TECHNICAL BRIEF

Energy Storage in Long-Term Resource Planning: A Review of Modeling Approaches and Utility Practices

1 INTRODUCTION

The pace of utility-scale battery storage deployment has accelerated since 2020, partly driven by continued technology cost reductions, renewable portfolio standards and, more recently, by storage targets set by some states[1]. According to the EIA [1], in 2023, developers plan to add 8.6 GW of battery storage power capacity to the grid, effectively doubling the total U.S. battery capacity (Figure 1). Rapid growth is expected to continue in the coming years, with developers scheduling more than 23 large-scale battery projects[2] ranging from 250 MW to 650 MW for deployment by 2025.

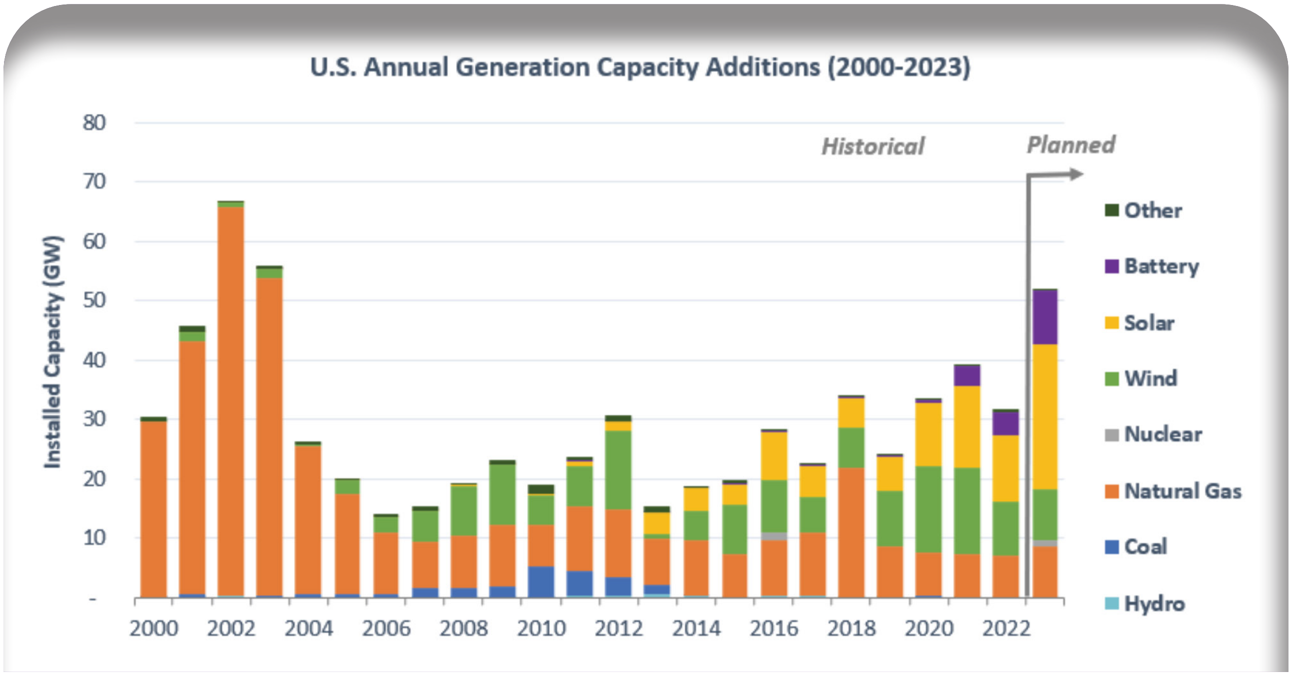

Figure 1. Wind, solar and battery storage account for more than 80% of the new utility-scale generating capacity planned in 2023. Data source: U.S. EIA Form EIA-860M [2].

1 To date, U.S. states that target specific amounts of large-scale battery energy storage capacity include California, Connecticut, Illinois, Maine, Massachusetts, Nevada, New Jersey, New York, Oregon, and Virginia. In addition, Maryland, New Hampshire, and Tennessee support the deployment of battery energy storage systems through tax credits [3].

