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

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ABSTRACT

Long-Duration Energy Storage (LDES) has gained interest due to its key role in attaining a decarbonized, low-cost, and stable grid driven by variable renewable electricity (VRE). Currently, there is a wide range of LDES technologies being developed to provide electricity with 8+ hours of consecutive discharge. However, current capacity expansion models used in long-term planning processes rarely consider low cost LDES as a candidate technology. If they do, the storage balancing horizon (SBH) of the model usually only considers non-consecutive 1-day periods that do not capture the potential of LDES to shift energy across multiple days or even seasons. Addressing these limitations in existing models, this work explores the ways in which the optimal energy storage changes when increasing the number of consecutive days in the SBH and how these changes will impact planners who are determining the future roles of energy storage. Our analysis uses SWITCH, an open-source capacity expansion model with a high spatial resolution for the entire Western Electricity Coordinating Council (WECC) in a zero-carbon scenario in 2050. We find that the number of consecutive days in the SBH changes both the total selected power and energy capacity of LDES when storage energy and power capacity overnight costs are $13 USD/kWh (or less) and $113 USD/kW, respectively. We also find that the amount of required energy in storage to drive a future VRE-driven WECC grid ranges from 2.5 TWh to 16.0 TWh depending on the length of the SBH. The optimal storage duration (energy to power ratio) we obtain ranges from 10 h to 620 h among all the scenarios. Furthermore, depending on the storage cost assumption, we observe different charge/discharge patterns when varying the length of the SBH. Given our results, we anticipate that as more LDES technologies become commercially available, it will be critical to increase the length of the SBH to fully capture the benefits of LDES assets in long-term planning processes of high VRE-driven grids.

1. Introduction

1.1. Background, motivation and research gaps

Around the world, energy storage paired with variable renewable energy (VRE) has been described as an indispensable technology that will play a pivotal role in achieving decarbonized energy policy goals and greenhouse gas (GHG) reduction targets, at the least cost compared to alternatives [1–4]. Storage at utility scale is a versatile technology that can (a) charge when there is surplus VRE and discharge during high electrical demand periods, (b) provide ancillary services with fast response times and (c) provide reserves when needed [5]. Some energy storage technologies can also provide cross-sectoral benefits like hydrogen production and thermal storage [6].

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 [7]. It is expected that many regions across the U.S. will deploy an additional 10 GW that will come online during 2021–2023 [8]. 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 [9–11].

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

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[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.

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Abbreviations

SOC	State of charge of storage asset [%]
LDES	Long-duration energy storage
NPV	Net present value
SBH	Storage balancing horizon
VRE	Variable renewable energy
WECC	Western Electricity Coordinating Council

Constants

η_c	Storage charging efficiency [%]
η_d	Storage discharging efficiency [%]
w_t	Time weight factor

Sets

$\mathcal{S}$	Set of energy storage assets
$\mathcal{T}$	Set of modeling timeseries

Decision variables

$C_{s,t}$	Charging of storage asset s at time t [MW]
$D_{s,t}$	Discharging of storage asset s at time t [MW]

electrical grid dominated by wind and solar power [12]. 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 [13]. 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 [14]. 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 [15].

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 [16,17] and works using detailed modeling of LDES and its interaction with a VRE-driven grid [11,12,18–20]. Such studies found that LDES can fulfill a variety of grid services to help balance the grid with discharge capabilities of consecutive hours that range from 10–650 h. The works related to economic opportunities for LDES [16,17] explore LDES technologies with 10 to 100 h of duration (ratio of energy capacity to power capacity). Other studies have calculated the required amount of energy storage to run the entire U.S. using a constrained energy balance model and constraining the operations of LDES using a state of charge (SOC) formulation with an hourly resolution [18]. Nonetheless, [18] 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 [21] for more details of the approaches). Multiple academic works and models used in long-term planning processes (e.g., [11,20,22]) 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 [23]. 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.

1.2. 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.

1.3. 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 2. Next, in Section 3 we present the main findings of the different balancing lengths and storage cost scenarios. Finally, in Section 4 we highlight some of the main conclusions on the importance of the length of the storage balancing horizon in capacity expansion formulations.

