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Improving Modeling Tools for Capacity Expansion Modeling for a Decarbonized Grid

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Improving Modeling Tools for Capacity Expansion Modeling for a Decarbonized Grid

by

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University of California, Merced

Improving Modeling Tools for Capacity Expansion Modeling for a Decarbonized Grid

To the love of my life Dalia Martinez Escobar
And my parents Mariía Azucena Pérez Paredes and Aáron Sánchez Juarez

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Chapter 1

Introduction

This chapter serves as an introduction to the overall dissertation work by providing context and motivation for the research. While each chapter can be read independently, they are designed to build upon one another, with Chapters 1 and 2 setting the stage and summarizing the methodological work and motivation for the research that is presented in the subsequent chapters. Chapters 2 and 3 include material that has already been published in peer-reviewed journals, while Chapter 4 is a conference paper. Finally, Chapter 5 provides the overall conclusion of the research.

1.1 Background and context of the work

Electricity is critical for global development and welfare, and while it can be generated at different economic sectors (e.g., utility, commercial and residential), it typically originates from the utility-scale power sector. However, the power sector has the second largest share of greenhouse gas emissions (Environmental Protection Agency, 2022). Consequently, the power sector has a pivotal role in worldwide efforts to mitigate climate change. Decarbonizing the power sector requires significant changes in the energy production and consumption patterns, which call for appropriate planning supported by advanced modeling tools. These tools can assist in identifying what is the optimal mix of technologies to meet future energy demands while ensuring system reliability and achieving climate goals.

One of the most common used tools for modeling the power sectors is a capacity expansion models (CEMs). This type of models are widely used in the energy industry to model the required capacity to meed the future demand while considering different technical and policy constraints. CEMs provide a framework for modeling the future electricity system by using variables such as technological performance, economic factors, environmental policies, and system constraints. CEMs are essential for evaluating the costs, benefits, and risks associated with different energy policies and investments.

However, CEMs face significant challenges when modeling the decarbonization of the power sector. One challenge is the uncertainty associated with the deployment of low-carbon technologies, such as renewable energy and energy storage. The variable nature of these technologies can cause fluctuations in power supply and demand, making it difficult to ensure system reliability. Another challenge is the variability of energy prices, which can significantly affect investment decisions and energy demand. Finally, there are many factors to consider in the transition to a low-carbon future, including the retirement of existing assets, infrastructure requirements, and the impact on local communities.

The objective of this thesis is to evaluate the importance of the input assumptions and the impact and improve existing CEMs for decarbonization in the power sector. Specifically, this thesis aims to identify the limitations and challenges of existing modeling tools for energy storage technologies and an emerging long-duration energy storage (LDES). The research questions guiding this thesis are:

- How do we need to adjust CEMs to be able to better understand new market opportunities for LDES?
- What are the trade-offs between high-temporal resolution and a simplified version in CEMs with energy storage?
- What are the potential impacts of inputs and methodologies of modeling tools on the decarbonization of the power sector, including the costs, benefits, and risks associated with different decarbonization scenarios?

1.2 Significance of the research

Understanding the input assumptions is paramount for capacity expansion modeling because it affects the accuracy and reliability of the model. Capacity expansion modeling is the process of projecting future energy supply and demand and determining the most cost-effective mix of energy resources to meet that demand over the long term. Input assumptions are the starting point of the capacity expansion modeling process, and errors or biases in these assumptions can lead to unreliable projections and suboptimal investment decisions.

One important input assumption is the cost of energy storage technologies, such as batteries and pumped hydro storage. LDES is essential in VRE-dominant grids because it helps to balance the supply and demand of electricity during periods of low renewable energy production. However, the cost of energy storage technologies can significantly affect the economics of the power system, and inaccurate cost projections can lead to suboptimal investment decisions. Not only cost, but the storage balancing horizon (a concept that we defined further in this dissertation) can widely affect the amount of storage needed.

Furthermore, the input assumptions for the modeling are crucial to identify market opportunities for emerging technologies. These will allow stakeholders to create programs to incentivize the adoption of new technologies that will help us reach a low carbon future on a cost-effective way.

Input assumptions also impact policy decisions related to energy policy mandates like energy storage mandates, renewable portfolio standards, and greenhouse gas reduction targets. Accurately modeling the potential impact of these policies can help policymakers set realistic targets and develop effective implementation strategies. For instance, understanding the cost-effectiveness of different long-duration energy storage technologies can help policymakers determine appropriate incentive structures to promote their adoption.

This dissertation work endeavors to expand the knowledge in the literature for the emerging LDES technology by examining the input assumptions in CEMs and how different assumptions can impact the optimal amount of LDES for a VRE dominant grid. By doing so, this research seeks to expand our understanding of how some of the input assumptions can change the size of the potential market for LDES technologies.

To achieve this goal, we utilized an open-source CEM to investigate the impact of different cost assumptions and temporal resolutions on the market size of LDES technologies. Through a series of scenarios, we examined various cost scenarios for LDES technologies under different temporal resolutions to determine the optimal amount for the entire Western Coordinating Council (WECC). By simulating the performance of LDES technologies under different cost assumptions and temporal resolutions, we identified key factors that can impact their adoption and diffusion, such as the cost of the technology, the duration of storage, and the availability of renewable generation sources.

By using the CEM model, we were able to simulate the performance of LDES technologies under different cost assumptions and temporal resolutions, providing valuable insights into their market potential and economic viability. Through our analysis, we identified key factors that can impact the adoption and diffusion of LDES technologies, including the cost of the technology, the duration of storage, and the availability of renewable generation sources.

Furthermore, we explored the Department of Energy's (DOE) LDES initiative, which aims to reduce the cost of LDES by 10% of Li-ion technologies by 2030. Under this cost assumption, we analyzed how LDES technology could interact with other storage technologies in a future grid dominated by variable renewable generation. Through this examination, we sought to provide insights into the potential benefits and challenges associated with integrating LDES technologies into the grid and how this could impact the overall cost and efficiency of the energy system.

Overall, this research represents a significant contribution to the literature on LDES technologies and the energy system. By exploring the impact of cost assumptions and temporal resolutions on the market size of LDES technologies and their interaction with other storage technologies, this research offers valuable insights into the potential benefits and challenges of these emerging technologies. These insights can inform future policy and investment decisions related to the development and deployment of LDES technologies, helping to accelerate their adoption and diffusion in the energy sector.

1.3 How Small Changes Can Have a Big Impact on Energy Modeling Results

As discussed in Chapter 1.1, decision-makers in the energy sector often turn to CEMs to aid in making long-term investment decisions. These models project future energy market trends over a period of typically more than ten years and estimate the optimal combination of investments necessary to meet future electricity demand at the lowest cost. This optimization aims to maximize social welfare, which can be achieved by minimizing the total system cost, as expressed in eq (1.1). CEMs offer a highly detailed view of the energy sector, but their reliability depends heavily on input assumptions. As a result, the input assumptions represent a significant source of uncertainty and are critical to the accuracy and relevance of the model's results. While CEMs can be highly accurate in terms of resolution, the validity of their output relies on the accuracy of their input assumptions.

This section will provide context on how the different publications that comprise this dissertation build upon improving the modeling input assumptions to enhance the accuracy and robustness of CEMs, ultimately improving their usefulness for decision-making in the power sector. Specifically, the last part of my dissertation focused on improving the representation of long-duration energy storage technologies and their associated costs, the characterization of uncertain parameters such as state of charge, operations and market opportunities. By advancing the state-of-the-art in CEMs input assumptions, my research aims to provide decision-makers with more accurate and actionable insights into the long-term energy investment options, and support the transition towards a more sustainable and resilient energy future.

1.4 Variable Renewable Generation: Paving the Way for the Future of Electrical Grids

The first part of my dissertation work was to understand the expected capacity factor of solar photovoltaic energy, which is expected to be the predominant variable-renewable technology in California. Given the massive deployment of solar energy in California, with a total online capacity 12.6 GW[1] and expected to add 18 GW of additional capacity by 2032 (California Public Utility commision (CPUC), 2022), it is crucial to have accurate estimates of its capacity factor to inform CEMs and other energy planning or reliability tools. To achieve this goal, we used the public forms from the Energy Information Agency (EIA) from the Department of Energy that reports the existing data on solar energy capacity as well as plant location (Energy Information Agency, 2018a) and the production (Energy Information Agency, 2018b) in the continental US. With this information, we analyzed the full US fleet and re-

[1] Data from CAISO Oasis: Master Control Area Generating Capability List by participant unit and photovoltaic technology

ported a statistical model to estimate the expected capacity factor of solar energy as a function of key weather and location variables.

In this work we provided an interpretation of the DC to AC ratio, also known as inverter-loading ratio (ILR), that is a design parameter that is often overlooked when reporting the characteristics of the solar PV power plant. Increasing the ILR also increases the alternating current (AC) capacity factor that is beneficial to PV technology since the intra-hour variability could be reduced by overbuilding the direct current (DC) side. From the historical data, we observed that as the cost of PV panels (relative to other system costs) has decreased over time, the ILR has considerably increased. We observed this increasing trend from the historical data with different aggregations (e.g., by latitude or longitude, type of mounting). With this information, we reported an empirical correlation to estimate the expected AC capacity factor for solar power plants as a function of key weather and geolocations.

Furthermore, we anticipate that the future of solar energy will be hybrid systems, such as VRE+storage. These types of systems store excess renewable electricity, allowing them to provide power even when the sun is not shining. By incorporating energy storage into these systems, they are able to produce more reliable and consistent levels of electricity, further increasing the combined capacity factors. As these hybrid systems become more common, we expect to see significant increases in solar energy capacity factors when considering the AC plant ratings.

By improving our understanding of solar energy capacity factors, this research was a first step to understand the importance of the input assumptions of CEMS. Since, the variable capacity factor is an input assumption of the model and is projected to the model time horizon, the accuracy of this calculation ultimately affects the results of the model.

1.5 Meeting the Energy Storage Needs of a Variable Renewable Energy Dominated Grid

As the world transitions towards a more sustainable future, the importance of renewable energy sources like solar and wind power is increasing rapidly. However, the intermittent nature of these sources poses a significant challenge to power systems, which must balance supply and demand in real-time. Energy storage is a key solution to this problem, enabling otherwise curtailed electricity to be stored and used later when needed. Storage can significantly improve the reliability and resilience of the power grid while facilitating the integration of additional renewable energy sources.

Despite the many benefits of energy storage, several challenges still need to be addressed to ensure its reliability and efficacy. For example, from an operator perspective, the state-of-charge represents a high uncertainty because with the evolving market dynamics and other climate effects it is challenging to accurately predict the amount of energy that can be delivered from a storage system at a given time. Additionally, capacity credits, which represent the contribution of energy storage to meeting peak demand, can be difficult to quantify accurately. These challenges require advanced modeling techniques to ensure that energy storage systems are integrated into power systems in a way that maximizes their benefits.

During my dissertation work, I participated in multiple research projects aimed at understanding the energy storage needs of the California market. One recent study, as documented in (Abido et al., 2022), focused on investigating the seasonal energy storage requirements for the California grid. In this study, we developed a simple yet effective energy-balance approach using the historical renewable electricity generated in California that incorporates a range of realistic varying factors, including weather patterns, and demand variability. Through our research, we concluded that the winter season presents a significant challenge for a solar-dominated grid in California, due to low levels of solar- and wind-electricity generation. This insight is critical to accurately forecasting energy storage requirements and ensuring that energy storage could be deployed in a cost-effective and reliable manner.

Similarly, in another study (Mahmud et al., 2023), I participated in understanding the amount of storage needed in the California grid. For this work, we proposed a novel, hierarchical approach to estimate the energy storage needs for different generation energy profiles and the minimum cycling frequency for that storage. Our study found that depending on the generation profiles and availability of new resources, such as off-shore wind, the need for diurnal energy storage could be reduced. Furthermore, we found that winter-dominant onshore wind could halve seasonal storage needs. Our proposed approach could be used as a blueprint for other kinds of studies like new candidate technologies for CEMs.

To fully understand the potential of energy storage, it is essential to use more comprehensive models that can capture the complex interactions between energy storage, renewable energy sources, and the power grid. These models must also account for investment decisions that are necessary for energy storage implementation and market opportunities that will inform stakeholders. By incorporating different kinds of energy storage technologies into CEMs, we can determine the optimal amount and type of energy storage required to meet the future needs of the grid. This approach enables us to identify market opportunities and the need for energy storage while achieving a more sustainable and reliable power system. Moreover, implementing energy storage in the power grid can help reduce greenhouse gas emissions and promote economic growth.

1.6 Peering into the Future: How Advanced Modeling Tools are Shaping Long-Term Planning for the Energy Sector

As mentioned in section 1.3, CEMs are the go-to tool for long-term planning processes. CEMs have been widely applied in various energy markets worldwide to evaluate energy policy options and inform energy planning decisions. The goal is to minimize the total cost of generation while ensuring that the demand is met. Typically, CEMs are formulated as linear optimizations where the objective function minimizes the total system cost across all the investment periods or maximizes the economic wellfare, as shown in the following equation:

$$\min \sum_{p \in \mathcal{P}} d_p \left\{ \sum_{c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}} c_p^{\mathrm{f}} + \sum_{t \in \mathcal{T}_p} \sum_{c^{\mathrm{v}} \in \mathcal{C}^{\mathrm{var}}} c_t^{\mathrm{v}} \right\}, \tag{1.1}$$

where c^{f} represents the fixed cost component $c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}$ indexed by investment period ($p \in \mathcal{P}$) that includes capital repayment for investments at a fixed financing rate over the lifetime of each asset, sunk costs from existing infrastructure, as well as fixed operating and maintenance (O&M) costs, and c^{v} is the variable cost component $c^{\mathrm{v}} \in \mathcal{C}^{\mathrm{var}}$ indexed by time ($t \in \mathcal{T}$) that includes fuel costs and variable O&M.

CEMs consist of several components, including economic dispatch, unit commitment, and energy policy constraints. Economic dispatch is a technique used to allocate generation from different power plants to meet demand at minimum cost (Chowdhury and Rahman, 1990). It determines the output of each power plant given the demand and cost of electricity generation. The unit commitment component determines which generators should be online and which should be offline at any given time to meet demand at minimum cost (Saravanan et al., 2013). It also takes into account the start-up costs and ramp rates of each generator.

Energy policy constraints refer to any mandate imposed by regulation authority or policies related to the energy system. These can include renewable energy targets, greenhouse gas emission limits, and energy efficiency standards. CEMs incorporate these constraints to ensure that the optimal resource mix aligns with these policies and regulations. Examples of this energy policy are:

- Energy Mandates: That requires a certain amount of capacity deployed by a give year or period. One example is *California AB-2514 Energy storage systems* (2009), that mandates the utilities to procure a certain amount of energy storage capacity by a specified deadline.

- Renewable Portfolio Standards (RPS) policies require utilities to generate a certain percentage of their electricity from renewable sources such as wind and solar. For example, in the United States, many states have adopted RPS policies that require a certain percentage of electricity to come from renewable sources by a specified deadline (National Conference of State Legislatures, 2021).

- Greenhouse Gas Target as a means of mitigating climate change. For example, the California passed the *California AB-32* (2006) "to reduce GHG emissions to 60 percent of 1990 levels (40 percent reduction) by 2030.

These policies can influence the deployment and operation of energy systems, and thus can be included as constraints in capacity expansion models to better reflect real-world conditions and policy goals.

CEMs have been adapted to address these specific challenges and opportunities of each market, and have been used to identify cost-effective and sustainable pathways for the expansion of power systems. Examples of these models are RESOLVE, SWITCH, ReEDS and TEMOA. RESOLVE is CEM developed by Energy + Environmental Economics (E3) and used for energy system planning in California. SWITCH is another popular CEM that has been used to analyze power systems in various countries, including the United States, Mexico, and China. Recent studies have used SWITCH to evaluate the impacts of various policy interventions, such as carbon pricing, renewable energy targets, and energy efficiency measures (He, Avrin, et al., 2016; Mileva, J. H. Nelson, et al., 2013; Sánchez-Pérez et al., 2022). In particular, with new energy storage technologies, careful consideration of the trade-offs involved in selecting the appropriate tool for the desired market is essential in long-term planning. As the energy landscape continues to evolve and new technologies emerge, decision-makers must weigh various factors when selecting a CEM for long-term planning. Examples of these factors could be the flexibility of the model, performance, scalability, and modeling assumptions. The selection of the most suitable tool for long-term planning can have significant implications on driving investments for emerging technologies.