2 Lithium-ion batteries are the preferred energy storage technology in these projects.

Given the growing importance of energy storage in the future, resource planners are interested in understanding how this technology should be integrated into their long-term planning studies and modeling tools. Energy storage is seen as a valuable resource to support grid decarbonization efforts because of its capability to provide flexibility to systems with an increasing penetration of renewables.

Questions that planners are asking include:

- What types of energy storage technologies and features should be included? What services should be considered when modeling energy storage?
- How spatially- and temporally- detailed does the model need to be in order to accurately value energy storage?
- What simplifications affect the assessment of energy storage in long-term planning?

The assessment of energy storage systems is more complex than many other technologies because of the range of storage types, state-of-charge dependencies, wide range of operational space at temporal and spatial levels, and potential provision of multiple services. Each of these features make it difficult to capture energy storage in a single modeling framework (Figure 2) [4].

Existing analytical tools have limitations that require making simplifications about the technology itself, energy storage features to be considered, and the level of granularity in temporal and spatial scope. These simplifications may result in inaccurate evaluations that underestimate or overestimate the costs and benefits of storage resources in planning studies. Attempts to improve this valuation and to better integrate storage into planning tools are being

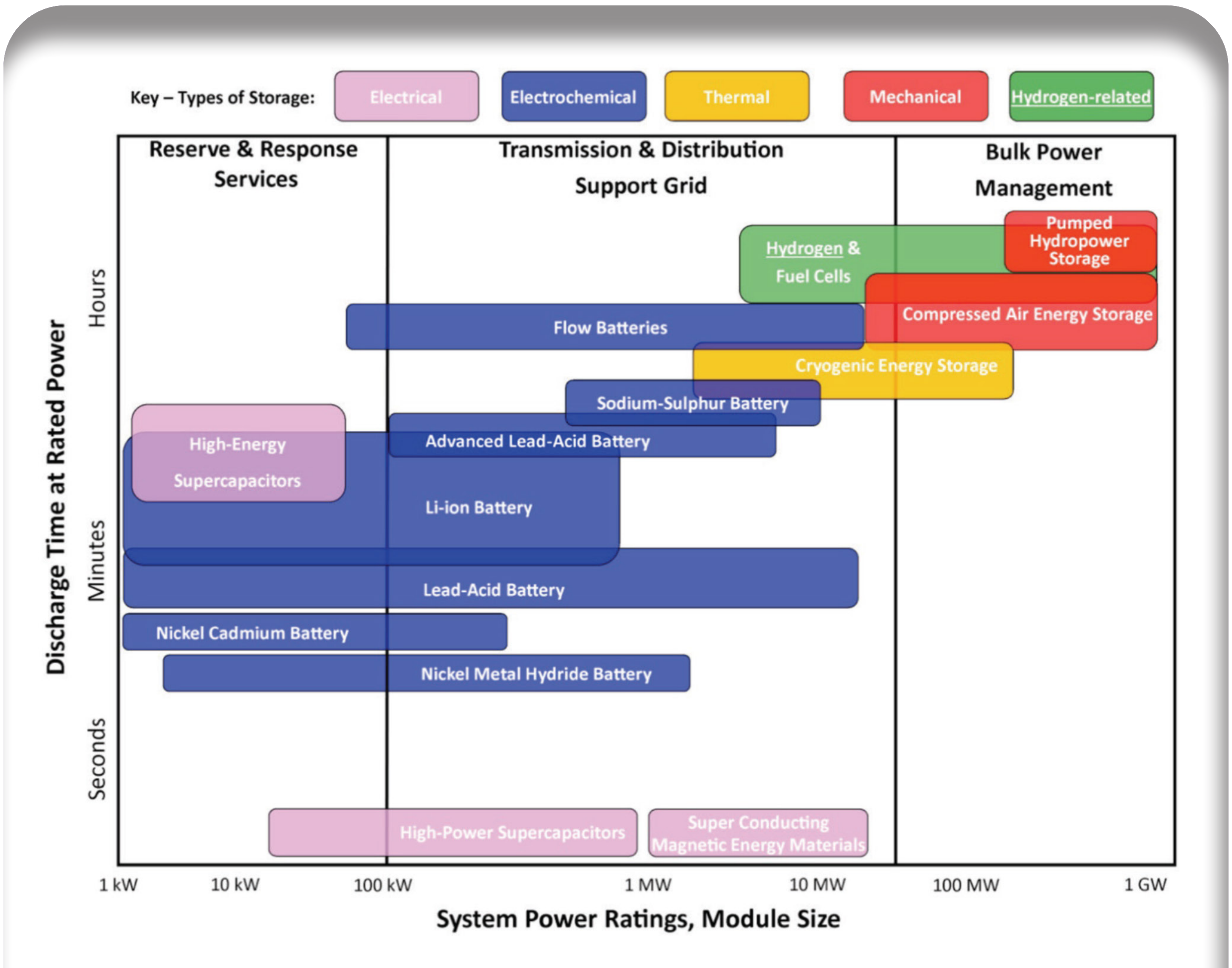

Figure 2. *Comparison of different types of energy storage technologies based on power rating (system size) and discharge time [5]. Authors: T.R. Jensen and H.-W. Li*

pursued. These efforts focus on developing more accurate technological representations, considering relevant cost and performance characteristics, enhancing spatiotemporal resolution, and employing advanced methods and modeling tools that, for example, can incorporate a combination of services and account for their value changes with deployment levels [4, 6].

This technical brief reviews information from recent integrated resource plans (IRPs) and planning studies, peer-reviewed journal articles, and several EPRI technical reports, to understand approaches and modeling practices used by electric companies and planners, as well as use cases of storage in long-term resource planning.

2 MODELING STORAGE IN LONG-TERM RESOURCE PLANNING

2.1 Approaches in the Literature