2. Methods

To develop this analysis, we use SWITCH [24], 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 [24]. 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) [25]. It has been widely used for decarbonization and energy transition scenarios in different regions around the world [26–35]. 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 the 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 refer to the Supplementary Materials.

2.1. 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 Supplementary 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.

2.2. 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 [36]. 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 [37]. 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).

2.3. 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).

[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 Supplementary Materials.

2.3.1. 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.

2.3.2. 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.

2.3.3. 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:

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

where η_c and η_d are the charging and discharging efficiency, respectively. Additionally to (1), the storage module incorporates a constraint that bounds the beginning SOC, $\mathrm{SOC}_{s,0}$, and end $\mathrm{SOC}_{s,f}$, 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 a.m. 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).

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 h of consecutive discharge) and using a subset of consecutive number of days to represent the entire year. There is no standardization on 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 h, 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. 1.

2.3.4. 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

Table 1
Cost assumptions for each of the candidate technologies provided to SWITCH. Data are shown for the 2050 period.

Category	Technology	Overnight cost[a] ($/kW)	Energy cost ($/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)[b]	2227	–	112.30	–	20
	Geothermal	6970	–	173.11	–	20
	Biogas — ICT[c]	2118	–	64.38	0.00	20
	Bioliquid — ST	3226	–	80.01	0.01	40
	Biosolid — ST	3226	–	80.01	0.32	20
Conventional technologies[d]						
	CCGT	925	–	12.86	6.31–7.36	40
	CCGT — Cogen	103	–	5.31		20
Energy storage						
	4 h Li-ion	113	130	15.80	–	10

Note: Overnight, energy and fixed O&M cost numbers [15] represent the average of the selected period to study from 2046–2055 year range.
[a]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.
[b]Offshore technology is only available for California load zones.
[c]For the baseline scenario there is no fuel cost associated with using biogas.
[d]Natural gas price varies according to the load zone.

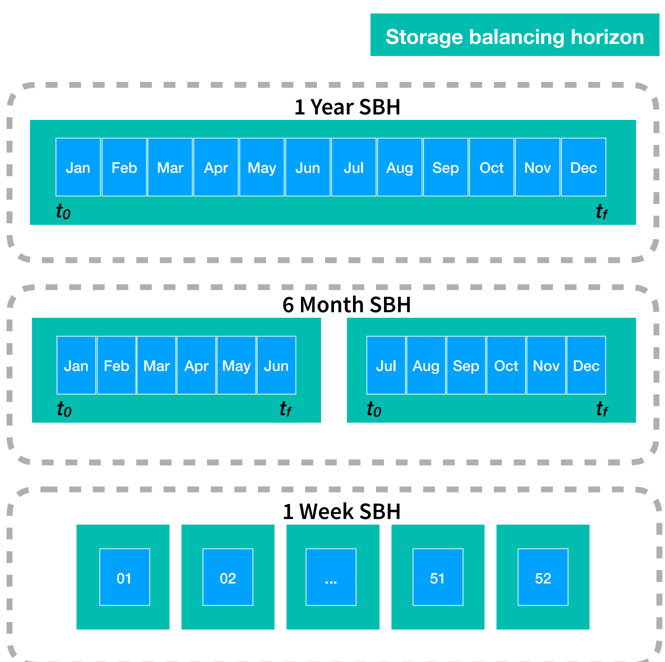

Fig. 1. Diagram showing the storage balancing horizon (SBH) concept for three different lengths: 1-Year, 6-Month and 1-Week.

4 hour resolution, producing a total of 2184 data points per year. The evaluation of the same 2184 data points for 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.

2.4. 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 [38] 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 [15]. From this source, we extracted the overnight, energy and O&M costs as shown in Table 1. For the capacity expansion, SWITCH-WECC provides one candidate resource per non-variable technology (see Table 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) modeled.

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 [39] 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 h.