1.7 Emerging energy storage technologies

In recent years, long-duration energy storage (LDES) has gained popularity due to its ability to store and dispatch electricity for durations of 8 hours or more. The U.S. Department of Energy has created a program to reduce the cost of LDES, and the California Energy Commission has also implemented policies to promote LDES deployment. Despite this growing interest in LDES, many energy system models, particularly those used for decision-making such as RESOLVE for the Integrated Resource Plans (IRPs) from California, do not capture the benefits of LDES due to the simplification in temporal resolution. This modeling gap motivated the next part of the dissertation work to understand the sensitivity of this kind of asset and provide best practices for modelers to accurately model the performance of LDES systems and their role in energy system optimization.

Storage balancing horizon

Modeling power systems typically requires a trade-off between resolution and run-time. In order to ensure that the models provide useful results, a certain level of resolution is required. However, as the level of resolution increases, the run-time for the model can increase, which can lead to longer stakeholder processes and increased costs. This trade-off between run-time and resolution is particularly important when dealing with energy storage systems, which can require high levels of resolution to accurately model the performance of the storage asset over time and identify clear market opportunities for emerging storage technologies.

One common approach to simplifying the resolution of energy system models is to reduce the number of modeled days. By identifying representative days that capture the key characteristics of weather patterns and load patterns, modelers can reduce the number of days that need to be modeled while still ensuring that the model captures the essential features of the market dynamics. However, the assumption that each day is modeled independently (e.g., 2021 Integrated Resource Portfolio from the CPUC) can compromise the usefulness of energy storage systems (Sioshansi et al., 2022), particularly long-duration energy storage systems.

To understand the importance of the temporal resolution for LDES we used SWITCH (Johnston et al., 2019), an open-source capacity expansion model for power systems, to work with large shares of variable renewable energy, storage and thermal power plants. SWITCH is a modular capacity expansion model that minimizes the net present value (NPV) of the cost for all investment periods and time points for an electrical grid (Johnston et al., 2019). It optimizes the investment in capacity (chooses an optimal power system design directly) and it optimizes the operational costs (evaluating the cost of running the power system design) (Fripp, 2018). It has been widely used for decarbonization and energy transition scenarios in different regions around the world (J. Nelson et al., 2012; Sanchez et al., 2015; Mileva, Johnston, et al., 2016; Mileva, J. H. Nelson, et al., 2013; He, Avrin, et al., 2016; He, Lin, et al., 2020; Hidalgo-Gonzalez, Johnston, and Kammen, 2021; Yin et al., 2021). Using a set of assumptions of the market, policies and technology, SWITCH optimizes capacity additions, transmission expansion, and system dispatch while simultaneously being mindful of the constraints in place, such as carbon targets, RPS (Renewable Energy Portfolio Standards), etc. This work uses the latest release of SWITCH-WECC [3] capacity expansion model that is formulated as a linear program (LP).

SWITCH models the state of charge by considering the electricity previously stored, $\mathrm{SOC}_{s,t-1}$, the discharge amount, $\mathrm{D}_{s,t}$, the charge amount, $\mathrm{C}_{s,t}$, and the duration of the time point, Δt (e.g., 4 h). The following constraint models it:

$$\mathrm{SOC}_{s,t} = \mathrm{SOC}_{s,t-1} + \left(\eta_c \mathrm{C}_{s,t} - \frac{\mathrm{D}_{s,t}}{\eta_d}\right)\Delta t \quad \forall s \in \mathcal{S} \quad \forall t \in \mathcal{T}, \tag{1.2}$$

where $\mathcal{S}$ is the set of energy storage assets, η_c and η_d are the charge and discharge efficiency, respectively. Additionally to (1.2), the storage module incorporates a constraint that bounds the beginning SOC, $\mathrm{SOC}_{t,0}$, and end $\mathrm{SOC}_{t,f}$, where f denotes the last time point of the time series. This constraint is added such that the time series is treated cyclically, which means that the SOC at 0:00 AM on the first day of the time series is the same as midnight SOC for the last day of the same times series. As we change the length of the time series from a week to a whole year, this modifies the number of consecutive days considered for the storage balancing decision (see Fig. 1.1).

[3] This work used an adapted version of SWITCH-WECC v2.0.0. The documentation of the model is available at: `https://github.com/REAM-lab/switch` and in the supplemental materials.

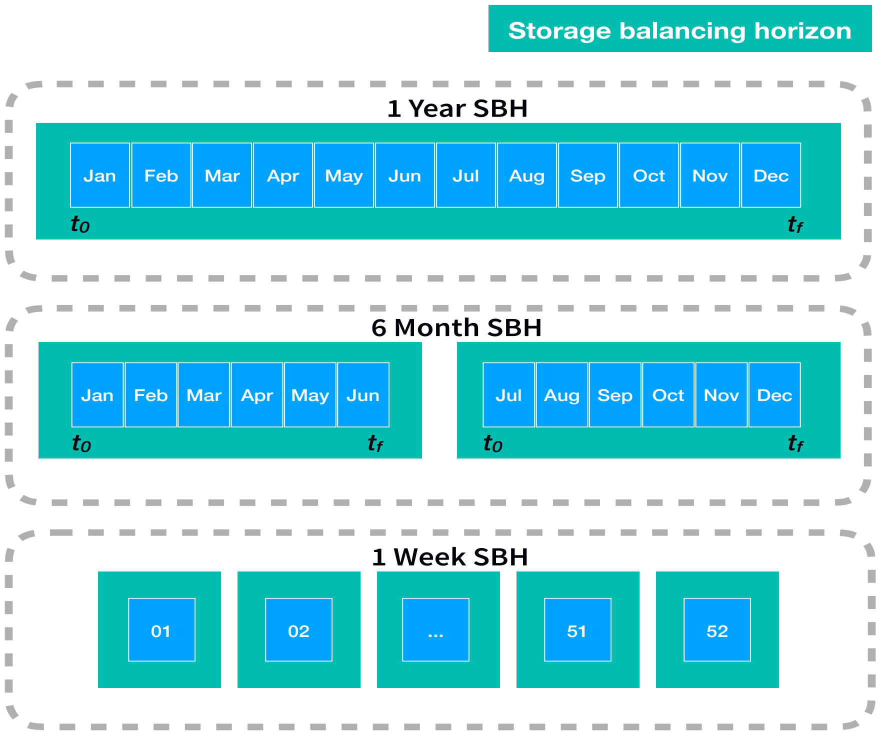


Figure 1.1: Diagram showing the storage balancing horizon (SBH) concept for three different lengths: 1 Year, 6 Month and 1 Week. As published in (Sánchez-Pérez et al., 2022)

1.8 LDES modeling work

Chapter 3 of the thesis focused on analyzing different time horizons for the WECC region and explored different sensitives for the energy storage price. The latest version of Switch-WECC uses 2007 as a representative weather year for the VRE generators since it was year where the most recent irradiance data and wind speed data were available. For the storage prices, we used the price of Li-ion from the latest annual technology baseline (National Renewable Energy Laboratory (NREL), 2020) as a proxy price for LDES technologies and created different scenarios for the energy cost ($/kWh). In this work and as explained in the chapter, we modeled only the 2050 period using a 4-hr timestep since it is modeling the full WECC with a high spatial resolution. The reasoning behind this was to understand the optimal energy storage duration when using the proxy energy cost and how it changed depending on the balancing horizon. This analysis is important because the time horizon should be carefully selected to align with the scope of the analysis proposed and the specific market and policy rules. By comparing the results obtained for different time horizons, the most appropriate time horizon can be selected for the specific analysis depending on the projected energy storage technologies.

Chapter 4 of this dissertation investigated how changing the time step used in the model could affect the results. Building on this, the work also modeled a LDES candidate technology for the first time using data from a survey conducted by Shan et al. (2022). Despite most companies not yet deployed large-scale LDES projects, the cost data obtained from the survey was used to capture the technology's projected costs for the future. The LDES technology was modeled for 2050 to understand its charging dynamics in a VRE dominant grid. To estimate future LDES costs, the ratio of the cost of LDES to that of Li-ion was assumed to remain constant for both capacity and energy prices. The Li-ion cost projections from the National Renewable Energy Laboratory NREL-ATB for 2050 were used to calculate the cost for LDES. In addition, this work aimed to explore a low-cost energy storage option, and therefore, the LDES asset was modeled to have a low round-trip efficiency of 45% to examine the market opportunities when high-round trip efficiency technology, such as Li-ion, is also present. To investigate the effect of the time step, the temporal resolution of the model was varied. The optimal capacity for LDES increased as the time step was reduced from 4 hours to 2 hours, which highlights the importance of selecting an appropriate timestep to balance model accuracy with computational cost. This analysis provides insights into how the time step affects the accuracy of the results and how to capture important system dynamics.

Chapter 2

Capacity Factor Analysis of US PV System Reliability and Performance

The text of this chapter is a reprint of the material as it appears in Sanchez-Perez, Pedro Andres, and Sarah Kurtz. "Capacity Factor Analysis of U.S. PV System Reliability and Performance." IEEE Journal of Photovoltaics 10, no. 3 (May 2020): 818–23. https://doi.org/10.1109/JPHOTOV.2020.2968418.

2.1 Introduction

While careful studies of PV system performance are essential for further optimization of system design and quantitative assessment of performance (IRENA, 2018; Marion et al., 2005; D. C. Jordan and S. R. Kurtz, 2015; D C Jordan and S R Kurtz, 2014; Raupp et al., 2016; Moore and Post, 2008; Golnas, 2013; Sharma and Chandel, 2013; Dirk C. Jordan et al., 2018), there is also value in studying metrics that can be readily applied to large data sets. Specifically, capacity factor is a metric that grid operators often track and that can be studied without need for irradiance data. Capacity factor values for PV power plants typically range from 10% to 35%. Remarkably, the global average DC capacity factor of utility-scale PV systems increased by 28% between 2010 and 2017, from an average of 13.7% to 17.6% (IRENA, 2018) Understanding such trends can aid projections of solar electricity.

In this paper, we study performance and reliability using capacity factor as the key metric. In Section II, we discuss how the choice of using AC or DC system ratings affects the calculated capacity factor. In Section III, we describe how we use a publicly available dataset from the U. S. Energy Information Agency (EIA). In Section IV, we show the results of that analysis, to explore how the AC capacity factor has changed over time and how it depends on multiple variables. In Section V, we discuss the challenges of analyzing this dataset, and identify meaningful conclusions including about reliability.

2.2 Capacity factor for solar plants

In the field of conventional power generators, the capacity factor is calculated relative to the AC nameplate, however, for solar PV the DC nameplate is often used. Solar PV has both DC and AC nameplate capacity ratings due to the nature of the technology. The DC nameplate capacity provides information about the number of modules installed, which has been useful for tracking growth of PV manufacturing and is used in some databases, though it is not always specified whether DC or AC nameplate capacities are reported. The AC nameplate capacity value reflects the capacity of the inverter. The ratio between the DC and AC capacities is often called the inverter-loading ratio (ILR). Using the DC nameplate capacity to calculate the capacity factor (we call this "DC capacity factor" even though we use the AC electricity data in the calculation) yields the same result as the AC nameplate capacity if the system ILR = 1. However, installations may have higher ILR to increase the revenue (Bolinger and Seel, 2018).

The theoretical AC capacity factor increases with ILR (see Figure 2.1), approaching 50% as the ILR increases and the system operates at full power when the sun is up. However, the DC capacity factor decreases with ILR since the denominator (the wattage of the modules) increases faster than the numerator (the generated electricity).

To compare PV capacity factors with other power generators, it makes more sense to use AC capacity instead of DC. For this reason, here we present only AC capacity factor, but caution the reader from confusing the AC and DC values.

2.3 Methodology

We used data from the U. S. Energy Information Administration (EIA) forms EIA-860 (Energy Information Agency, 2018a) and EIA-923 (Energy Information Agency, 2018b) to evaluate capacity factor and inverter-loading ratio trends for existing grid-connected U. S. PV power plants.

The EIA-860 dataset

The EIA-860 has generator-level data for existing and planned generators, identifying each by a unique generator ID and plant ID, which may apply to multiple generators. This dataset includes the AC nameplate capacity, location, number of inverters, and operating date. The DC nameplate capacity, mounting configuration, tilt angle, azimuth, and technology were added in 2013 as Part 3_3_Solar of the EIA-860 data files. From this dataset, we extracted the metadata for each PV plant reported in the form.

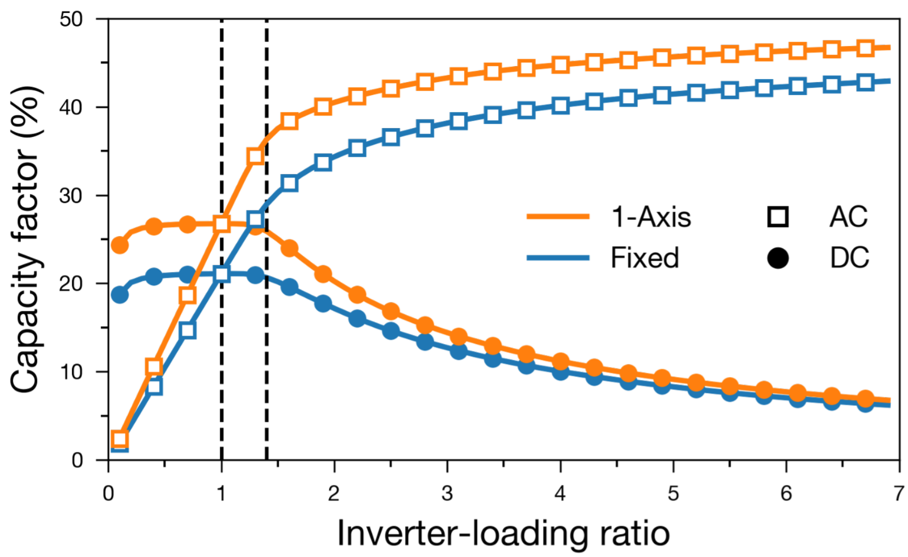


Figure 2.1: DC and AC nameplate capacity factor as a function of inverter-loading ratio (ILR). Current common ILRs fall between the dashed vertical lines. Electrical generation data were simulated using the System Advisor Model (SAM) (National Renewable Energy Laboratory, 2019) and Typical Meteorological Year (TMY) files from the National Solar Resource Database (NSRDB) (National Renewable Energy Laboratory, 2018) for Daggett, CA. These data provide an example to illustrate the general trend; other modeled systems will exhibit different values, but will show similar trends.

The EIA-923 dataset

The EIA-923 form has plant-level generation for each month. Each plant is identified by the same unique plant ID given in EIA-860. The form reports the monthly generation for each plant, however, for this work, we used monthly generation to calculate the annual generation for the reported year.

Joined dataset

To match the generator-level metadata and the plant generation, we joined the two datasets as follows: first, we filtered the EIA-860 for data entries where the prime mover was reported as “PV” to remove generators associated with different technologies under the same plant ID. Next, for each unique plant ID we summed the total summer AC (inverter) capacity (which is usually identical to the winter AC capacity) and total DC (module) capacity for all generators for each reported year. Then, we matched both datasets using the plant ID and the reported year.

Analysis

We calculated the annual AC capacity factor for all of the data using the yearly total electricity generation and the AC nameplate capacity reported for that year. Additionally, we calculated the ILR by dividing the DC nameplate capacity by the AC nameplate capacity. Since the DC nameplate capacity values started to appear in the updated version of the EIA-860 form in 2013, we back-propagated the data using the plant ID, assuming there was no change in the DC capacity of the plant, which is not always a good assumption (see Appendix).

We also screened the join dataset to ensure high-quality data. A handful of data were implausible as described in the Appendix. After screening, <5% of the data entries had missing critical information. We excluded records for the first (partial) year of generation. We show the subset of the dataset used in this work for each year in Fig. 2.2 as indicated by the dark-blue bars labeled as "Legacy". To minimize the effects of outliers, we report median values for grouped sets of data. The locations of the plants included in the 2017 EIA dataset are shown in Fig. 2.3.

We analyzed the relationship between the AC capacity factor and the inverter-loading ratio using the median values and the binned inverter-loading ratio ranges. Also, we include an expected range of AC capacity factor using a high insolation place for the upper limit and a low insolation place for the lower limit.