Capacity expansion and portfolio planning models, production cost models, and resource adequacy models are extensively used for resource planning and valuation. In many cases these tools are not sufficient for a detailed examination of energy storage technologies, and consequently a suitable assessment of the value they provide to energy systems. For example, tools may be limited in their ability to capture full hourly resource dispatch, detailed consideration of transmission network constraints, or ancillary services. Moreover, extended solution runtimes and high model development costs tend to limit the type of analyses that can be performed when assessing storage [7]. Therefore, it would be valuable for planning entities to have access to improved methods for modeling energy storage systems within the tools they currently use [8, 9].

There are many challenges in modeling storage within long-term capacity expansion planning [16]. For example, storage systems have different configurations depending on the type of technology and whether they are hybrid or standalone systems; they have uncertain costs and technological parameters; and there are various operational-related performance characteristics (e.g., efficiency and degradation) that are difficult to model. In addition, the value of the wide range of applications such as energy arbitrage, firm capacity, regulation, spinning and non-spinning reserves, voltage support, congestion and network deferral, among others, depend not only on the services provided but also the amount deployed and the state of the system[3]. Only a subset of these services is commonly modeled within a long-term planning model. Other challenges, applicable not only to storage but to emerging technologies more broadly, include the evolving nature of the several policies and incentives at national and sub-national levels; forecast errors for load and variable renewable resources; uncertainty about load profile changes and growth; and others [6, 16].

Finally, accurately representing the technology's "State of Charge (SoC)" and preserving key spatial elements of variability on a system are among the most challenging issues in modeling energy storage systems for long-term planning. By nature, storage systems support power systems by storing system-generated energy during certain periods, and dispatching energy to meet system load during other periods. Thus, at any given time, a storage system contains a specific charge, defining how much energy it has at that time to meet load should it be called upon. The ability to keep track of a storage system's SoC requires careful preservation of temporal chronology in a model—a feature that is often lacking within long-term planning models. Moreover, system variability, introduced in a power system as a result of demand, renewable energy generation and/or location-specific contingences, is a key economic characteristic for renewables and storage [10] which emphasizes the significance of spatial resolution in long-term models that assess the value of storage.