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. 2. From Fig. 2, we observe that most of the western load zones are dominated by both solar and storage technologies. In the southwest 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 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. 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(a). This overbuild from both solar and

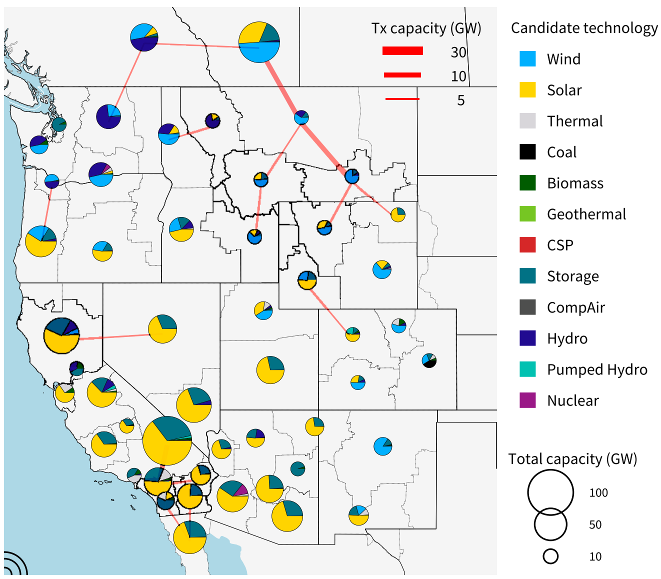

Fig. 2. Map of optimal online capacity and new installed transmission for a zero-carbon WECC in 2050. Cost assumptions correspond to the baseline storage energy cost scenario using a 1-Week SBH. Solar and storage dominate the capacity mix in most of the WECC. Additional transmission is required in the northern balancing zones to accommodate extra capacity selected.

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 Figs. 3(b) and 3(c) 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 (1-Week SBH) to 707 GW (1-Year SBH) as seen in Fig. 3(c). 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 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. 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 h 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 h for all SBH lengths as shown in Fig. 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

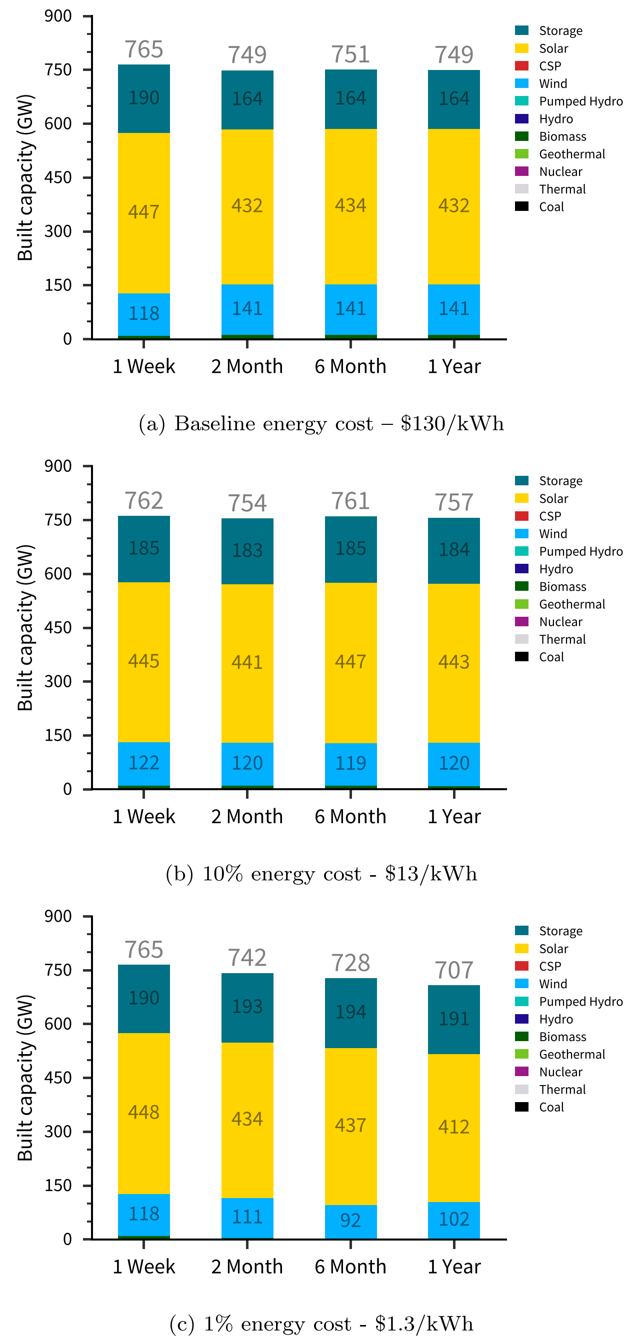

Fig. 3. Optimal selected capacity mix for a zero-carbon WECC in 2050 considering the different lengths of storage balancing horizons and storage energy costs with the storage cost being (a) $130/kWh, (b) $13/kWh, and (c) $1.3/kWh.

