine how the models' resulting least-cost resource portfolios differ, including how these differences impact overall cost, land-use needs, new transmission needs and air pollutants.

Step 3: Transition

After building expertise and familiarity with new best-in-class modeling practices through the evaluation and benchmarking exercises, establish a plan to transition to using best-in-class modeling capabilities in future years' resource planning exercises.

Funding for New Modeling Tools and Studies

We recommend that federal and state agencies fund new studies to build a stronger industry consensus about best-practice decarbonization modeling tools and approaches, and that they also fund the development of new public domain and commercial modeling tools.

Need for Broad Industry and Academic Consensus

The electric grid decarbonization studies that have emerged in the last several years have often relied on capacity expansion modeling tools that lack the ability to evaluate the full variability of weather and system conditions within a year, let alone across multiple years. These studies demonstrate that deep electric decarbonization is achievable, while also highlighting the challenges that are likely to emerge. However, as our case studies and other literature demonstrate, historical approaches to capacity planning are inadequate to accurately understand near-term operational challenges and long-term optimal resource portfolios. As a result, they risk sending misinformed near-to-mid-term investment signals to utilities and grid planners. Broader industry awareness of the shortcomings of typical modeling approaches is needed, as well as a greater understanding of why newer capabilities should be quickly adopted.

Need for Better Public Domain Modeling Tools

Although several new modeling tools have the ability to model grids with the appropriate fidelity, and we list a few in Table 2 above, further work is needed to advance the maturity and adoption of many of these tools, and to introduce new tools to the market, so that utilities and grid planners have a set of robust enterprise-class modeling options from which to choose. Both the federal government, through the Department of Energy and the national labs, and California through its research and development funding programs, have successfully demonstrated that grant funding can result in transformational advances in modeling capabilities that bring broad public benefits.[38]

38 *See* for example the federally funded National Renewable Energy Lab ReEDs model and the Energy Information Agency's NEMS model, and E3's RESOLVE model funded by California.

Actions Form Energy is Taking

Releasing New Open Source Modeling Tools

Form Energy will be developing an open-source capacity expansion modeling tool in partnership with E3 and the University of California at San Diego and with funding from the California Energy Commission.[39] The result will be a public-domain capacity expansion modeling tool with the ability to model full year, hourly resolution grid operations and to co-optimize resource portfolios across multiple scenarios of future grid conditions.

Demonstrating Best-In-Class Tools in Practice

- Role of Long Duration Storage in California Decarbonization Plans: In partnership with E3, the University of California at San Diego, and funding from the California Energy Commission, Form Energy will be supporting a study to assess different scenarios of long duration energy storage deployment in California to understand what role long duration energy storage can and should play in meeting the state's decarbonization goals.[40]
- Long Duration Storage as a Risk Mitigation Strategy: Form Energy and Enel Foundation partnered on a study that showed how different energy storage technology attributes (energy capex, power capex, and round trip efficiency) can impact the risk and cost of firmed renewables at the project or portfolio level.[41]
- Utility and Partner-Specific Studies: Building on this paper and case study, we continue to partner with utilities and project developers on case studies that build broader understanding about the value that advanced analytical methods can bring to their electric resource portfolios.

39 *See* California Energy Commission GFO-19-308: Assessing Long-Duration Energy Storage Deployment Scenarios to Meet California's Energy Goals

40 *See* California Energy Commission GFO-19-308: Assessing Long-Duration Energy Storage Deployment Scenarios to Meet California's Energy Goals

41 *See* Enel Foundation and Form Energy: Large Scale, Long Duration Energy Storage, and the Future of Renewables Generation, December 2019.

Appendix: Methods and Inputs

Methods

Construction of Time Sampling Cases:

We developed the "Time Sampled Case: Modeled" using a methodology based off of NREL's Regional Energy Deployment System (ReEDS) model.[42] We chose this framework because the methods that NREL employs are common to many other models, and their open source code is readily available. NREL's time sampling methodology (which differs slightly from our method, discussed below) uses 17 time slices: four average hours from each of the average days in spring, summer, fall, and winter, as well as the total system peak day.

We constructed the Time Sampled Case: Modeled using a greater number of hours than NREL's ReEDS model, a conservative approach. To construct this case we use 120 hours of the year: five slices of 24 hours each that represent the average spring, summer, fall, and winter days, as well as the peak day. Our time slices use our partner's 2030 forecasted load and 2011 wind data. The exact time slices modeled are shown in Table 4.