Unfortunately, increasing temporal and spatial resolution in a model also increases computational run times. Recognizing this challenge, modelers and planners typically include simplifications in their optimization studies to have tractable results within reasonable times. Temporal modeling simplifications include time sampling based on representative sequences (days or weeks); system states analysis; static optimization that preserves the full 8760 hourly chronology within a year; sequential myopic or

3 This effect, known as value deflation (or "decreasing returns"), refers to the declining marginal value of energy storage as deployment increases on a particular system. For further information refer to https://esca.epri.com/pdf/Back-Pocket-Insights/EPRI-P201-Decreasing-Returns.pdf

recursive dynamic modeling approaches using an annual rolling basis; and other advanced optimization methods[4]. Spatial modeling simplifications include grouping generating units into larger clusters based on features such as location, engineering characteristics, technology type, and size; regional or zonal network aggregation; and reduced-form representations of the transmission system, among others[5].

All these approaches have disadvantages, and modelers need to weigh the tradeoffs between improved spatiotemporal resolution and model complexity. Simplifications along spatial and temporal modeling dimensions may:

- Dampen variability by averaging or flattening differences between peak and off-peak energy values, potentially understating the value of storage.
- Impact the assessment of storage systems of different durations, i.e., overestimating or underestimating the optimal installed capacity of short or long-duration storage, as it may limit the energy that can be effectively managed over multiple days or across seasons.
- Impact the valuation of storage applications for deferring network investments or alleviating congestion by failing to capture the potential value streams associated with them due to the reduced number of transmission and distribution lines.

4 The representative sequence method is the most common temporal aggregation strategy used throughout the literature. It involves the aggregation of days (or other sequences such as weeks) with similar characteristics, allowing chronology to be maintained within days, but not usually across them.

The system states approach identifies unique states that comprise time periods with similar characteristics and estimates a probability transition matrix between states [11]. It includes a structure to infer the hourly balance from the state transitions and aims to ensure it is within the storage technology's available energy capacity.

The static approach relies on decoupling planning from operation decisions. Storage is only represented in an operation model that considers one year as a snapshot, or alternately, a planning model that considers one future year only with all 8760 hours and annualized costs [12, 13].

In a sequential myopic method, each year is solved individually (for all 8760 hours), and the capital stock is carried over to the next year.

5 For further reference, Bistline et al. [6] and Merrick et al. [10] provide additional background on the relevant temporal and spatial modeling approaches found in the literature, as well as their main advantages and disadvantages in long-term energy system models.

2.2 Approaches in Practice

Many electric companies and planning entities across North America are including energy storage in their long-term planning assessments, and numerous IRPs incorporate utility-scale storage in their preferred portfolios. Planned battery and pumped hydro storage (PHS) additions through 2050 for select electric companies are shown in Figure 3.

A review of official dockets and direct communication with a selection of electric companies allowed examining the modeling challenges the industry currently faces and the strategies being adopted to evaluate storage in their expansion plans.

There is a wide range of approaches being used in practice to incorporate energy storage into planning, including:

- Prescreening based on assumed costs and feasibility to determine which technologies to include in more detailed modeling;
- Exogenous selection added to optimal portfolios and evaluated using hourly production costs models for operational feasibility and economic benefits;
- Cost-benefit analyses using storage technology models (e.g., price-taker models) to assess the costs and benefits associated with sub-hourly flexibility of storage; and
- Endogenous evaluation using a capacity expansion tool to determine the optimal portfolio.

The forecasted need for energy storage for the next 20-30 years is primarily driven by renewable energy goals, carbon policies, economic conditions, and the retirement of conventional generation resources. The information presented in Table 1 shows that while recent IRPs have featured well-established energy storage technologies with readily available data on cost and technical specifications, emerging and less mature energy storage technologies are often excluded from the planning exercises due to a lack of available or reliable data. Also, hybrid solar and energy storage systems, typically featuring 2-hour to 8-hour duration batteries, are commonly considered candidates in assessment studies. In fact, this configuration is often preferred within portfolios over standalone battery systems.