modeled in the 10% and 1% cost scenarios with a higher reduction in the latter as shown in Fig. 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 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 h) storage selected is being utilized for daily arbitrage to balance solar and wind generation. The model also selects 8+ hour duration at baseline cost

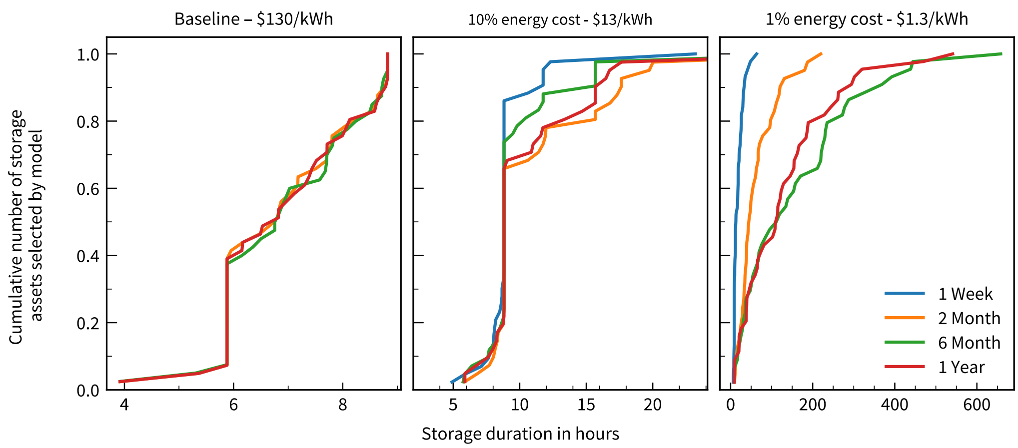

Fig. 4. Cumulative number of storage assets selected by the model for the optimal energy storage duration (energy to power ratio). The different panels show results depending on the storage energy capacity cost assumption: the left corresponds to the baseline cost, the middle panel corresponds to $13/kWh, 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.

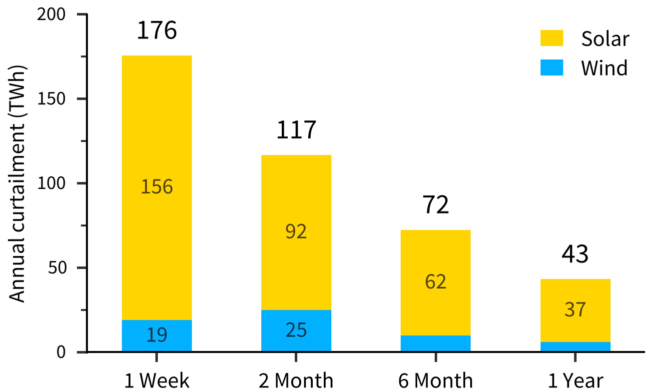

Fig. 5. Total solar and wind curtailment for the $1.3/kWh energy capacity cost scenario for each SBH scenario. Curtailment is defined as the difference of the available dispatch capacity at each time point and the dispatch decision. Curtailment is reduced as the SBH duration increases.

that is also utilized mostly for daily arbitrage, but only in 4 load zones. In Fig. 7(a) the model selects 5–10 h storage (orange line) and some 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 the use the baseline cost 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. 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 power capacity difference obtained by changing the SBH for the baseline energy cost as shown in Fig. 7. Overall throughout the WECC, the 1-Week SBH requires an additional storage power capacity of up to 4 GW per load zone (shown in dark red). On the other hand, 15 balancing zones, mostly in the East of the WECC (shown in dark blue), show the need to add more storage power capacity of up to 2 GW mostly to balance the different usage of storage in neighboring zones. In total, 5 out of the 50 zones did not see any change from the different SBH.

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 h in the baseline cost scenario up to 620 h 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. Additionaly, 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.