It is worth noting that this paper is not a critique of NREL's ReEDS model. ReEDS is designed to provide nationwide indicative outlooks of resource needs for the U.S., and it includes many elements that we did not model here. Our goal is simply to highlight the potential impact of time sampling methods using a technique in a well-known model.

We used the resource portfolio from the Time Sampled Case: Modeled to create the Time Sampled Case: Achieved. In the Time Sampled Case: Achieved, we operate the assets from the Time Sampled Case: Modeled over a full year, developing a more realistic view of the actual costs of the portfolio. The resources in the Time Sampled Case: Achieved are therefore not a result of a capacity expansion optimization; they are the same as the portfolio developed in the Time Sampled Case: Modeled.

In both time sampled cases as well as the 8760 Case we used the forecasted 2030 load provided by our partner. We simulated wind production profiles for 2000-2018 in the wind regions adjacent to the utility using **Renewables Ninja**. Renewables Ninja is an open source tool that has been vetted extensively in academic publications.[43] We assumed an 80 meter hub height and a 2.5 MW turbine size, which is likely to slightly underestimate potential future wind production, as newer turbines are installed at higher hub heights and have larger capacities.

We identified a typical (2011), low wind (2010), and high wind (2014) year within this period. For each of these weather years, we ran a low and high cost scenario for the 8760 Case, the Time Sampled Case: Modeled, and the Time Sampled Case: Achieved. The costs for these scenarios are shown in Table 1 in the main body of the text.

In both the time sampling cases and the co-optimization cases, we used linearized versions of minimum up and down time constraints, ramp rates, starts, stops, and other techno-economic details of the utility's gas fleet. We modeled all of the gas and dual fuel units in our partner's portfolio, excluding our partner's primary coal-fired power plant.

In both the time sampling cases and the co-optimization cases, we allowed the model to choose not to serve demand at any point. We imposed a penalty of $9,000/MWh for "lost load" when the model chose to shed demand rather than build resources to meet it.[44]

42 Cohen, Stuart, et al. 2019. Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-72023. https://www.nrel.gov/docs/fy19osti/72023.pdf.

43 *See: 1)* S. Pfenninger and I. Staffell, 2016. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy, 114, 1251–1265. And 2) I. Staffell and S. Pfenninger, 2016. Using Bias-Corrected Reanalysis to Simulate Current and Future Wind Power Output. Energy, 114, 1224–1239.

44 The value for "lost load" varies dramatically by estimate, but $9,000/MWh is generally in the middle of a wide range of VOLL estimates.

Time slices used in time sampling

The following table shows the time slices used in the time sampled cases.

Table 4: Time slices used in the time sampled cases

Season	Time Period	Number of Hours From Each Period
Summer (June - August)	Hourly average: 10 p.m. to 6 a.m.	8
Summer (June - August)	Hourly average: 6 a.m. to 1 p.m.	7
Summer (June - August)	Hourly average: 1 p.m. to 5 p.m.	4
Summer (June - August)	Hourly average: 5 p.m. to 10 p.m.	5
Fall (September - November)	Hourly average: 10 p.m. to 6 a.m.	8
Fall (September - November)	Hourly average: 6 a.m. to 1 p.m.	7
Fall (September - November)	Hourly average: 1 p.m. to 5 p.m.	4
Fall (September - November)	Hourly average: 5 p.m. to 10 p.m.	5
Winter (December - February)	Hourly average: 10 p.m. to 6 a.m.	8
Winter (December - February)	Hourly average: 6 a.m. to 1 p.m.	7
Winter (December - February)	Hourly average: 1 p.m. to 5 p.m.	4
Winter (December - February)	Hourly average: 5 p.m. to 10 p.m.	5
Spring (March - May)	Hourly average: 10 p.m. to 6 a.m.	8
Spring (March - May)	Hourly average: 6 a.m. to 1 p.m.	7
Spring (March - May)	Hourly average: 1 p.m. to 5 p.m.	4
Spring (March - May)	Hourly average: 5 p.m. to 10 p.m.	5
Summer Peak Day	Hourly demand and renewables on the peak load day	24
Total	**4 representative days and 1 peak day**	**120**

Construction of Co-Optimization Cases

Our co-optimization case study accounts for future uncertainties by considering six possible futures: low wind, typical wind, high wind, high cost of gas, high demand, and transmission constraints. In the high cost of gas, high demand, and transmission constrained scenarios, we used a typical year's wind production profile (2011). In the transmission constrained case, we limited new wind deliverability to no more than twice existing wind capacity. In the transmission constrained case, new wind capacity can grow without bound; however, only twice the existing capacity can be delivered at any time (any excess wind generation is curtailed).