Furthermore, we analyzed the degradation of the systems by plotting the relative (to the maximum annual capacity factor) capacity factor as a function of year since installation. We omitted the data for the first partial year. We tried using the first full-year generation as defining 100% performance for subsequent years but found that the reported generation in the first year was sometimes low. Using the maximum annual generation reported for a plant as the 100% performance metric gave fewer anomalies in the analysis. We then calculated the performance for each subsequent year relative to the maximum reported performance, calculating the box-plot statistics for plants grouped by the number of years installed in the field. We explored the effect of limiting this analysis to only those plants that have many years of performance relative to adding data for plants with only a few years in the field.

2.4 Results

We first present the median annual AC capacity factor as a function of system size, partitioned by mounting configuration and longitude. Fixed-tilt system (see Fig. 2.4a) show a lower median AC capacity factor than One-axis-tracked systems (see Fig. 2.4b) for all capacity ranges, as expected, because the tracked system generate more electricity early and late in the day compared to fixed tilt system. Systems in the western U.S. show higher capacity factors than in the east, as expected because of the higher insolation in the southwest, where most western installations are located (Fig. 2.3). Both mounting configurations and both longitudes show increasing capacity factors with increasing system size.

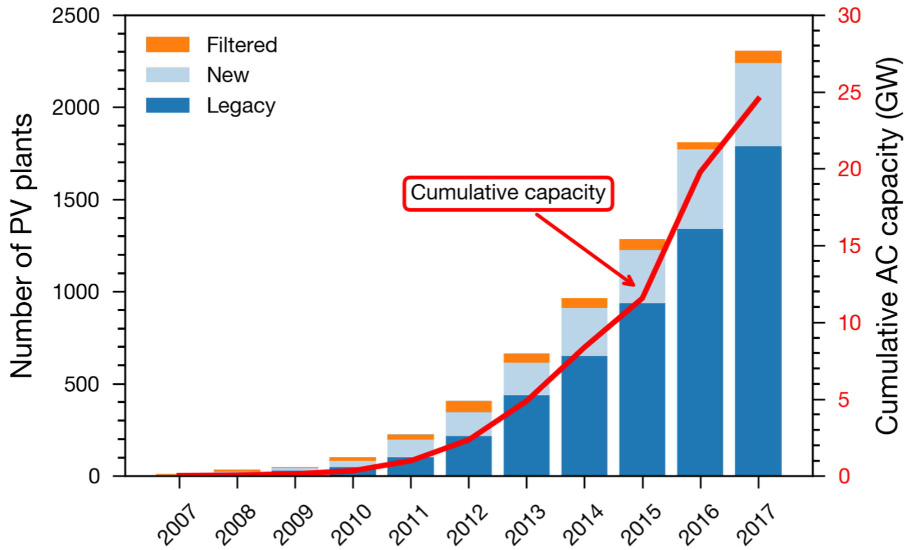


Figure 2.2: Number of PV plants reported in the EIA-860 form for each year (left axis) and cumulative AC capacity (right axis). Orange “Filtered” bars represent plants with non-operating status, missing DC capacity or AC generation or low-quality data. Light blue “New” bars represent plants that were installed during the indicated year. Dark blue “Legacy” bars represent the data used for each year in this paper. Data sources: EIA-860 (Energy Information Agency, 2018a) and EIA-923 (Energy Information Agency, 2018b).

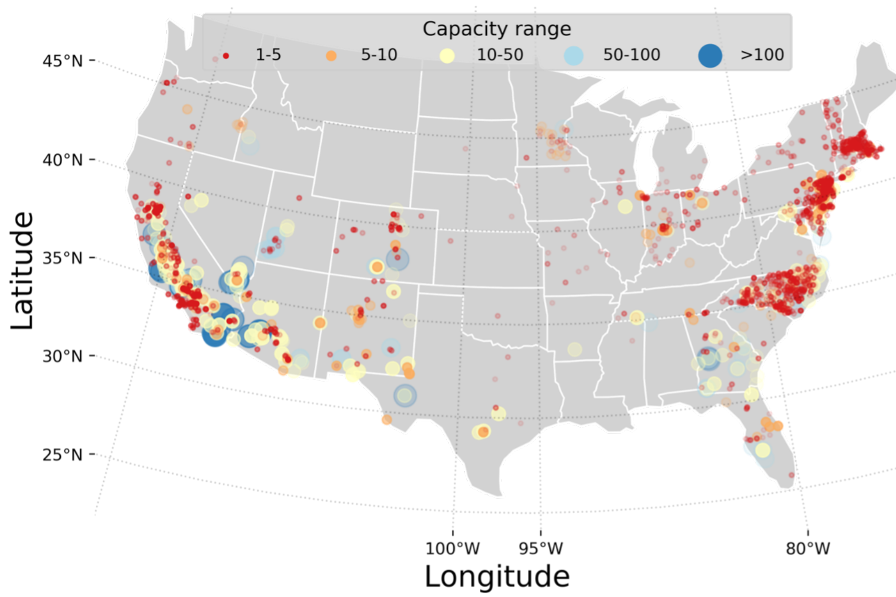


Figure 2.3: Locations of PV power plants documented in the EIA-860 form from 2017 (Energy Information Agency, 2018a). The legend indicates plant size in MW.

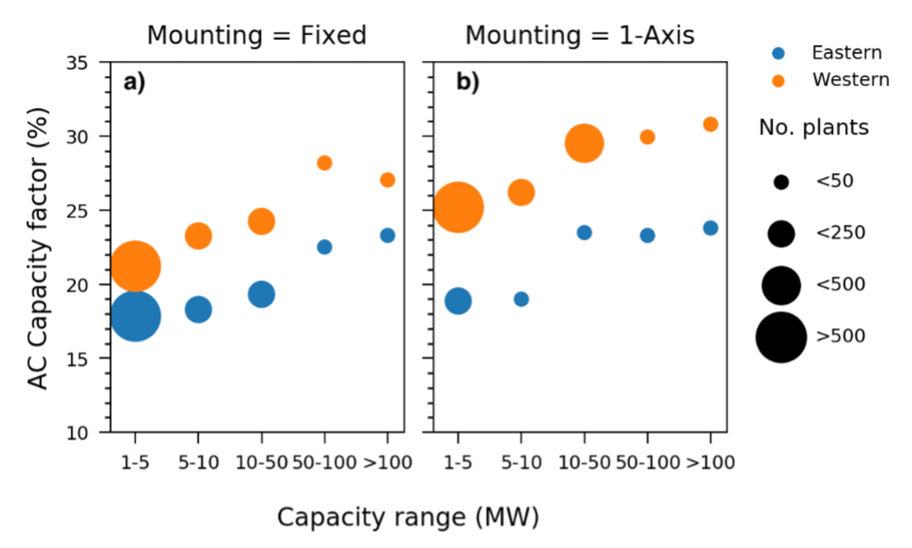


Figure 2.4: Median AC capacity factor a) for fixed-tilt and b) 1-axis-tracked mounting configurations for western (< -95º longitude) and eastern (> -95º longitude) locations, binned by AC capacity range. The number of plants is indicated by the point size.

The median annual AC capacity factor is shown in Fig. 2.5 by year, partitioned by latitude and longitude. The higher latitudes show lower AC capacity factors. In general, the capacity factor increases with time. The eastern U.S. shows substantially lower capacity factors for both mounting configurations, especially for the one-axis tracked configuration (see Fig. 2.5b).

Fig. 2.6 shows that the median ILR has increased with time (Bolinger and Seel, 2018) for all categories. Fig. 2.7 shows the median AC capacity factor as a function of the ILR. As shown in Fig. 2.7 we expected the AC capacity factor to increase with ILR, so for comparison we include data from a high-irradiance and a low-irradiance location to show the anticipated trend. In Fig. 2.8 we plot the relative performance of plants as a function of the number of years of operation, as described above. Fig. 2.8(a) shows the analysis for plants with ≥ 3 years of data (after filtering) and the right side shows data for the plants that had good data for ≥ 9 years. The early years of Fig. 2.8(a) include analysis of 800 data points, as indicated at the bottom for each year. Only 19 plants had data for ≥ 9 years. The AC capacity factors for these 19 plants are shown in Fig. 2.9.

V. Discussion of results

Capacity factor is a simple, yet important, metric for characterizing plant performance. Coal and nuclear plants usually run at full power, resulting in capacity factors of 80% to 90%. Other plants are intended to meet peak load and operate with low capacity factors. Thus, utilities use capacity factor as a metric to understand a plant's role in supplying the grid with power.

In the case of PV plants, the AC capacity factor reflects not only the system design,

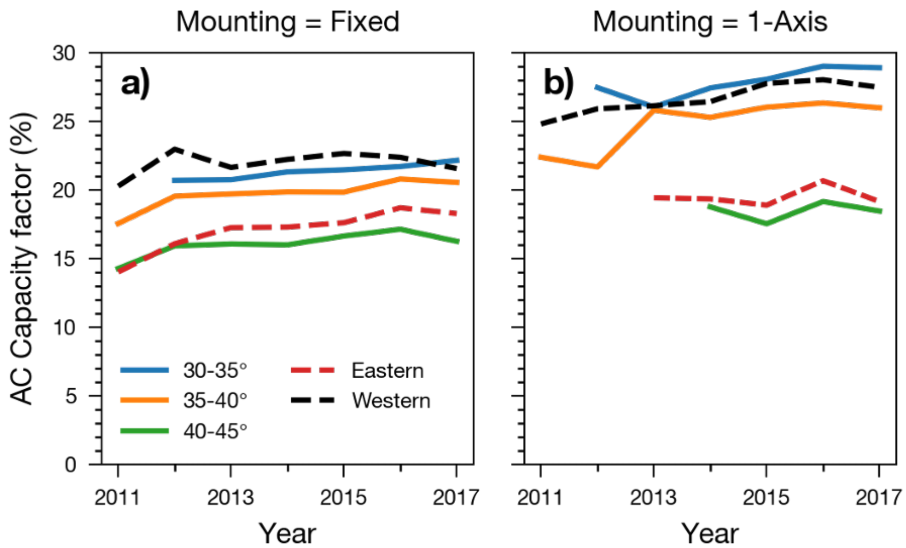


Figure 2.5: Median AC capacity factor for binned latitude ranges (solid lines) and for western (< -95º longitude) and eastern (> -95º longitude) parts of the continental U. S. (dashed lines). Data points were omitted if the number of plants for that year was < 15.

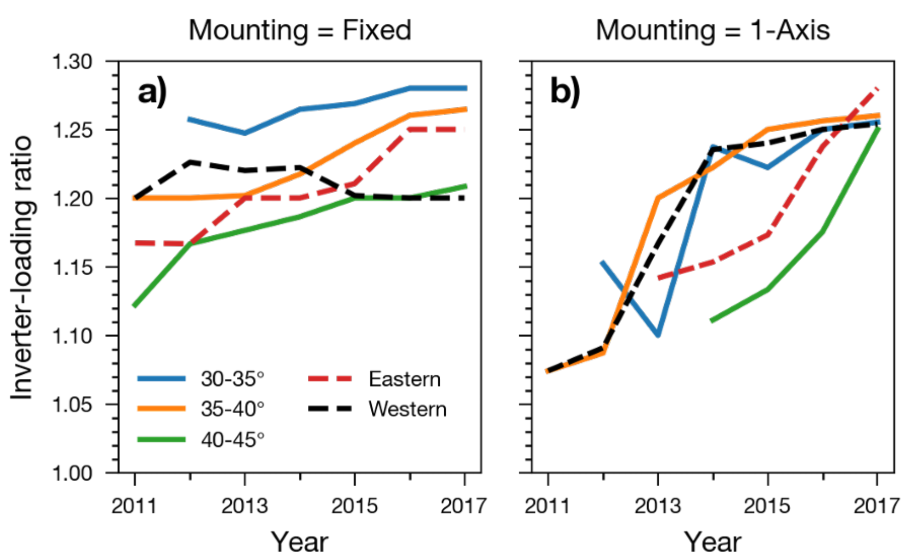


Figure 2.6: Median inverter-loading ratio for binned latitude ranges (solid lines) and for western (< -95º longitude) and eastern (> -95º longitude) parts of the continental U.S. (dashed lines). Data points were omitted if the number of plants for that year was < 15.

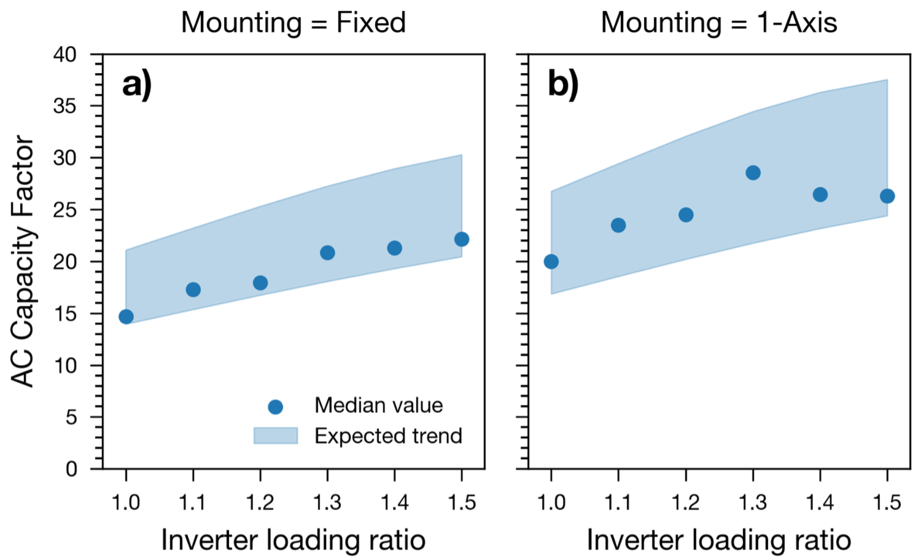


Figure 2.7: Median AC capacity factor for different inverter-loading ratios (ILR). Shaded areas indicate the expected trend using simulated data as calculated in Fig. 2.1 for Daggett, CA (high-irradiance site top of shaded area) and Coventry, VT (low-irradiance site – bottom of shaded area).

but also variations in weather and grid outages that may be beyond control of the plant. Differentiating poor performance because of weather from poor performance because of poor workmanship is also useful, but there is value in evaluating observed AC capacity factor, regardless.

The EIA data provide all information needed to calculate the AC capacity factor of solar PV plants. However, the results depend on multiple variables with correlations that confound the analysis. For example, the locations of the plants (latitude and longitude) correlate with insolation (the northeastern U.S. typically experiences less sunshine than the southwest and most of the plants located north of 40° latitude are in the northeast). We need to be careful not to draw a conclusion that is accidentally based on a confounding variable.

From Figs. 2 and 3 we note that the data are dominated by plants installed in the last couple of years and for geographical locations clustered in California, New England, and some east-coast states. More careful analysis shows that there is an increasing trend of new systems in the eastern U.S. We kept these characteristics of the data in mind for the analysis. Also, there is considerable variability in the calculated values for AC capacity factors and ILRs that suggest data entry errors. Therefore, we used median values to reduce sensitivity to these.