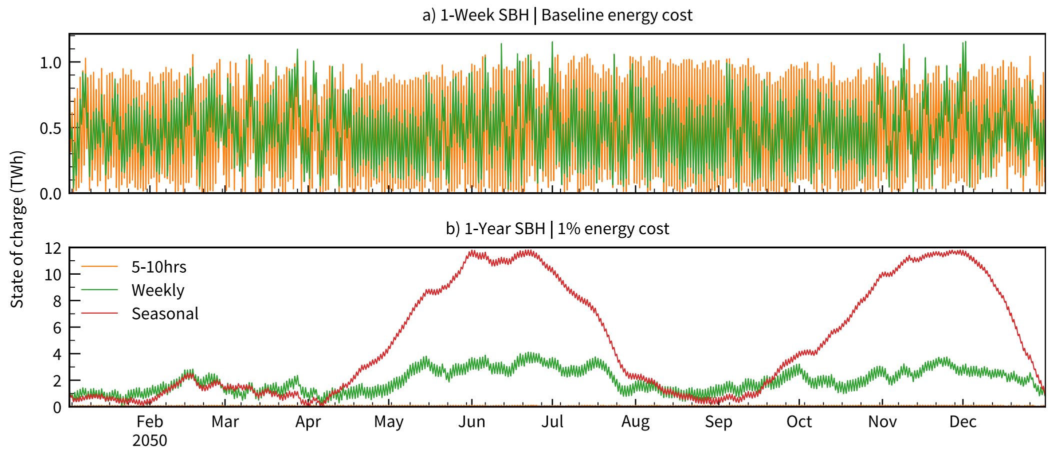

Fig. 6. Aggregated state of charge for all energy storage technologies installed throughout the WECC region. (a) For the 1-Week SBH using \$130/kWh and (b) for the 1-Year SBH using \$1.3/kWh. Duration of energy storage is classified according to its optimal range of duration (energy to power ratio). The range between 10–100 h is classified as weekly and 100+ hours is classified as seasonal. In panel (b) we observe seasonal storage to balance summer and winter peak.

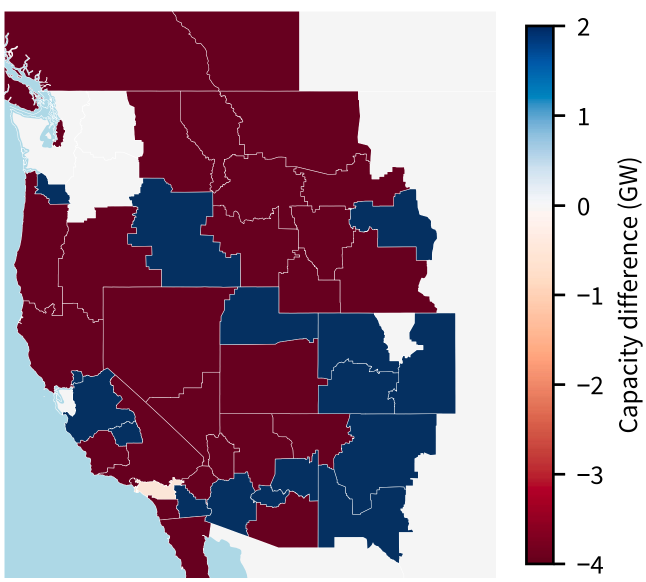

Fig. 7. Storage power capacity difference between 1-Week SBH and 1-Year SBH for the baseline energy cost for each of the WECC regions.

CRediT authorship contribution statement

P.A. Sánchez-Pérez: Writing – original draft, Writing – review & editing, Methodology, Software, Data curation, Formal analysis, Validation, Visualization. **Martin Staadecker:** Methodology, Software, Visualization, Data curation, Writing – review & editing, Validation. **Julia Szinai:** Methodology, Software, Writing – review & editing, Data curation. **Sarah Kurtz:** Supervision, Funding acquisition, Writing – review & editing, Project administration. **Patricia Hidalgo-Gonzalez:** Conceptualization, Methodology, Supervision, Project administration, Validation, Writing – review & editing, Resources, Funding acquisition, Software.

Declaration of competing interest

The authors have no conflicts of interest to declare.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2022.119022.

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