

# Effect of time resolution on capacity expansion modeling to quantify value of long-duration energy storage

P. A. Sánchez-Pérez, Sarah Kurtz  
*School of Engineering*  
*University of California, Merced*  
Merced, USA

Natalia Gonzalez, Martin Staadecker, Patricia Hidalgo-Gonzalez  
*Mechanical and Aerospace Engineering*  
*University of California, San Diego*  
La Jolla, USA

**Abstract**—Long-duration energy storage (LDES) technologies have been recently included in capacity expansion models for long-term planning. Many of these models have a simplified temporal resolution to reduce the computation time to achieve faster scenario results. However, it is unclear if these simplifications change the optimal solution for LDES, especially when modeling grids dominated by variable renewable energy (VRE) generation. For this reason, we studied how such temporal simplification changes the modeled optimal power and energy capacity of LDES technologies. We formulated a capacity expansion problem for the California region using three different temporal resolutions. We obtained that decreasing the model complexity by using fewer time points yielded different configurations and utilization of LDES technologies.

**Index Terms**—capacity expansion, long-duration energy storage, temporal resolution

## I. 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 [1] 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 [2]–[4] and how changing the temporal resolution can yield different optimal solutions [5]–[7]. 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.

## II. 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 [8]. 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 [9] and updated in [7]. 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.

#### A. 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. 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.

#### B. 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 [1] 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



Fig. 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.

1%/day idle losses. We summarize the cost assumption and technical parameters for energy storage in Table I.

TABLE I  
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

#### C. 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 [10]. For the generation profiles, we used the latest leasing area for the Morro Bay area [11], then we calculate hourly capacity factors using the 2019 year dataset for offshore wind in California from the Wind Tool Kit developed by NREL [12] and the 2020 offshore wind reference turbine power curve from the NREL-ATB (see [13]).

#### D. 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 [8] 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.

TABLE II  
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	✓		

### E. 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 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 [14] 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.

## III. FINDINGS

First, we present the online capacity by period for each scenario as shown in Fig. 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 II-E, 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. 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

TABLE III  
OPTIMAL ENERGY STORAGE POWER CAPACITY AND ENERGY CAPACITY FOR THE DIFFERENT SCENARIOS STUDIED.

Scenario	Power capacity (GW)		Energy capacity (GWh)	
	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

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.

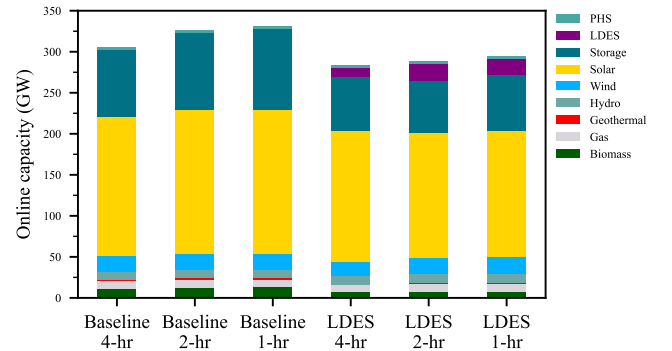


Fig. 2. Optimal online capacity in the California model broken out by technology type for the 2050 period. Only the capacity component for energy storage, LDES and pumped-hydro storage (PHS) is included in this graph.

We show results of the optimal power and energy capacity in Table III. 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 2-hr scenario yielded an overall increased load. This result is expected since the sampling strategy considers 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. 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

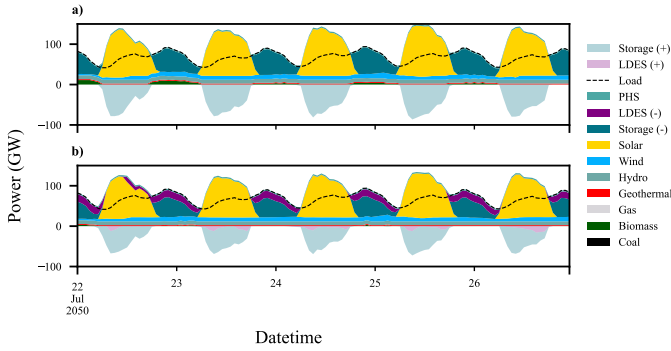


Fig. 3. Aggregated electrical dispatch during the summer peak event. a) Baseline scenario with 1-hr resolution, b) LDES scenario with 1-hr resolution. Dashed lines represent the load which is the same for both scenarios. Negative areas represent charging while positive discharging.

nighttime. Also in Fig. 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.

Fig. 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, 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 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 III, hence, all three scenarios charge a similar amount of energy in February and March.

Finally, Fig. 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. 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,

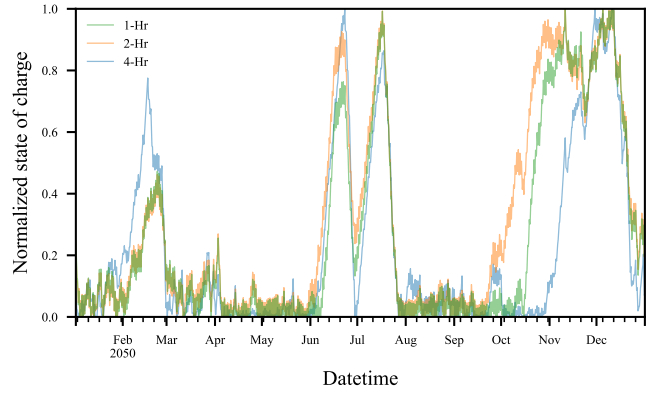


Fig. 4. Normalized aggregated state of charge for all LDES technologies for the three different temporal resolutions.

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.

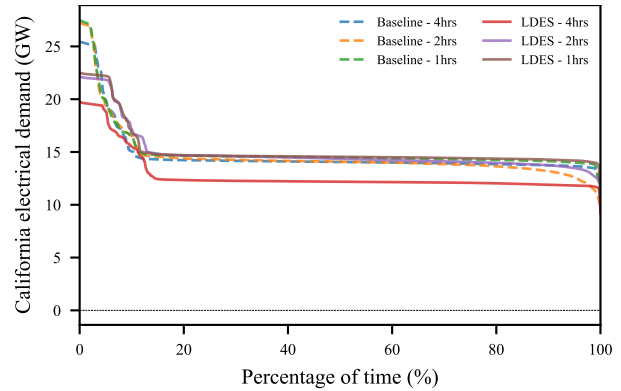


Fig. 5. Net-load duration curve constructed by adding the charging for both Storage and LDES (for LDES scenarios) to the demand and subtracting the VRE generation.

#### IV. 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.

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