There is a strong correlation between the AC capacity factor and the size of the system (Fig. 2.4). This correlation holds across all categories analyzed in Fig. 2.4. Part of this difference may be a result of low tilt angles for systems installed on rooftops and use of latitude tilt for larger ground mount systems. Alternatively,

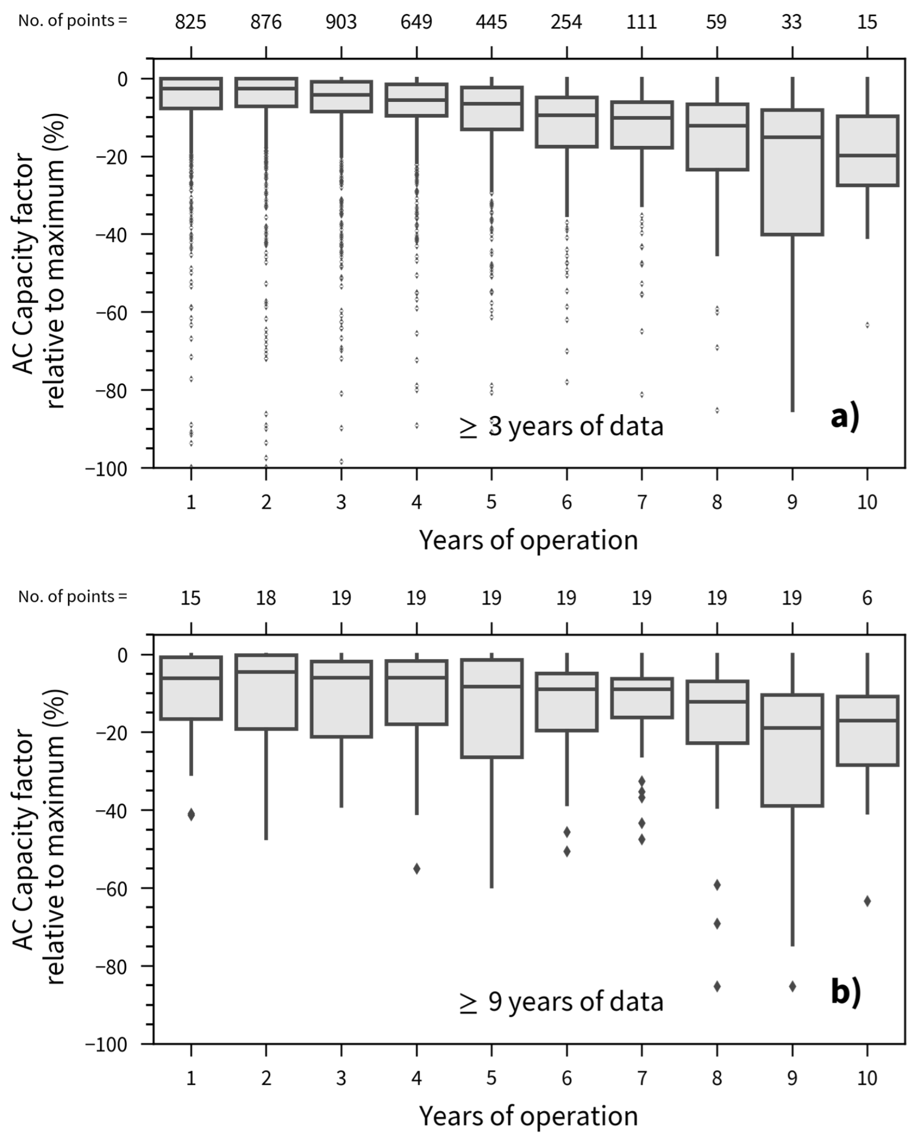


Figure 2.8: Boxplot statistics showing the performance relative to the year with the maximum performance. The number of data points summarized for each year is shown at the bottom for each year. The line in the middle of the box gives the median, the extremes of each box indicate the 20th and 80th percentiles and the uncertainty bars indicate the 5th and 95th percentiles. Outliers are indicated by dots.

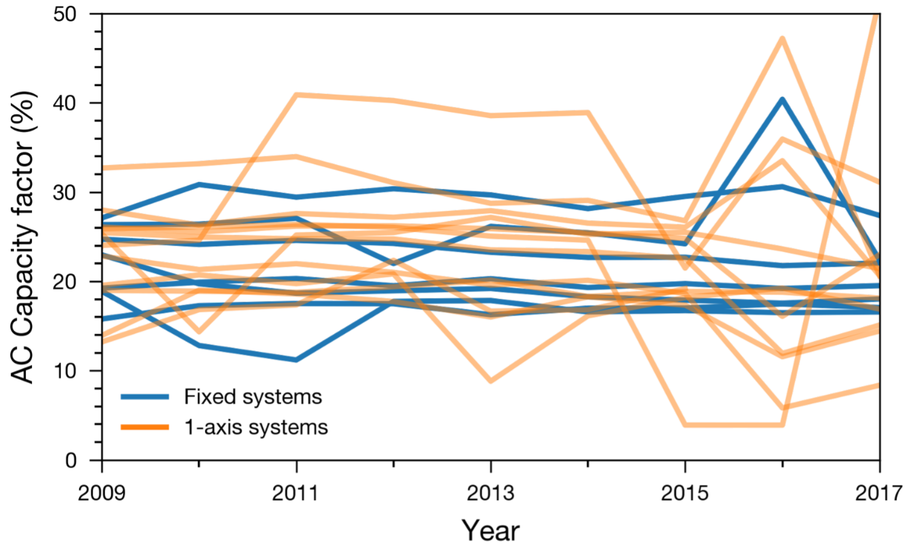


Figure 2.9: Annual AC capacity factor by year for the 19 plants in Fig. 8(b).

it may reflect better maintenance of larger systems or that large plants are more common in high insolation locations.

Without considering the geographical distribution of the systems, the large decrease of the median AC capacity factor for higher latitudes (Fig. 2.5, solid lines) is quite surprising. However, when one considers that the high-latitude plants are found mostly in the northeast, the data make sense. Similarly, the median AC capacity factor for one-axis-tracked systems at high latitudes is considerably lower than at lower latitudes.

For all the categories analyzed (Fig. 2.5), we observed a slight upward trend in the AC capacity factor with time. The slight upward trend balances a systematic increase in ILR (Fig. 2.6) with the trend toward more installations in the eastern part of the U.S. (data not shown, but the ratio of number of systems in the east to the west increased from ˜ 1 in 2013 to ˜ 2 in 2017). The strong increase in the median ILR is very consistent, increasing over time for all latitude and longitude bins (Fig. 2.6). Interestingly, the ILR converged for all latitudes for the one-axis-tracked mounting configurations (Fig. 2.6b). An increase of ILR is expected to increase the AC capacity factor (Fig. 2.7), making it difficult to separate other causes of changing capacity factor. If the trend toward higher ILR continues, we may expect continuing increases in AC capacity factor.

We attempted to analyze the frequency of months with zero generation with the anticipation that these would characterize some types of reliability issues. However, we found that most of the reports of zero generation were for every month (12 months) in a given annual report, suggesting that these were a result of reporting methodology more than of actual performance (see Appendix).

The graphs in Fig. 2.8 both give evidence of slow degradation of the plants over the

10 years shown, but the evidence changes between the two graphs. Fig. 2.8(a) appears to imply with substantial confidence that the median performance is degrading with time and that after nine years, the performance of the median system has degraded by about 20%. However, the tightness of the data for years one and two reflect the ~900 systems included in this analysis. The larger boxes on the right side of Fig. 2.8(a) reflect the smaller number of data points available after ten years. To remove the bias introduced by having some points reflect ~900 data points and others ~20 points, we repeat the analysis in Fig. 2.8(b), limiting the analysis to plants for which we have good data for 9 or more years. The smaller data sets result in larger uncertainties for the early years, giving much less confidence in the linear degradation trend that appears so clearly in Fig. 2.8(a).

The performance in the first full year of operation shown in Fig. 2.8(b) most closely matches that of the fourth year. Evidence of degradation in years 9 and 10 appears to be the most convincing, though it would not appear to be the result of a slow, linear degradation as is often assumed. Fig. 2.9 gives better understanding of what confidence we can have in the degradation analysis by giving the shapes of the evolution of performance for the 19 systems documented in Fig. 2.8(b). In Fig. 2.9, the legend differentiates fixed tilt from tracked systems. Anecdotal evidence suggests that tracked systems sometimes exhibit inaccurate tracking, leading to inconsistent performance. Careful inspection of Fig. 2.9 suggests that the fixed-tilt systems tend to give more consistent performance.

One of the most striking things about Fig. 2.9 is the significant increase in the reported data for some of the plants in 2016 and 2017. As shown in the Appendix, we describe our suspicion that the large variation in performance in 2016 was associated with the bankruptcy of SunEdison. Although an argument could be made for eliminating such data from the analysis, it is useful to identify reliability issues that arise when a company goes bankrupt. In this case, we suspect the bankruptcy prevented accurate reporting of performance in 2016, and that in 2017, when the company was recovering operations, poor maintenance in the previous year took a toll. The SunEdison data cause much of the evident decrease in years 9 and 10 shown in Fig. 2.8. Similarly, some data in Fig. 2.9 are suspicious but were retained to demonstrate how poorly maintained data monitoring hardware could affect income.

Many evaluations of degradation rates can be found in the literature (D. C. Jordan and S. R. Kurtz, 2015; Hasselbrink et al., 2013; Raupp et al., 2016; Bolinger and Seel, 2018). These typically analyze expected linear degradation, but Fig. 2.9 suggests that the bigger issue with system performance may be intermittent or inconsistent performance, consistent with Golnas (2013) conclusion that: "high-resolution monitoring on the DC side does not seem to be critical as most of the lost energy can be attributed to outages of mission-critical subsystems such as the inverter and the AC subsystem". Thus, our data highlight the importance of looking at more than linear degradation as evidence of reliability issues, especially as ILRs increase and inverters, rather than modules, often limit the output of the systems (Golnas, 2013)

At the highest level, our most important observation is that we observe a median AC capacity factor of ~20% for the entire dataset with a median AC capacity factor of 20.3% for the legacy data in 2017. This is a metric overall for the entire set of systems that suggests that the majority of systems are working well. Tracking this metric by year can provide an overall metric for both performance and reliability. Care must be taken to not confuse this with the DC capacity factors that may be easily calculated from cumulative installed PV modules relative to solar generation as documented in many databases. We calculate the median U.S. DC capacity factor in 2017 to be 16%, about 4% lower than the AC value. If ILRs continue to increase, we expect that the difference between the AC and DC capacity factors will also increase.

In the future, we anticipate that PV plants may be installed in a larger range of geographical locations, possibly causing the capacity factor to decrease if more are installed along the coasts, but also, potentially leading to increase in capacity factor as systems are installed preferentially in sunny locations. As noted above, the increasing ILR should increase the AC capacity factor. However, perhaps, the most important cause for higher capacity factors will be the addition of batteries coupled with very high ILR, enabling plants to inject electricity onto the grid for more hours each day.

2.5 Conclusion

Capacity factor is a useful metric because it can be evaluated with minimal information, while giving a representation of the value of the plant to the grid. The solar industry's habit of reporting DC capacity factors leads to a naïve reporting of lower capacity factors, which will create increasing confusion as ILRs increase.

The AC capacity factor is observed to be higher for larger systems, possibly reflecting better design orientation, better care, or higher insolation for the larger systems. The decrease in capacity factors reported for higher latitudes in this data set is a result of the many high-latitude systems in the New England area, which has lower insolation. The use of one-axis tracking and larger ILRs caused systematic increases of the observed AC capacity factor.

We expect that the biggest trend in future capacity factors will relate to the addition of batteries to many systems. We also expect that AC capacity factors will continue to increase as ILRs continue to increase and as more systems are installed in sunny locations. However, we also see a possibility that more installations in low-insolation locations and/or mounting configurations could lead to decreases in capacity factors.

Finally, consistent with some other studies, we find that the data often show inconsistent operation, especially for tracked systems, and that this inconsistency is a greater reliability issue that the linear degradation that is often studied. We anticipate that utilities and their commissions will find these results useful as they anticipate the capacity factors them may expect for PV systems in coming years and as they develop metrics for how to value the dispatchability of PV systems.

Table 2.1: Summary of data adjustments

Plant Code	Adjustment	Metric changed
1172	2016 DC capacity increased from 0.3 to 0.9 MW.	ILR increased from 0.4 to 1.1
10823	All DC capacity reduced from 0.7 to 0.1 MW.	ILR reduced from 7 to 1
56667	2008-2014 DC capacity reduced from 1.2 to 0.1 MW for each of the 12 generators.	ILR reduced from 12 to 1.
57776	2011-2013 DC capacity increased from 1.2 to 2.4 MW.	ILR increased from 0.5 to 1
58178	2012 Generation increased by a factor of 1000.	Total generation from 2 to 2000 MWh
58204	2013-2015 DC capacity increased from 1.3 to 2.5 MW.	ILR increased from 0.5 to 1
58422	2015 AC and DC capacity adjusted to match 2016 data.	ILR reduced from 2 to 1.75.
58632	2013-2015 DC capacity increased from 1.1 to 3.3 MW to match 2016 data	ILR increased from 0.36 to 1.1
60810	2016 AC capacity increased from 0.3 to 2.1 MW	ILR reduced from 7 to 1

Appendix

In this work we present data extracted for the years 2007 to 2017. As discussed in Section 2.3, we found apparent recording mistakes from the EIA-860 data that resulted in unlikely ILRs and AC capacity factors. To fix these, we manually changed data entries by taking the last year values and propagating these to earlier years. Such changes are summarized in Table 2.1.

We also found that the EIA-923 file sometimes reported zero output for some months. A surprising number (50) of annual reports included zeroes for all twelve months. Neglecting installation years, 92% of the zeroes that are reported in the data set are for annual reports with all twelve months reporting zero generation. In many of these cases, the previous year and following year reported normal generation in all twelve months. Given the improbability of many systems being turned off for exactly the calendar year, we treated any report with 12 zeroes as missing data. There were 50 such reports. We excluded from the analysis plants 8223, 56228, 56915, and 56966 because of variable AC capacity. It is sometimes difficult to assess when to treat data as incorrectly entered and when to treat unusual data as "real." For example, Fig. 2.10 summarizes the data for seven SunEdison systems. SunEdison declared bankruptcy in 2016 and the resulting situation apparently introduced reliability issues. The unlikely increases in generation reported for some of the plants in 2016 suggest that one of the first casualties may be the data monitoring/reporting accuracy. However, poor maintenance may have resulted in real degradation in generation in 2017.

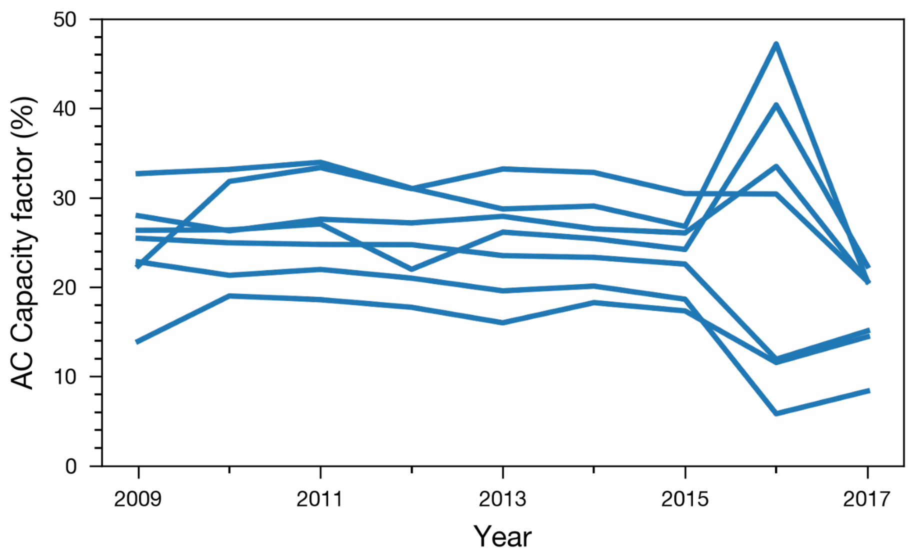


Figure 2.10: AC capacity factor reported by year for seven (7) SunEdison systems.

Chapter 3

Effect of modeled time horizon on quantifying the need for long-duration storage

The text of this chapter is a reprint of the material as it appears in Sánchez-Pérez, P. A., Martin Staadecker, Julia Szinai, Sarah Kurtz, and Patricia Hidalgo-Gonzalez. "Effect of Modeled Time Horizon on Quantifying the Need for Long-Duration Storage." Applied Energy 317 (July 1, 2022): 119022. https://doi.org/10.1016/j.apenergy.2022.119022.

3.1 Introduction

Currently, in the U.S., the cumulative energy storage power capacity in the electrical grid[1] surpassed 28 GW with 420 GWh of energy capacity (Sandia National Laboratories, 2021). It is expected that many regions across the U.S. will deploy an additional 10 GW that will come online during 2021-2023 (Energy Information Agency, 2021). Nevertheless, the required amount and type of energy storage to deliver renewable electricity to a growing electrical demand with a high level of reliability are still unclear (Converse, 2012; Hunt et al., 2020; J. Guerra et al., 2020).

Recently, there has been an increased interest in longer duration energy storage (LDES) in research and industry as a solution to the intermittency challenge and seasonal imbalance produced under an electrical grid dominated by wind and solar power (Guerra, 2021). In this vein, the U.S. Department of Energy (DOE) launched the Long Duration Storage Shot initiative that sets a bold target to reduce the cost of grid-scale LDES by 90% within the decade (Long duration energy storage Council, (LDEC), 2021). A study by multiple LDES companies forecasts that around 1.5-2.5 TW and 85-140 TWh will be deployed globally by 2040 from a diverse range of LDES technologies that are capable of discharging electricity for 8+ hours (Long duration

[1] Most of it comes from pumped hydro storage with 23 GW and around 2 GW of electrochemical storage and the rest from other technologies.

energy storage Council, (LDEC), 2021). However, one of the biggest challenges of these LDES technologies is to store and maintain energy in storage at a cheaper price point than competing Li-ion technology where the capital energy cost ranges from 247-309 $/kWh (National Renewable Energy Laboratory (NREL), 2020).