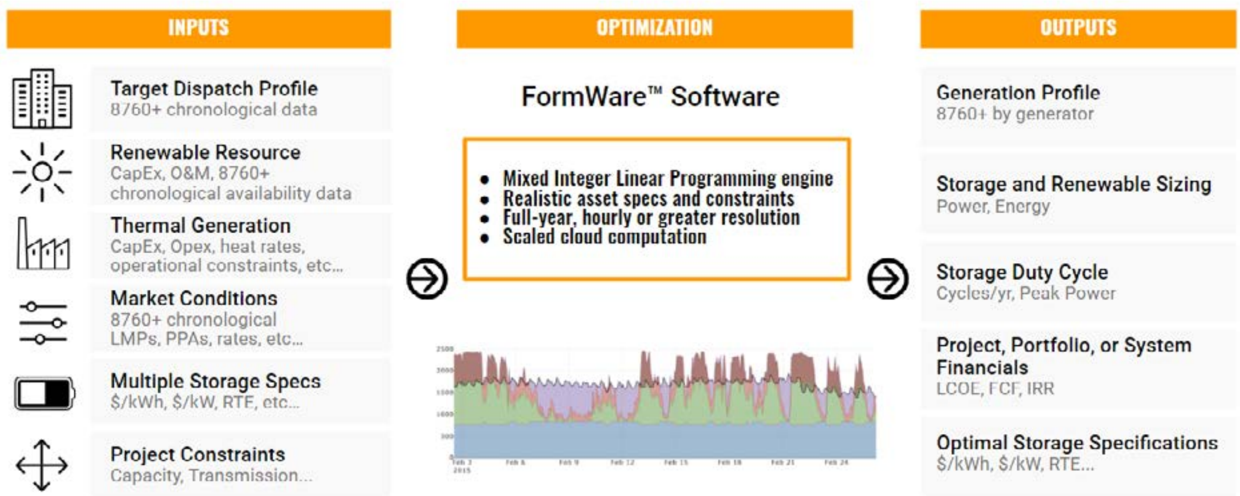
In the Co-Optimized Case, we optimized the resource portfolio across all six futures, generating a single asset build and an average operational cost for the six futures. For this case study we used a simplifying assumption that all six futures are equally likely. A more extensive portfolio modeling effort intended to send investment signals would typically use probability-weighted futures. For example, we would weigh each weather year according to its relative probability, avoiding over-weighting low probability weather events.

In each of the other cases shown in Figures 7 and 8, we used Formware to generate a unique optimal resource portfolio based on the scenario in question (for example, the Low Wind or the High Cost Gas scenario). We then operated the resulting resource portfolio, generated from each single scenario, across all six scenarios with hourly resolution. We then compared the costs and resource portfolios of these test year cases with the cost and resource portfolio of the Co-Optimized case.

Formware Modeling Tool and Set-Up

To perform these case studies we used Formware, Form Energy's capacity expansion and economic dispatch model. Formware finds the least cost mix of both assets and operational strategies required to meet electricity demand across diverse weather, load, and contingency scenarios. Formware's inputs are common to many capacity expansion models, with the exception of the time granularity it requires. Formware optimizes assets over a full year or longer period with an hourly or more granular time profile. While Formware optimizes for a single time horizon, that horizon can be flexible and quite long. For example, Form Energy has used Formware to model the optimal storage sizing and operations for ten continuous years on an hourly basis.

Figure 9: Formware overview



The model's inputs include required loads and capacity, renewable resource availability and cost, market conditions including electricity pricing and fuel prices, storage resources' characteristics and costs, and system level constraints such as transmission capacity and limits on minimum and maximum generation. Formware outputs the asset mix, a set of operational decisions for each hour of the year (or multiple years when modeled), capital expenditures, and operational costs that meet all specified system constraints at lowest net present cost or highest net present value.

Cost Estimates

Wind costs are based on the 2030 low-range estimate from NREL's 2019 Annual Technology Baseline. Lithium ion storage costs are extracted from the National Renewable Energy Lab's (NREL's) 2019 Annual Technology Baseline, and assume a full system replacement in year 15 of the asset life (assuming an 8% nominal interest rate and 2% inflation). Electrochemical long duration energy storage (LODES) cost estimates are derived from a survey of techno-economic modeling and industry and academic expert judgements about the potential cost and performance parameters of emerging long duration storage technologies. These costs are not intended to represent Form Energy's technology. The cost specifications and technology capabilities are shown in Table 3 in the main body of the study.