The required amount of energy storage to ensure a reliable VRE-grid is not well understood and will most likely depend on the share of VRE and regional seasonal energy needs. With this in mind, the design for the duration of energy storage required will not only depend on daily or weekly balancing of VRE output but also balancing and shifting energy across longer periods of time. Still, current tools used to model long-term planning and capacity additions are not designed to capture the full benefits and operations of a weekly or seasonal storage asset. Accurately modeling the different types and duration of energy storage is pivotal to finding the least cost solution to meet clean energy targets and GHG reduction goals.

There is a growing literature related to LDES technologies that spans a wide variety of electrical markets and modeling assumptions. We identified some works that focus on understanding the economic valuation of LDES technologies and economic opportunities (Albertus, Manser, and Litzelman, 2020; Kittner et al., 2021) and works using detailed modeling of LDES and its interaction with a VRE-driven grid (Dowling et al., 2020; J. Guerra et al., 2020; Guerra, 2021; Sepulveda, Jenkins, Edington, et al., 2021; Gabrielli et al., 2018). Such studies found that LDES can fulfill a variety of grid services to help balance the grid with discharge capabilities of consecutive discharge that range from 10-650 hours. The works related to economic opportunities for LDES (Albertus, Manser, and Litzelman, 2020; Kittner et al., 2021) explore LDES technologies with 10 to 100 hours of duration (ratio of energy capacity to power capacity). Other studies have calculated the required amount of energy storage to run the entire US using a constrained energy-balance model and constraining the operations of LDES using a state of charge (SOC) formulation with an hourly resolution (Dowling et al., 2020). Nonetheless, (Dowling et al., 2020) does not use a multi-nodal transmission network which could result in an increased need for LDES. Even though the work considers a full year arbitrage, the authors did not systematically study the impact of changing the Storage Balancing Horizon (SBH).

Modeling a full 8760 hourly resolution in a capacity expansion model can be computationally intensive depending on the problem size. Yet, there are multiple approaches or simplifications in the formulation of the time horizon to address this (see (Bistline, 2021) for more details of the approaches). Multiple academic works and models used in long-term planning processes (e.g., (Sepulveda, Jenkins, Sisternes, et al., 2018; J. Guerra et al., 2020; Gabrielli et al., 2018)) have used these approaches to simplify the computational burden. However, the research gap remains as we have not quantified the errors incurred by these simplified approaches; we cannot truly understand the interactions between LDES and the grid without a full 8760 hourly resolution within a large-scale balancing area with a high geographical nodal resolution.

Lastly, some authors have highlighted that the availability of zero-carbon firm technologies could diminish the need for LDES (Baik et al., 2021). Yet, most of these types of studies faced challenges in correctly modeling LDES as the temporal resolution was either using a subset of the year or representative days.In summary, simplifying the temporal resolution decreases the SBH which ultimately modifies the utilization of storage and the need of it. To accurately calculate the benefits of LDES assets it is key that the model includes several consecutive days to properly capture balancing and shifting energy across longer periods of time.

Statement of Contributions

For this work, we endeavor to understand and build capacity expansion models that correctly capture the value of LDES toward accelerating decarbonization of the electrical sector. To perform this, we systematically explore how changes in the modeled SBH or number of consecutive days changes the need and utilization of LDES. We also analyze, for different LDES cost assumptions, how the different modeled SBH affect optimal LDES deployment and operation. We create a set of future scenarios using SWITCH, an open-source capacity expansion model with high spatial resolution, for various storage balancing horizon lengths and storage energy capacity cost scenarios. We model future LDES assets by using an energy storage candidate technology without any duration constraint and let the model identify the optimal LDES duration for the proposed scenarios. To the best of our knowledge, the impacts of how different lengths of storage balancing horizons can affect the optimal selected power and duration of energy storage under a high temporal and spatial resolution capacity expansion model of the U.S. have not previously been explored.

Manuscript Outline

The structure of this manuscript is as follows: First we introduce the methodology and input assumptions to formulate the capacity expansion model in Section 3.2. Next, in Section 3.3 we present the main findings of the different balancing lengths and storage cost scenarios. Finally, in Section 3.4 we highlight some of the main conclusions on the importance of the length of the storage balancing horizon in capacity expansion formulations.

3.2 Methods

To develop this analysis, we use SWITCH (Johnston et al., 2019), an open-source model for power systems, to work with large shares of variable renewable energy, storage and thermal power plants. SWITCH is a modular capacity expansion model that minimizes the net present value (NPV) of the cost for all investment periods and time points for an electrical grid (Johnston et al., 2019). It optimizes the investment in capacity (chooses an optimal power system design directly) and it optimizes the operational costs (evaluating the cost of running the power system design) (Fripp, 2018). It has been widely used for decarbonization and energy transition scenarios in different regions around the world (J. Nelson et al., 2012; Sanchez et al., 2015; Mileva, J. H. Nelson, et al., 2013; Leon Barido et al., 2015; Mileva, Johnston, et al., 2016; He, Avrin, et al., 2016; He, Lin, et al., 2020; Li et al., 2021; Hidalgo-Gonzalez, Johnston, and Kammen, 2021; Yin et al., 2021). Using a set of assumptions of the market, policies and technology, SWITCH optimizes capacity additions, transmission expansion, and system dispatch while simultaneously being mindful of the constraints in place, such as carbon targets, RPS (Renewable Energy Portfolio Standards), etc. This work uses the latest release of SWITCH-WECC [3] capacity expansion model that is formulated as a linear program (LP). For a detailed explanation of all the variables, constraints and parameters in the SWITCH model see attached Supplemental materials.

SWITCH model formulation

SWITCH has different modules that create the capacity expansion and dispatch problem. Each module incorporates system constraints and parameters on top of the base formulation allowing the user to expand and customize the functionality of the model according to the intended analysis. For this work, we use the SWITCH formulation and inputs as described in the Supplemental materials. Here we present a short summary of the modules we use in this study:

- Timescales - Defines the time horizon for the energy balancing and the multi-period optimization,
- Financial - Defines the base year for the NPV calculation and the discount and interest rate for the investments,
- Generator – Optimizes new generation build-out and electricity dispatch based on fuel costs, variable O&M, and overnight costs,
- Transmission – Handles the operation of the transmission assets and expansion using a lossy-transport model,
- Storage – Defines energy storage assets, optimizes new power and energy capacity, and optimizes their operation (e.g. state of charge constraint),
- Hydro – Enforces monthly minimum and average flows for hydro resources for a given time horizon,
- Policies – Enforces energy policy constraints like RPS and carbon targets, and
- Reserves – Enforces minimum capacity requirements for the system.

[3] This work used an adapted version of SWITCH-WECC v2.0.0. The documentation of the model is available at: https://github.com/REAM-lab/switch and in the supplemental materials.

Geographical scope.

This analysis considers a tailored version of SWITCH that encompasses the entire WECC region that we refer to as "SWITCH-WECC." There are 38 functional Balancing Authorities (BA) in the WECC, seven of which are generation-only BAs (Western Electricity Coordinating Council (WECC), 2016). For this model, The geographical resolution divides the WECC into 50 representative load zones (see Fig S.1). Each load zone is interconnected according to the (aggregated) existing transmission line topology and using the latest thermal capacity limits (Wei, Raghavan, and Patricia, 2019). In total there are 126 existing transmission lines connecting the load zones. We add up the capacity for the different transmission lines that interconnect each of the load zones such that the capacity for the simplified load zones is the same as the aggregated thermal capacity of each of the individual transmission lines for the respective interconnection points. This not only simplifies the model, but also captures the existing thermal transmission line ratings between zones (see Fig S.2 for detailed transmission map).

Time resolution and storage balancing horizon

The multi-period analysis commonly used for long-term planning can be easily implemented using the SWITCH timescale module. Under the SWITCH modeling toolkit, the time resolution is treated using a three-level hierarchy that accounts for the temporal dimension in various scales: periods ($\mathcal{P}$), time series ($\mathcal{T}$) and time points (t).

Periods.

The periods, which are a set of multi-year timescales, describe the times when the investment decisions are taken. SWITCH has been frequently framed as a multi-period optimization across multiple decades. However, the formulation we use in this analysis considers a single period that stretches 10 years from 2046 to 2055 which we refer to as 2050. This period uses the load of 2050 and is scaled such that it represents the length of a 10-year period.

Time series.

The next level of granularity is the time series that denotes blocks of consecutive time points within a period. An individual time series could represent a single day, a week, a month, or an entire year. A time series also limits the length of time energy may be stored. For example, if a time series is composed of 7 days it means that energy can be stored on day 1 and be discharged on any day from 1 to 7, but the model does not allow any surplus or deficit to be carried into a later time series.

Storage balancing horizon.

To properly account for the energy stored in each of the storage assets, the storage module of SWITCH includes a state of charge formulation that keeps track of the current state of charge (SOC) based on the time series provided. This is one of the main constraints that captures the usage of energy storage assets (s). The set of all the assets in the model is denoted by $\mathcal{S}$. The state of charge is modeled by considering the electricity previously stored, $\mathrm{SOC}_{s,t-1}$, the discharge amount, $\mathrm{D}_{s,t}$, the charge amount, $\mathrm{C}_{s,t}$, and the duration of the time point, Δt (e.g., 4 h). The following constraint models it:

$$\mathrm{SOC}_{s,t} = \mathrm{SOC}_{s,t-1} + \left(\eta_c \mathrm{C}_{s,t} - \frac{\mathrm{D}_{s,t}}{\eta_d}\right)\Delta t \quad \forall s \in \mathcal{S} \quad \forall t \in \mathcal{T}, \tag{3.1}$$

where η_c and η_d are the charge and discharge efficiency, respectively. Additionally to (3.1), the storage module incorporates a constraint that bounds the beginning SOC, $\mathrm{SOC}_{t,0}$, and end $\mathrm{SOC}_{t,f}$, where f denotes the last time point of the time series. This constraint is added such that the time series is treated cyclically, which means that the SOC at 0:00 AM on the first day of the time series is the same as midnight SOC for the last day of the same times series. As we change the length of the time series from a week to a whole year, this modifies the number of consecutive days considered for the storage balancing decision (see Fig. 3.1).

The duration of the SBH should be selected to align with the scope of the analysis proposed and the specific market and policy rules. We have identified that most of the existing models focus on short-duration storage (up to 4 hours of consecutive discharge) and using a subset of consecutive number of days to represent the entire year. There is no standardization of how to select the appropriate balancing horizon to understand the role of long-duration energy storage. The selection of the storage balancing horizon mostly depends on the purpose of the modeling, but can also be related to the type of load shape and storage utilization. The ideal scenario will run a single time series with 8760 hours, yet this could be computationally intensive for large-scale capacity expansion models. For this work, we use four storage-balancing horizons: 1 week, 2 months, 6 months, and 1 year. This is done by changing the input file that is handled under the timescale and storage module. Each time series scenario has a different ending for the SOC as illustrated in Fig. 3.1.

Time points.

Finally, time points describe unique time steps within a time series. The duration and number of time points per time series depends on the analysis intended but they are typically on the order of one or more hours. Time points are the smallest timescale in the model and are used to index exogenous variables such as electricity demand and renewable energy generation profiles. All of the time series scenarios used in this study include exactly the same days (364 days) with a 4-hour resolution, producing a total of 2,184 data points per year. The evaluation of the same 2,184 data points for

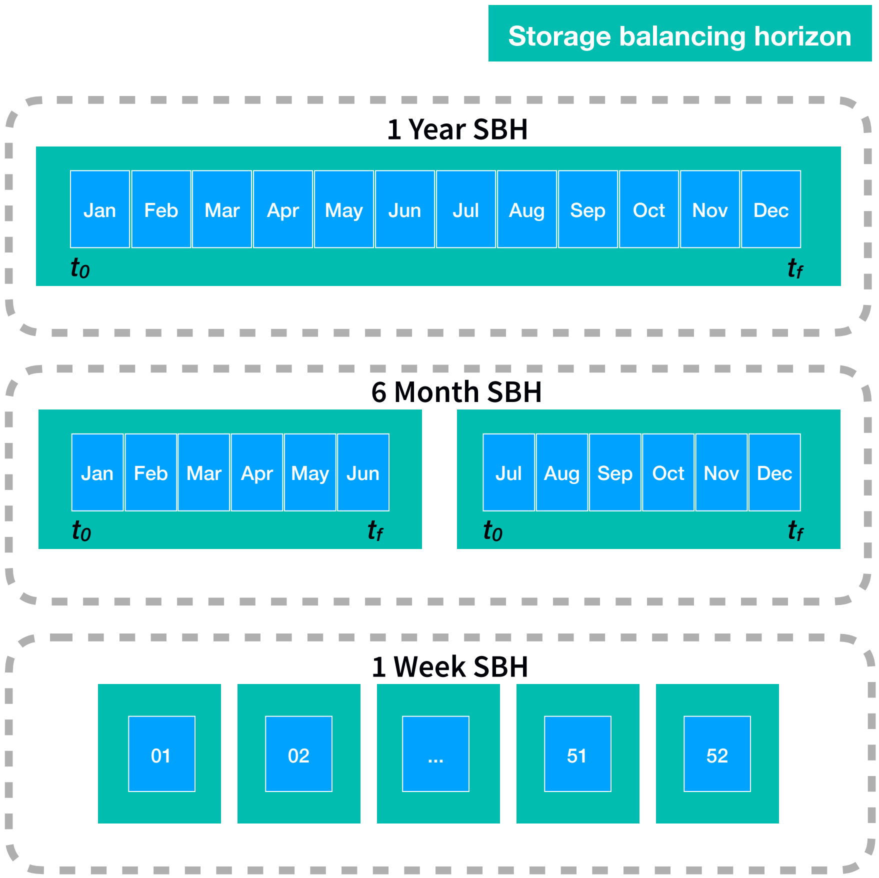


Figure 3.1: Diagram showing the storage balancing horizon (SBH) concept for three different lengths: 1 Year, 6 Month and 1 Week.

each of the horizons avoids variability in the results dependent on which input data (e.g., sampled hourly loads, capacity factors, etc.) are or are not included.

Existing and candidate generator and cost data.

The list of existing generators in the WECC is from the latest version of the form EIA-860 (Energy Information Agency, 2018a) geolocated to its respective load zone using the latitude and longitude reported. The overnight costs for each of the candidate plants were provided using the baseline scenario from the NREL-ATB 2020 (National Renewable Energy Laboratory (NREL), 2020). From this source, we extracted the overnight, energy and O&M costs as shown in Table 3.1. For the capacity expansion, SWITCH-WECC provides one candidate resource per non-variable technology (see Table 3.1) per load zone. In total, there are 7,149 candidate locations for new power plants (from which approximately 6,000 correspond to solar and wind sites). The cost numbers represent an average of the projected cost for the 10-year period (2046-2055)

Table 3.1: Cost assumptions for each of the candidate technologies provided to SWITCH. Data are shown for the 2050 period

Category	Technology	Overnight cost[1] ($/kW)	Energy cost ($/kWh)	Fixed O&M ($/kW)	Fuel cost ($/unit)	Lifetime (years)
Zero-emissions technologies						
	Fixed tilt solar (20-33% CF)	703	-	8.29	-	20
	Wind (23-46% CF)	1042	-	33.70	-	30
	Off shore wind (30% CF)[2]	2227	-	112.30	-	20
	Geothermal	6970	-	173.11	-	20
	Biogas – ICT[3]	2118	-	64.38	0.00	20
	Bioliquid - ST	3226	-	80.01	0.01	40
	Biosolid - ST	3226	-	80.01	0.32	20
Conventional technologies[4]						
	CCGT	925	-	12.86	6.31 - 7.36	40
	CCGT - Cogen	103	-	5.31		20
Energy storage						
	4hrs Li-ion	113	130	15.80	-	10

Note: Overnight, energy and fixed O&M cost numbers (National Renewable Energy Laboratory (NREL), 2020) represent the average of the selected period to study from 2046-2055 year range.

[1] The overnight capital cost is the capital expenditure required to achieve commercial operation of a plant, excluding the construction period financing cost and the interconnection cost.

[2] Offshore technology is only available for California load zones.

[3] For the baseline scenario there is no fuel cost associated with using biogas.

[4] Natural gas price varies according to the load zone.

modeled.

3.3 Results

All the input files for each of the scenarios are constructed and run individually in a server with 24 cores, 2.8 GHz clock speed, and 512 GB of RAM memory located at UC San Diego. We use Gurobi (Gurobi Optimization, LLC, 2021) as the solver for all the runs using one thread and crossover as the solving mechanism. On average, the solutions to the optimization problems are found in 4-5 hours.

First, we show the results of the optimal online capacity and transmission expansion for the entire WECC using the baseline energy cost scenario as shown in Fig. 3.2. From Fig. 3.2, we observe that most of the western load zones are dominated by both solar and storage technologies. In the south-west region, i.e. California and Arizona, we observe that utility-scale solar and energy storage dominate the share of capacity with up to 80% of the installed capacity. Three out of five load zones with highest annual electrical demand are located in this region. Wind energy is deployed in the northern part of the WECC in the load zones of Alberta and British Columbia with up to 70% and 50% of the new capacity additions respectively. Also, in the same region, new transmission is needed to balance and transmit wind and solar energy. For biomass, only one load zone located in the Northern part of Oregon expands this

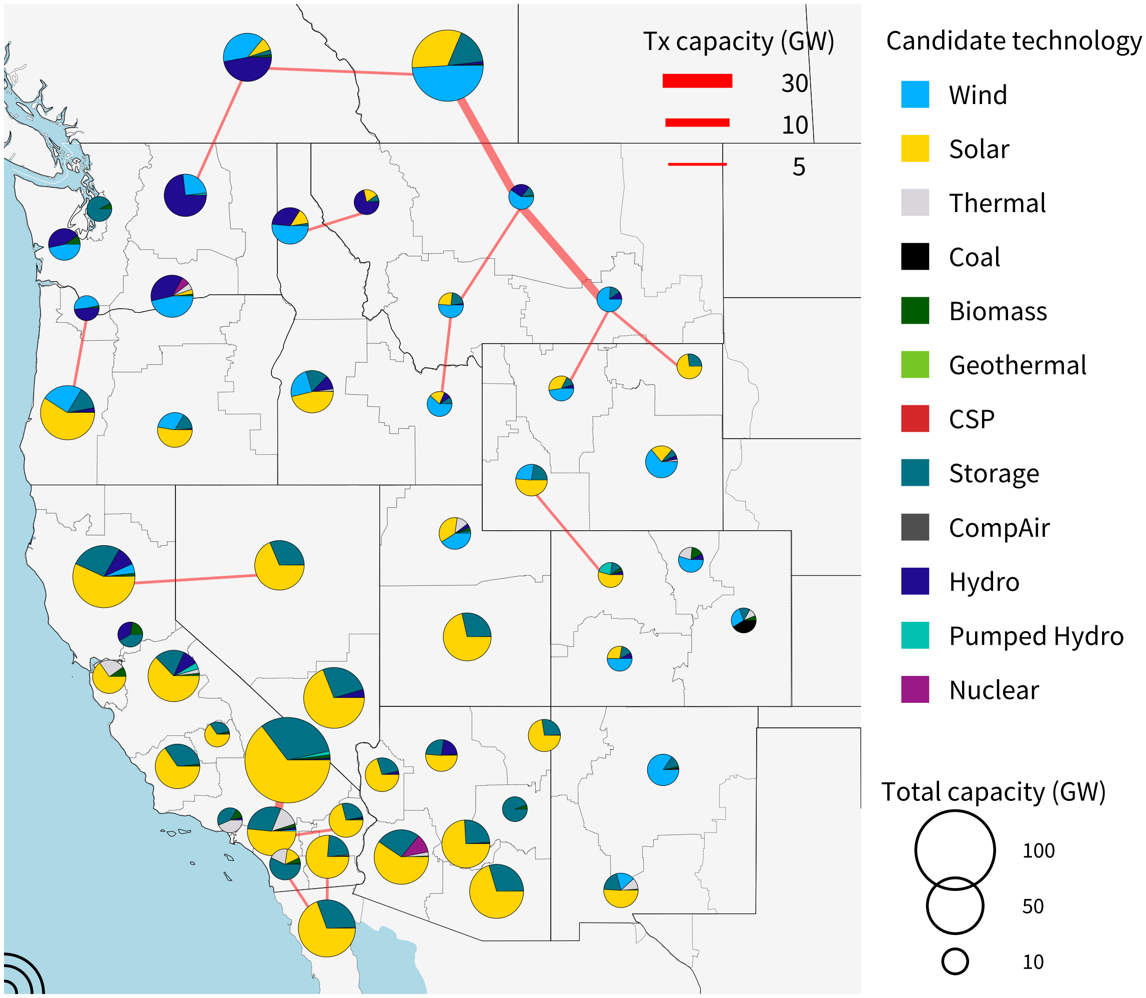


Figure 3.2: Map of optimal online capacity and new installed transmission for a zero-carbon WECC in 2050. Cost assumptions correspond to the baseline storage energy cost scenario using a 1-week SBH. Solar and storage dominate the capacity mix in most of the WECC. Additional transmission is required in the northern balancing zones to accommodate extra capacity selected.

technology due to low solar and wind annual capacity factors for this zone (10% for solar and 20% for wind) in comparison with other regions of the WECC.

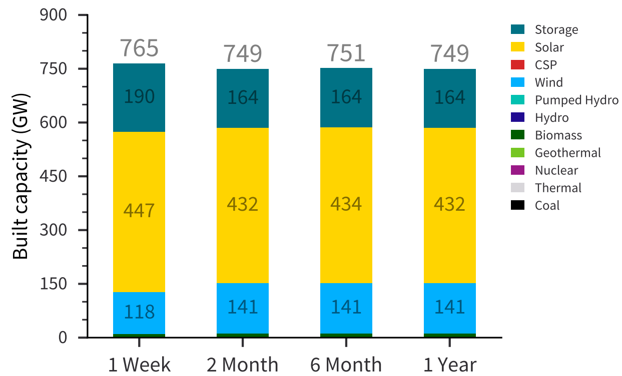
The results of the optimal new built capacity are shown in Fig. 3.3. The ratio of solar to wind remains almost constant across the different scenarios with an average ratio of 3. The maximum capacity deployed for solar power is 17% of the potential available capacity WECC-wide, while the maximum capacity deployed for wind power is 11%. From these results, we observe that the 1-Week SBH always results in additional solar and storage being deployed in comparison with longer SBH where the optimal power capacity remains almost constant in all cost scenarios as seen in Fig. 3.3a. This overbuild from both solar and storage is required to adjust the energy balance constraint to meet the high load week that occurs from July to August. We observe a similar overbuild in all cost scenarios and in particular in the 6-month SBH scenarios as seen in both Fig. 3.3b and Fig. 3.3c where the first week of the second SBH coincides with the summer peak. Changing the storage energy capacity cost did not substantially change the total installed power capacity until reaching 1% of the cost. In this case, we observe a decrease in total power capacity from 766 GW (1W SBH) to 707 GW (1 Year SBH) as seen in Fig. 3.3c. Another interesting trend is that wind power is deployed less as we reduce the cost of storage energy capacity. In the baseline energy capacity cost scenarios the installed capacity for wind power ranges from 118 GW to 141 GW, while in the 1% energy cost scenarios, the capacity ranges from 92 GW to 120 GW.

Next, we present results related to the optimal duration for the storage technologies. As we explain in section 3.2, the model is able to optimize both the power and energy ratings of each of the storage candidate assets for each load zone. The optimal cumulative number of storage assets is shown in Fig. 3.4. For the baseline cost scenario we observe that 50% of the storage assets have 7 or fewer hours of duration. Furthermore, we also observe that for the baseline cost scenario, the SBH length does not change the optimal storage duration.

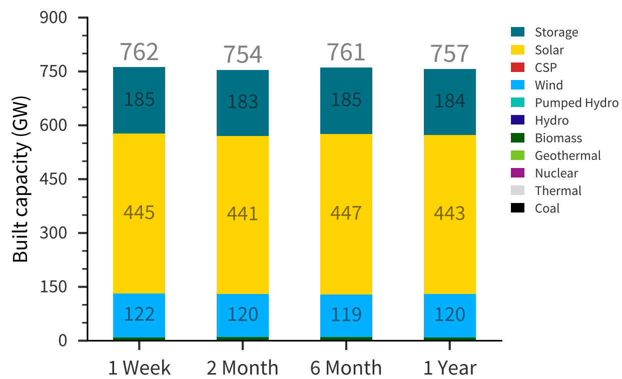
As the storage energy cost decreases, we obtain that the optimal duration deployment depends on the length of the time series. We observe this behavior in both 10% and 1% of the baseline cost scenarios with the latter showing the biggest difference and longer duration with up to 600 hours of duration. For the 10% cost scenario, we observe that there is a shift of the 50th percentile to at least 8+h duration with up to 24 hours for all SBH lengths as shown in Fig. 3.4. Although the 10% cost scenario represents an aggressive cost reduction, by 2050 such a low cost may be a reasonable assumption especially if the DOE is successful in reaching this cost in 2030. For both the 10% and 1% costs, the model finds optimal seasonal storage duration with up to a month of energy discharge capacity.

Moreover, results show that the length of the balancing horizon reduces the amount of renewable curtailment. For all the scenarios, we observe the peak of curtailment occurring between April and May, mostly from solar energy. We observe a reduction in the total amount of curtailed electricity as we increase the number of consecutive days modeled in the 10% and 1% cost scenarios with a higher reduction in the latter as shown in Fig. 3.5. For the 1% energy cost scenario, the curtailment is highest for the 1-week SBH with up to 171 TWh and lowest for the full year horizon with 43 TWh. In both these cases, most of the curtailment comes from solar technologies. For these low-cost storage scenarios, the model finds it optimal to store additional energy instead of building new VRE capacity, in particular in load zones where both VRE generation profiles are low.

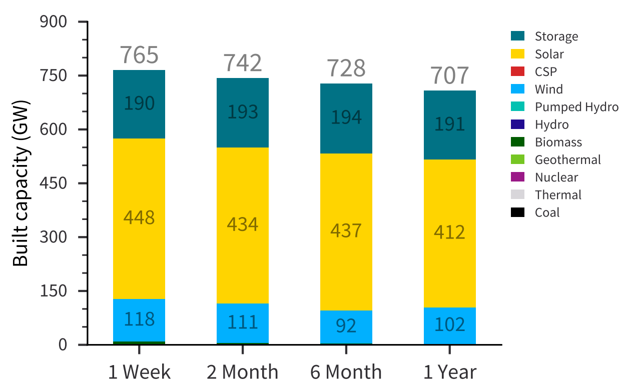
The utilization of storage also changes with the balancing horizon. For the baseline cost, most of the short duration (5-8 hours) storage selected is being utilized for daily arbitrage to balance solar and wind generation. The model also selects 8+ hour duration at baseline cost that is also utilized mostly for daily arbitrage, but only in 4 load zones. In Fig 7 a) the model selects 5-10 hour storage (orange line) and some



(a) Baseline energy cost – $130/kWh



(b) 10% energy cost - $13/kWh



(c) 1% energy cost - $1.3/kWh

Figure 3.3: Optimal selected capacity mix for a zero-carbon WECC in 2050 considering the different lengths of storage balancing horizons and storage energy costs with the storage cost being a) $130/kWh, b) $13/kWh, and c) $1.3/kWh.

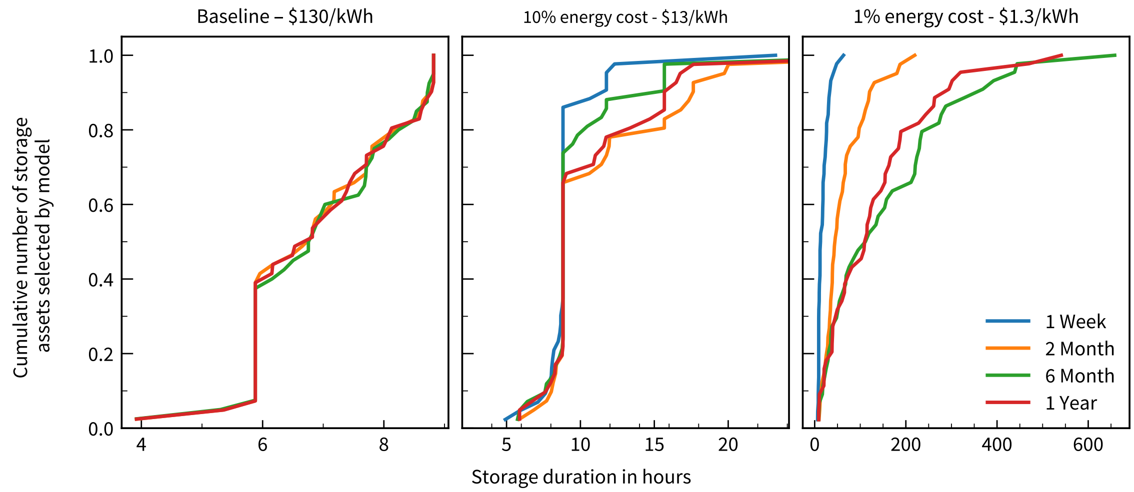


Figure 3.4: Cumulative number of storage assets selected by the model for the optimal energy storage duration (energy to power ratio). The different panels show results depending on the storage energy capacity cost assumption: the left corresponds to the baseline cost, the middle panel corresponds to \$13/kWh, and the right panel corresponds to \$1.3/kWh. Each color represents a different storage balancing horizon (SBH) where the blue line represents the 1-week, orange 2-month, green 6-month and red 1-year. We observe an increase in optimal storage duration deployment as the storage energy capacity costs decrease.

weekly storage (green line) and, for both, the amount of energy in storage reaches up to 1 TWh for the entire WECC.

The model does not add additional energy capacity for any of the balancing horizons as it becomes more expensive than overbuilding solar or wind capacity. On the other hand, we observe a complete utilization of storage for the 10% and 1% energy cost scenarios. The model selects LDES starting from the 2-month horizon at 10% cost and for all horizons at 1% of the energy cost (see Fig. 3.6). In particular, for the 1-year scenario at 1% energy cost, the model selects two types of storage only: weekly and seasonal. The weekly storage is also used for daily arbitrage and is capable of discharging up to 2 TWh while maintaining a minimum SOC of 1 TWh throughout the year. The seasonal storage is also being used for daily arbitrage but it is optimized to meet two main discharge events that match the summer and winter peaks of the entire WECC with a total of 12 TWh of energy in storage.

Finally, we show the storage capacity difference obtained by changing the SBH for the baseline energy cost as shown in Fig. 3.7. Overall throughout the WECC, the 1-week SBH requires additional storage power capacity up to 4 GW per load zone (shown in dark red). On the other hand, 15 balancing zones, mostly in the eastern-WECC (shown in dark blue), show the need to add more storage capacity up to 2 GW mostly to balance the different usage of storage in neighboring zones. In total,

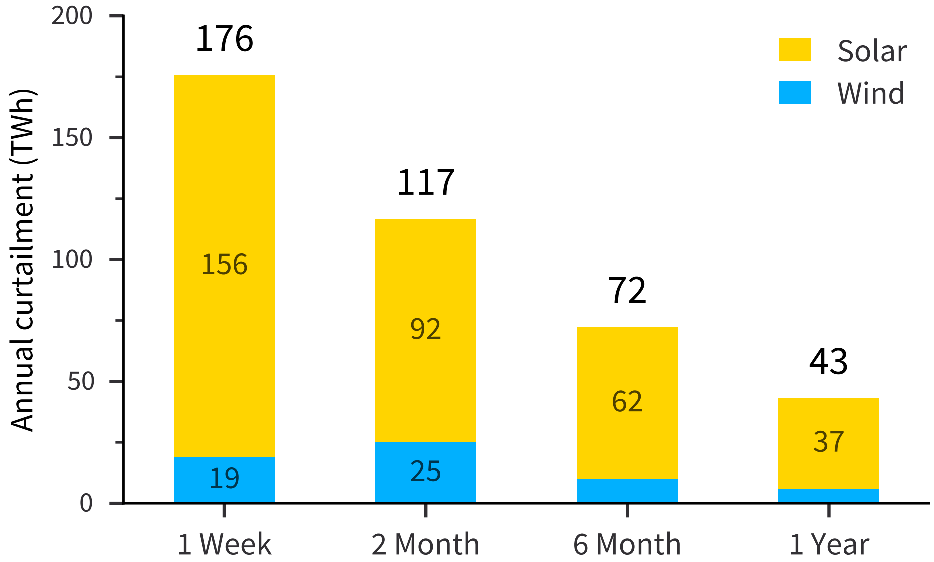


Figure 3.5: Total solar and wind curtailment for the \$1.3/kWh energy capacity cost scenario for each SBH scenario. Curtailment is defined as the difference of the available dispatch capacity at each time point and dispatch decision. Curtailment is reduced as the SBH duration increases.