High cost resource portfolios

The main body of the text presented only the resource portfolios form the low cost cases. The following figures present the resource portfolios for the high cost cases. We see that in both cases, the model still chooses to build long duration energy storage. We also see that the general patterns of resource builds, in both the time sampled and multi-scenario case studies, are very similar between the low cost and high cost cases.

Figure 9: Resource portfolio by scenario (high cost Time Sampling case)

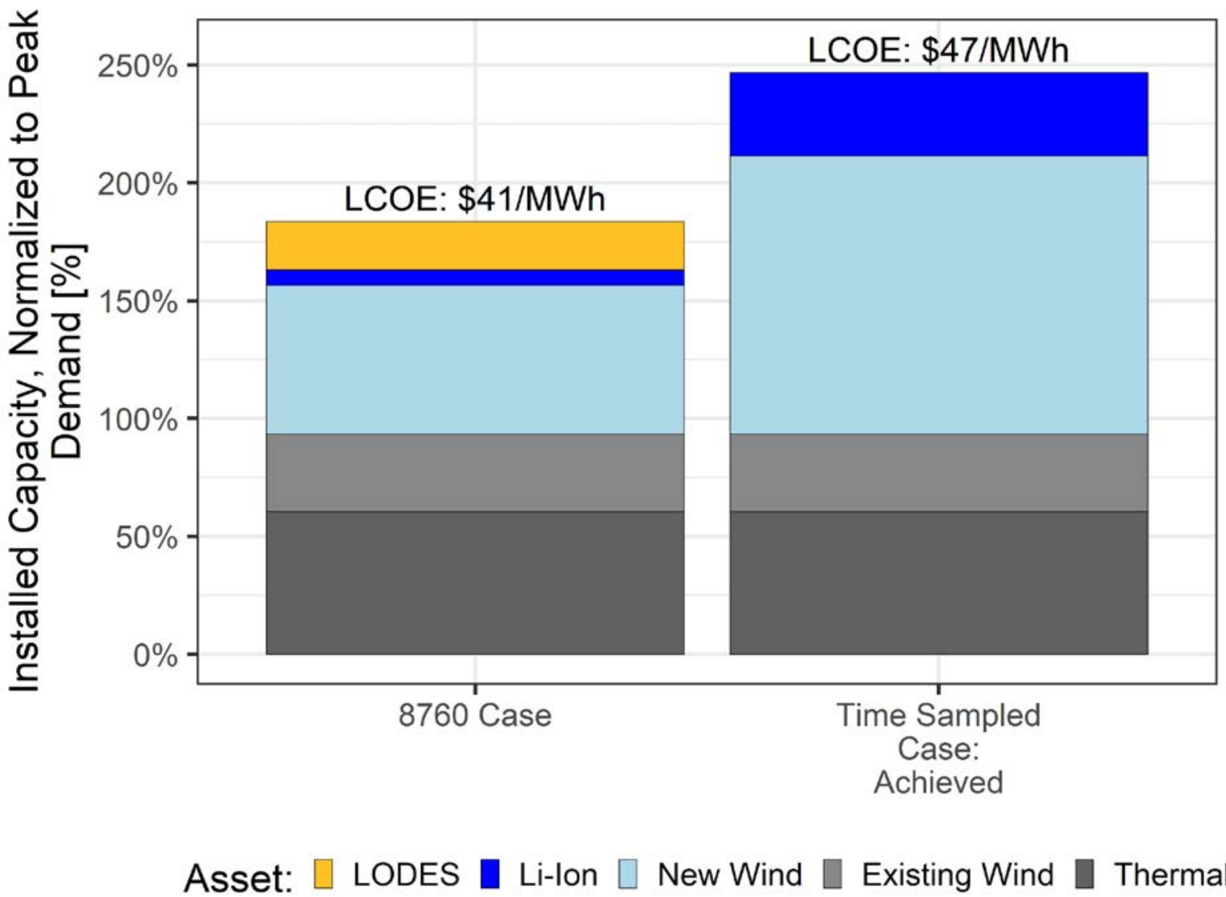


Figure 10: Resource portfolio by scenario (high cost co-optimization cases)