5 out of the 50 zones did not see any change from the different SBH.

3.4 Conclusions and future work

In this work, we systematically explore the impact of extending the SBH to longer time frames and how the initial assumption of SBH changes the role of low-cost LDES in a capacity expansion formulation. From our results, we conclude that shortening the SBH undermines the true potential of LDES technologies for seasonal storage or energy shifting. While LDES technologies are still in early stages, we expect that their costs will further decrease and anticipate them playing a bigger role to support additional VRE deployment.

When we compare extreme scenarios, i.e., a full year of consecutive days for storage balancing using \$1.3/kWh as the cost for energy capacity versus one week of consecutive days at \$130/kWh, the installed storage energy capacity varies by up to 13%. We also find that the total amount of energy required to balance the WECC increases as the SBH increases. Moreover, we find that the amount of storage needed for an optimal WECC ranges from 2.47 TWh for the 1-Week SBH at \$113/kWh scenario to 16.05 TWh for the 1-Year SBH at \$1.3/kWh scenario.

In terms of energy storage duration, we find that the model adds weekly (10-100 h) and seasonal (100+ h) energy storage for the \$13/kWh and \$1.3/kWh energy capacity cost scenarios, respectively. The length of the SBH increases the optimal deployment of storage duration from a maximum of 8 hours in the baseline cost scenario up to 620

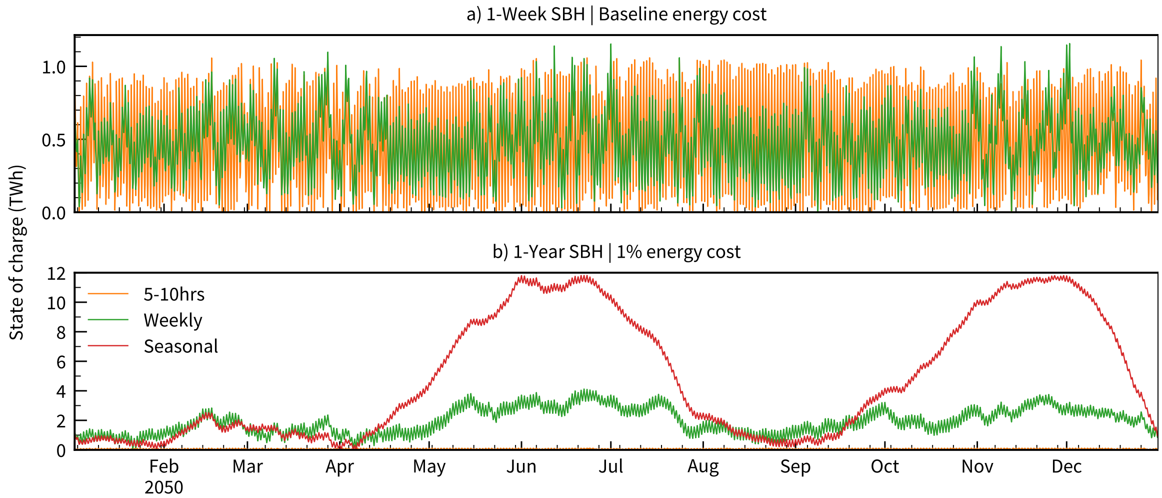


Figure 3.6: Aggregated state of charge for all energy storage technologies installed throughout the WECC region. a) For the 1-week SBH using \$130/kWh and b) for the 1-year SBH using \$1.3/kWh. Duration of energy storage is classified according to its optimal range of duration (energy to power ratio). The range between 10-100 hours is classified as weekly and 100+ hours is classified as seasonal. In panel b) we observe seasonal storage to balance summer and winter peak.

hours when the cost is \$1.3/kWh. When we model 1-Year SBH for each of the energy capacity cost scenarios, we obtain a total optimal energy capacity WECC-wide that ranges from 1.5 TWh to 12 TWh for the 10% and 1% energy capacity cost scenarios, respectively.

An accurate power system modeling of LDES technologies is key to understand the importance of LDES for a high-VRE electrical grid. This work takes the first step towards correctly modeling LDES in capacity expansion models and understanding the errors incurred and differences found when not modeling a full year of consecutive days for storage balancing. We expect that this work will not only identify limitations of existing models in capturing the value of low-cost LDES technologies, but also motivate new work related to capacity expansion formulation. Additionally, the approach we present in this work aims to inspire energy modelers to adopt a year-long SBH for LDES technologies in their capacity expansion models.

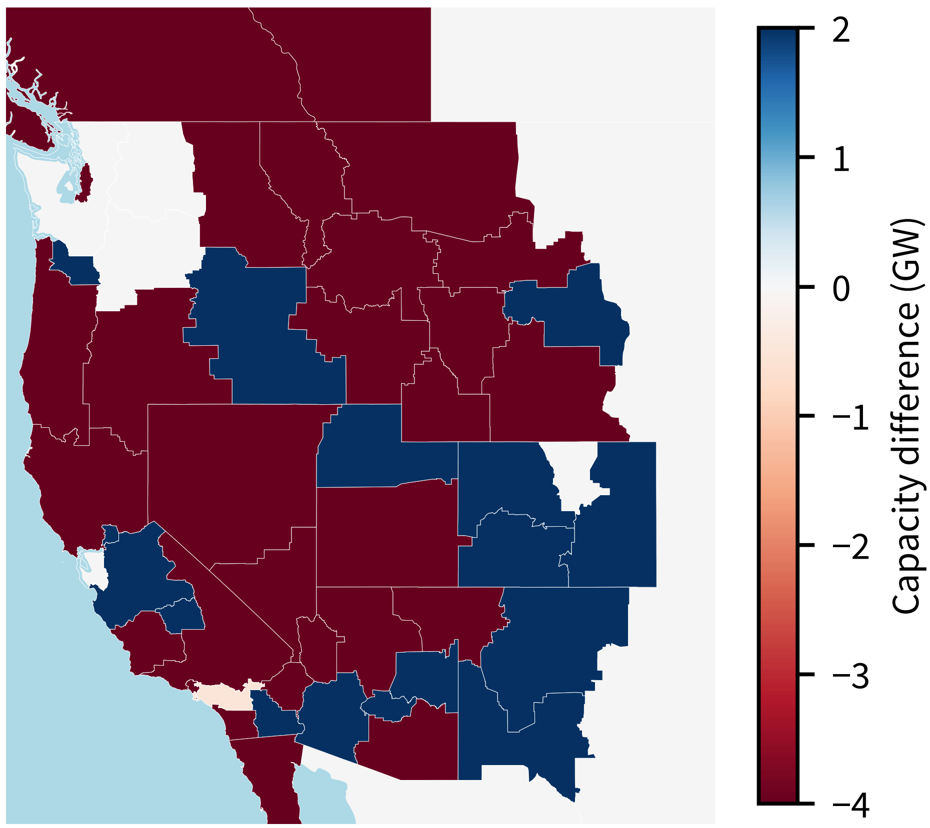


Figure 3.7: Storage capacity difference between 1-Week SBH and 1-Year SBH for the baseline energy cost for each of the WECC regions.

Chapter 4

Effect of Time Resolution on Capacity Expansion Modeling to Quantify Value of Long-Duration Energy Storage

The text of this chapter is a reprint of the material as it appears in Sanchez-Perez, P. A., Sarah Kurtz, Natalia Gonzalez, Martin Staadecker, and Patricia Hidalgo-Gonzalez. "Effect of Time Resolution on Capacity Expansion Modeling to Quantify Value of Long-Duration Energy Storage." In 2022 IEEE Electrical Energy Storage Application and Technologies Conference (EESAT), 1–5. Austin, TX, USA: IEEE, 2022. https://doi.org/10.1109/EESAT55007.2022.9998031.

4.1 Introduction

In capacity expansion modeling, it is common to find model formulations that simplify the temporal resolution to reduce the computational time. The above statement is true for different models that cover a large geographical area and have a substantial number of generators, making it challenging to model 8760 hours of simulations over multiple periods. Since the results of capacity expansion models are meant to assist long-term planning processes, the capability to quickly modify and assess a wide variety of sensitivity scenarios is highly valuable.

Recently, there has been enthusiastic interest in energy storage assets capable of storing energy for a duration longer than current Li-ion technologies (more than 10 hrs rather than up to 4 hrs). This type of energy storage, long-duration energy storage (LDES) technologies, could be used as a commodity for system operators to reduce renewable curtailment and shift electricity across multiple weeks or seasons. There is a wide variety of emerging LDES technologies. Reference (Shan et al., 2022) has already explored the different kinds of emerging LDES technologies with a wide assortment of methods to store energy (e.g., electrochemical, gravitational, and thermal) with different efficiencies and operational constraints. The wide variety of types of LDES creates uncertainty for modelers on how most kinds of LDES technologies will participate in the future electrical market and how the different assumptions will change the modeled optimal size and need for LDES assets.

Multiple authors have already explored LDES in capacity expansion models or simplified models (Sepulveda, Jenkins, Edington, et al., 2021; J. Guerra et al., 2020; Dowling et al., 2020) and how changing the temporal resolution can yield different optimal solutions (Bistline, 2021; Hoffmann et al., 2020; Sánchez-Pérez et al., 2022). However, to our knowledge, no work has explored the change in storage usage and optimal capacity for temporal simplifications with LDES assets, mainly when aiming for a future dominated by variable renewable generation. From our perspective, understanding how LDES could be used in future grids will: 1) shape the design and configuration of energy storage assets, 2) strengthen current efforts to invest in LDES, 3) build certainty for stakeholders in long-term planning around LDES technologies, and 4) improve the understanding of temporal constraints for LDES assets.

In this work, we evaluated the sensitivity of LDES technologies in future variable renewable energy (VRE) grids with different temporal resolution simplifications. We studied the storage deployment, utilization, and curtailment reduction for three different temporal resolution scenarios and contrasted them against a future where LDES is not in the capacity mix. This manuscript is organized as follows: first, we detail in the methodology section the modeling framework used and the baseline scenario constructed to test our different temporal scenarios, then we examine some of the main findings regarding the storage deployment and utilization in the results section, and finally, we outline some of the main conclusions.

4.2 Methodology

This work aims to understand the change in the total capacity and usage of LDES assets in capacity expansion models under different timescales resolution. To explore this, we used the Switch 2.0 model, an open-source power system planning tool that co-optimizes transmission/capacity additions and operations over multiple investment periods (Johnston et al., 2019). The objective function is to minimize the total system cost over multiple investment periods, including generation and transmission capacity additions and operations subject to operational constraints, policy, and emission constraints. We selected Switch as our main modeling framework due to its flexibility and modularity in creating different timescales, a key feature for this work's implementation. Furthermore, Switch has a built-in module to model energy storage assets, including idle losses, state of charge (SOC), discharge/charge efficiency, and minimum energy to power constraint.

Switch is a Python-based model that requires a set of input assumptions in ".csv" format to create the optimization problem. For this work, we used Switch-California, which is derived from the input assumptions of the Western Electrical Council branch of Switch ("Switch-WECC"). Results using Switch-WECC were published first in (J.

Nelson et al., 2012) and updated in (Sánchez-Pérez et al., 2022). The input assumptions include the network topology (load zones) and transmission lines, existing and candidate generators for each load zone, technical operation of the generator assets, build cost per period, predetermined builds, investment periods and timescales, and transmission limits. This work created a subset formulation based on the the Switch-WECC model just for California with newly updated assumptions for storage technologies, including LDES assets and timescale scenarios. We detail the changes made in the input assumptions in the following subsections.

Geographical resolution

For this work, we selected the study region to be California due to its high variable renewable energy penetration, geographical diversity, energy policy goals, and current interest in LDES. The model includes a total of 12 load zones that represent most of the load-serving entities and investor-owned utilities within the California footprint, as shown in Fig. 4.1. Since this version of the model considers only California zones, all the new infrastructure investment required to meet the future load needs to be in-state; therefore, any imports or exports are outside the scope of this work.

Candidate generators cost assumptions

The list of existing and candidate generators comes from the Switch-WECC version derived from the existing power plants listed on the EIA-923 form. Each generator asset belongs to the corresponding load zone based on its location. For energy storage assets, the baseline scenario considers only Li-ion technology. As mentioned in the introduction, there is a considerable variety of LDES technologies. To explore LDES technologies, we added LDES to the candidate technology mix for each load zone that will compete with the Li-ion. We took the capacity and energy cost numbers for LDES reported in (Shan et al., 2022) and projected that the exact cost ratio (LDES vs. Li-ion) would remain constant in the modeling period. The previous statement is one of the main biases of the work, and we are aware that different cost numbers yield different results. However, we used this assumption due to the lack of cost projection for LDES technologies.

For the operational characteristics of the LDES assets, we include an asset representing a low-cost and long-duration (> 100hr) LDES product with 45% round-trip efficiency and 1%/day idle losses. We summarize the cost assumption and technical parameters for energy storage in Table 4.1.

State policies

Additionally to the list of pre-existing generators, we included an offshore wind candidate technology with a capacity of 10 GW located in "CA_PGE_S". This candidate technology will be online by the 2050 period and was included in accordance to the latest AB-525 bill from the California government (*California AB-525* 2021) . For

Figure 4.1: Grid topology proposed for California. The shape and area of the load zones are similar to those previously developed by the Switch-WECC team.

Table 4.1: Technology and cost assumptions for energy storage technologies. Cost numbers are the projection for the 2050 period.

Technology	Power capacity cost ($/kW)	Energy capacity cost ($/kWh)	Round-trip efficiency (%)	Idle losses (%)	Minimum duration (hrs)
Li-ion	113.22	130.03	95	0.10	4
LDES	48.68	16.90	45	1.00	100

the generation profiles, we used the latest leasing area for the Morro Bay area (Bureau of Ocean Energy Management, 2021), then we calculate hourly capacity factors using the 2019 year dataset for offshore wind in California from the Wind Tool Kit developed by NREL (Draxl et al., 2015) and the 2020 offshore wind reference turbine power curve from the NREL-ATB (see National Renewable Energy Laboratory, 2021).

Timescale

Switch includes a module that defines the temporal resolution with three timescales for decision making: periods of one or more years where investment decisions are made, time points within each period when operational decisions are made, and time series that group time points into chronological sequences (Johnston et al., 2019) for storage arbitrage. For the scope of this work, we model only the 2050 period, which considers a future zero-carbon California grid with most of the electricity being supplied by either VRE or non-emitting firm assets. This 2050 period considers a single time series (from January 1st till the end of the year, December 31st) of sequential modeling time points. To create the different time scale scenarios, we took the load projection from the Switch-WECC model for California that is on an hourly resolution and sampled every 4-hr, 2-hr, and 1-hr resolution starting from the first modeling timepoint of the time series. This sample only considers a snapshot of the current status of the load and the matching VRE generation at the same timestamp.

Additional modeling details

In addition to the previous changes, we retained the default module configurations for the planning reserve assumptions. For all the scenarios explored, we used a conservative 15% planning-reserve margin (PRM) for each load zone. Also, all the generators can provide reserves for the load zone, and this assumption resulted in some capacity being online by 2050, even though it is not dispatched. Removing the gas capacity to be applicable for planning reserves could yield an opportunity for

Table 4.2: Scenario descriptions

Scenario name	LDES included	Time resolution	No. time points
Baseline_4hr	-	4hrs	2190
LDES_4hr	✓		
Baseline_2hr	-	2hrs	4380
LDES_2hr	✓		
Baseline_1hr	-	1hr	8760
LDES_1hr	✓		

energy storage; however, further analysis is required on how storage and LDES will provide planning reserves and is out of the scope of this work,

To run the model, we used the solver Gurobi (Gurobi Optimization, LLC, 2021) on an M1 Macbook pro machine with 32 GBs of RAM for all the scenarios. The run time falls between 30 minutes for the 4-hr runs up to 480 minutes for the 1-hr runs.

4.3 Findings

First, we present the online capacity by period for each scenario as shown in Fig. 4.2. We obtained that VRE generation and storage for all scenarios constitute the highest share of online capacity. The remaining capacity comes from geothermal, biomass, pumped-hydro, and non-pumped hydro. As mentioned in Section 4.2, the gas capacity (combined-cycle gas turbines) is only present in the solution for planning reserves purposes and is not dispatched. We observe from Fig. 4.2 a systematic increase in the total installed capacity as we increase the number of timepoints modeled (from 4-hr resolution to 1-hr). Likewise, we observe the same pattern in both baseline and LDES scenarios. Increasing the number of time points in the model increases the number of time points without solar generation, driving the model to build more VRE and storage to maintain a higher state of charge. Furthermore, we obtained less installed capacity when including LDES in the capacity mix compared with the baseline scenario. This reduction comes mainly from solar and energy storage due to shifting some needs of power capacity to energy capacity.

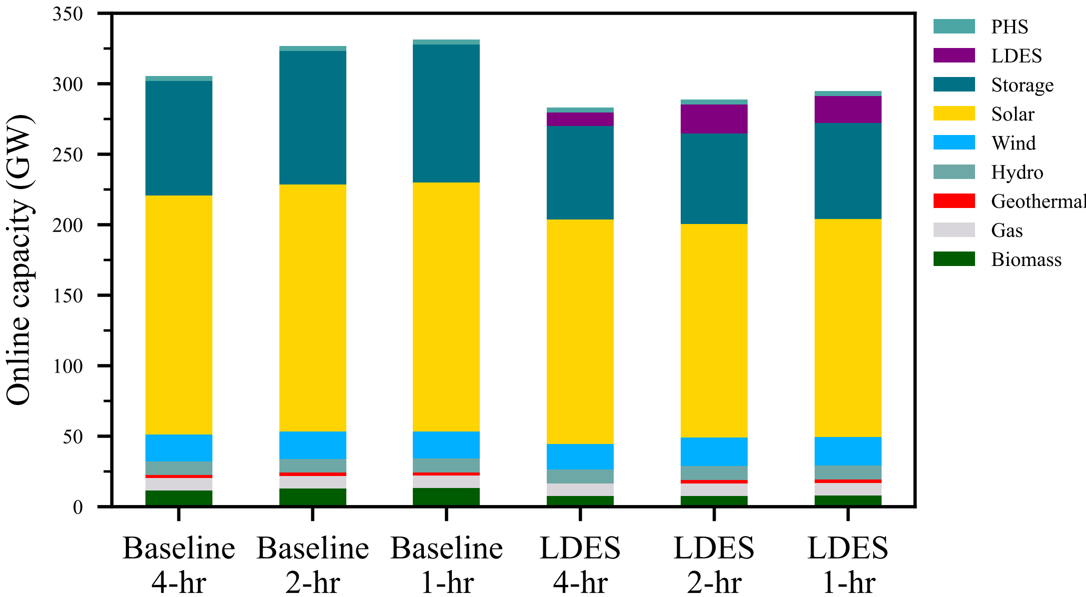


Figure 4.2: Optimal online capacity in the California model broken out by technology type for the 2050 period. Only the capacity component for energy storage, LDES and pumped-hydro storage (PHS) is included in this graph.

We show results of the optimal power and energy capacity in Table 4.3. The LDES scenarios included 10 to 20 GW of new LDES capacity. We obtained that Li-ion's capacity and energy requirements increase with the temporal resolution for the baseline scenarios. The highest LDES energy capacity required was for the 2-hr scenario with 2,087 GWh and the lowest for the 4-hr scenario with 987 GWh. Interestingly, the 2-hr scenario resulted in a higher energy capacity needed than the 1-hr scenario. The increased energy capacity results for the the 2-hr scenario yielded an overall increased load. This result is expected since the sampling strategy considered evenly spaced time points, therefore the 2-hr scenario have more VRE lulls than the 4-hr and 1-hr scenarios. In any LDES scenarios, the model did not find it optimal to add additional duration rather than the minimum duration included (100hr).

Fig. 4.3 shows the dispatch for the different scenarios during the peak load days in July. In both 1-hr scenarios, the surplus electricity, mainly from solar, is being redirected to energy storage and being utilized to supply electricity during nighttime. Also in Fig. 4.3 a), some biomass and geothermal capacity are utilized in conjunction with energy storage to supply nighttime demand. For the LDES scenarios, the LDES dispatch replaces a fraction of the Li-ion energy storage and geothermal and biomass contribution. We also obtained that for the LDES scenario, the amount of daily charging is considerably less than for Li-ion storage. The charging behavior could further be analyzed in the state of charge plot as shown in Fig. 4.4.

Table 4.3: Optimal energy storage power capacity and energy capacity for the different scenarios studied.

	Power capacity (GW)		Energy capacity (GWh)	
Scenario	Li-ion	LDES	Li-ion	LDES
Baseline	81.42	-	543.22	-
Baseline 2hrs	94.89	-	584.83	-
Baseline 1hrs	98.01	-	588.23	-
LDES 4hr	66.27	9.88	504.80	987.81
LDES 2hr	63.96	20.66	365.98	2065.68
LDES 1hr	68.05	19.26	387.32	1925.67

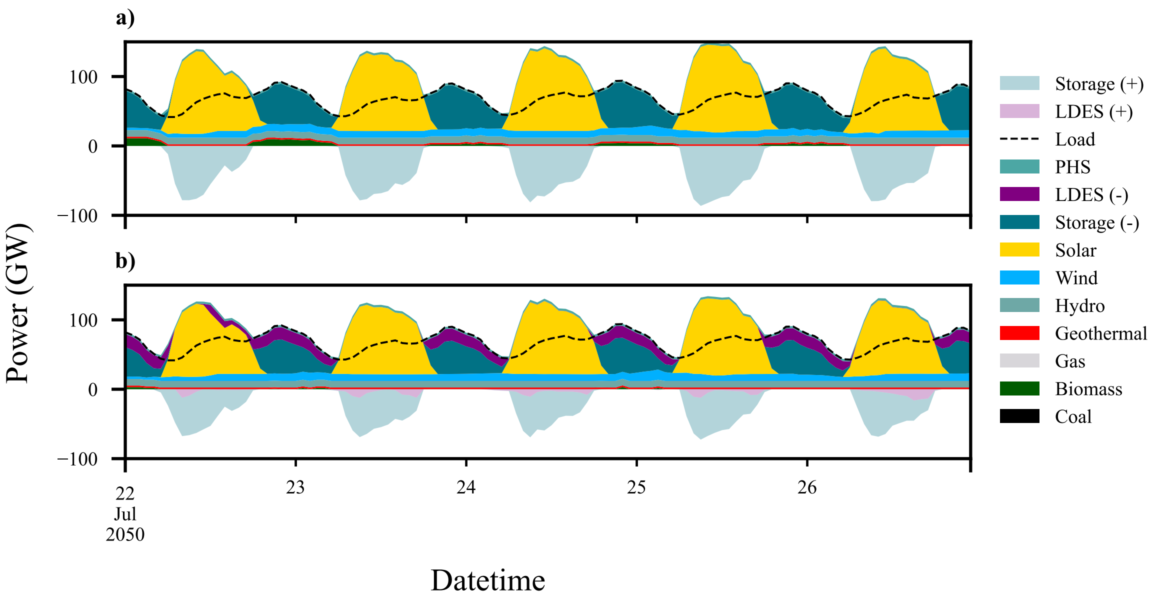


Figure 4.3: Aggregated electrical dispatch during the summer peak event. a) Baseline scenario with 1-hr resolution, b) LDES scenario with 1-hr resolution. Dashed lines represent the load which is the same for both scenarios. Negative areas represent charging while positive discharging.

Fig. 4.4 shows the aggregated state of charge for all the Li-ion and LDES assets. We observe that, in general, the model optimizes the SOC for two full discharge events in the summer and one the winter. Since the model has perfect foresight of the demand and VRE generation, it charges the LDES assets ahead of the peak demand. From Fig. 4.4, we observed two main differences: 1) there is a substantial change in the charging behavior for the winter peak between the different temporal resolutions, 2) the 4-hr scenario optimizes for an earlier discharging event during

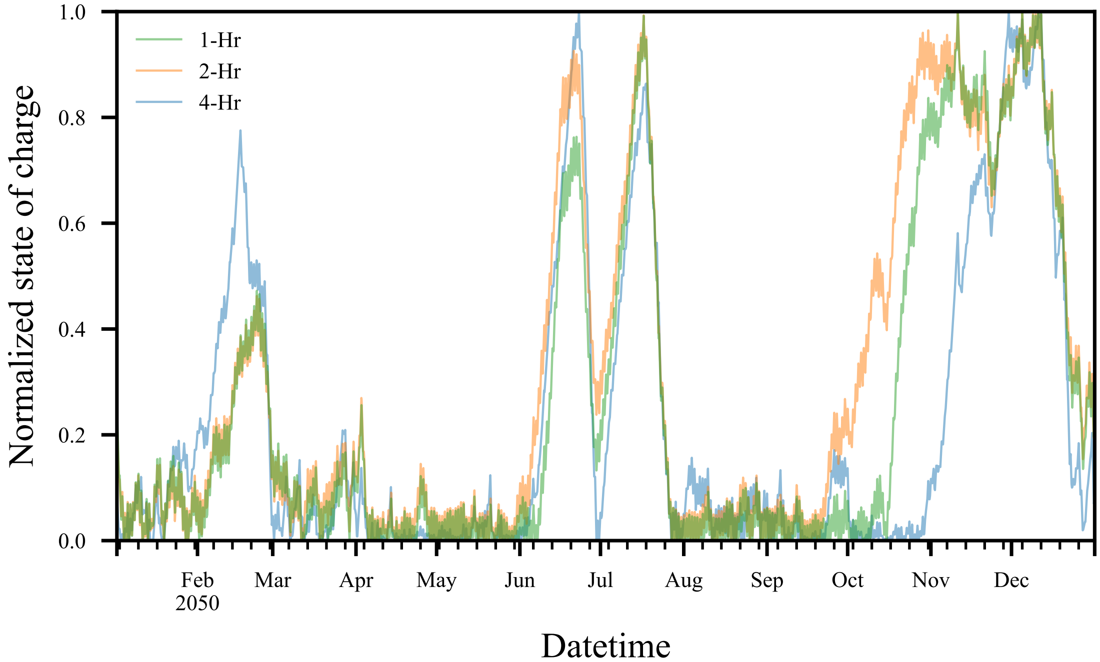


Figure 4.4: Normalized aggregated state of charge for all LDES technologies for the three different temporal resolutions.

February and March, which is not present in the 1-hr and 2-hr scenarios, and 3) the 2-hr scenario maintains a higher average SOC during the year. Notice that the 4-hr scenario shows almost a 0.8 SOC during February and March while the other two scenarios only get to 0.5 in that time frame. This is explained because the latter scenarios roughly double the energy capacity built in the 4-hr scenario as shown in Table 4.3, hence, all three scenarios charge a similar amount of energy in February and March.

Finally, Fig. 4.5 shows the net load duration curve constructed by adding the charge from the batteries to the load and subtracting the VRE generation and the discharge of the batteries leaving the generation from biomass, geothermal and hydro left. Fig. 4.5 highlights firm capacity requirements to run the electrical grid that can come from firm or dispatchable generators. For our scenarios, this capacity is supplied mainly by biomass, geothermal and hydroelectric. Also, we observe the model's sensitivity for different time resolutions between the 0-20% range, which is the region for peak demand. The 4-hr scenario has lower peak demand values than the 2-hr and 1-hr, with the latter having the highest peak. Furthermore, adding LDES to the capacity mix reduces the total peak load compared to the baseline for all temporal resolution scenarios. We obtained the lowest capacity needs for the LDES - 4hr scenario. We explain this as an artifact of the sampling method not capturing some of the peak demand time points.

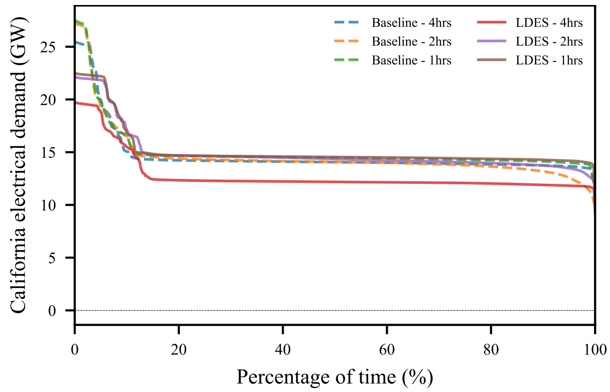


Figure 4.5: Net-load duration curve constructed by adding the charging for both Storage and LDES (for LDES scenarios) to the demand and subtracting the VRE generation.

4.4 Conclusions

Capacity expansion models are excellent tools for exploring long-term capacity needs. In this work, we analyzed a capacity expansion formulation for California with LDES candidate technology under different temporal resolutions. We explored how the temporal resolution impacts capacity expansion models' results for low-cost LDES technologies and obtained that it changes the capacity, energy and utilization patterns.

We obtained that LDES is affected depending on the number of time points. The maximum LDES energy capacity requirements were obtained for the 2-hr scenario, with need for up to 2 TWh of aggregated energy capacity. The most significant difference was between the 4 to 2 hours scenarios where 10 GW more of LDES power capacity was selected in the latter case.

A limitation of this study pertains to how time was sampled. Originally, the sampling of the time was designed to capture demand peak hours across the WECC, while the study focused only in California (assuming peak hours would coincide).

We conclude that time sampling can yield different LDES needs, and modelers should also explore additional scenarios. We obtained that having a lower number of time points can underestimate two elements, the peak demand events, and the firm capacity requirements. We obtained different state of charge patterns and optimal power capacity and energy capacity values. If LDES becomes an essential technology, we need improved modeling and assumptions since, ultimately, the results of the capacity expansion will likely drive the design of these assets.

Chapter 5

Conclusions

In this dissertation work, I have explored the input assumptions utilized in the long-term capacity planning process, especially focusing on their impact on the optimal selection of energy storage technologies. Given the increasing dominance of variable renewable energy technologies in the energy mix, energy storage has become a critical player that will help to balance the energy supply, reduce the variability of VRE and increase their value to the electrical grid. Moreover, as new energy storage technologies like LDES become widely available and cost competitive, there is a potential to further accelerate decarbonization efforts. Therefore, it is imperative for those responsible for updating planning models to have a deep understanding of the input assumptions and simplifications employed in the framework to identify pathways for adoption of new technologies.

Limitations of existing models in capturing the value of LDES technologies have been identified, highlighting the need for further work in capacity expansion formulation. The approach presented in this dissertation aims to inspire energy modelers to understand the storage balancing horizon for LDES technologies and its impact in capacity expansion models. It emphasizes the importance of carefully considering input assumptions, as they can significantly impact the results. Constructive feedback loops among modelers, in terms of sharing insights and experiences, can enhance the accuracy and reliability of capacity expansion models, especially when considering emerging technologies like LDES.

Capacity expansion models are powerful tools for understanding the impacts of climate policies on power systems, but they need to be adapted to accurately model the unique characteristics of emerging technologies.

Furthermore, the research identifies that different state of charge patterns and optimal power capacity and energy capacity values can be obtained based on modeling assumptions. Given the pivotal role expected for LDES technologies in future power systems, continuous improvement of modeling techniques and assumptions is imperative, as the results of capacity expansion models are likely to influence the design and deployment of these assets.

5.1 Future work

Moving forward, there are numerous opportunities for further research in the realm of modeling LDES technologies. While this dissertation has shed some light on the potential benefits and some limitations of these systems, there are still many open questions that require further exploration. For example, multi-period optimization with LDES could be a promising area of research, as it would enable us to better understand when and where it might become more feasible to install LDES in different locations. Another example would be to analyze particular load regions of interest where LDES could be implemented. Additionally, modeling different types of LDES technologies in conjunction with each other could provide valuable insights into how these systems can be optimized and integrated with other grid technologies.

Another important area for future research is the development of new strategies for creating additional synergies between energy storage and VRE technologies. This could include exploring how hydrogen interacts with low-cost LDES, as well as identifying a proper methodology to quantify the capacity credit for low-cost LDES and how to model the reserve capacity services they can provide. Ultimately, by addressing these and other open questions and opportunities for further research, we can gain a deeper understanding of the potential benefits of LDES technologies and how they can be optimized and integrated with other grid technologies to help us transition towards a more sustainable energy future.

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