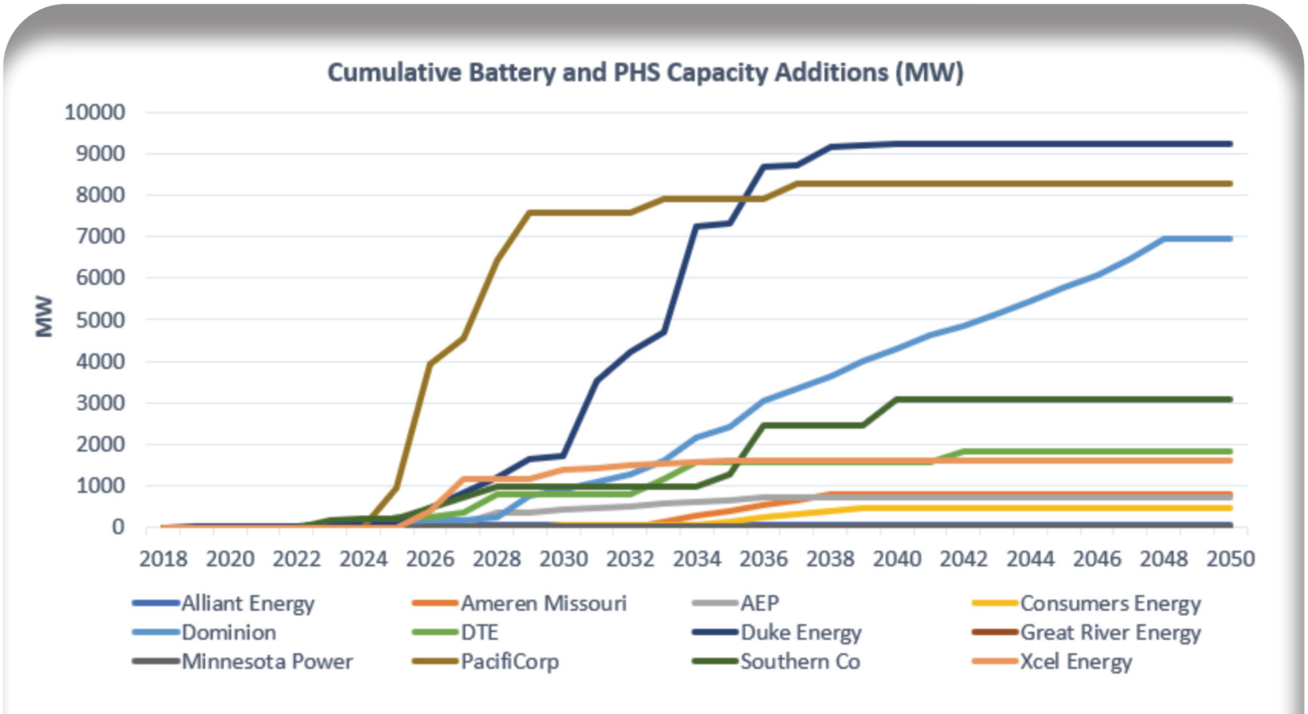

Figure 3. *Battery and Pumped Hydro Storage capacity additions through 2050 for a sample of electric companies*[6]*.*
Source: EQ Research IRP as a Data Service.

6 Some companies have been aggregated as follows: Alliant (Alliant IA, Alliant WI), Southern Co. (Alabama Power, Georgia Power, Mississippi Power), Dominion (Dominion Virginia, South Carolina Electric and Gas), AEP (Appalachian Power Company, SWEPCO, Indiana Michigan Power), Duke Energy (Duke Energy Florida, Duke Energy Kentucky, Duke Energy Carolinas, Duke Energy Progress, Duke Energy Indiana), Xcel Energy (Xcel Energy, Xcel Energy Upper Midwest Region, Southwest Public Service).

Table 1. *Energy storage in recent IRPs[7]. Source: EQ Research IRP as a Data ServiceTM and official IRP filings [6]*

UTILITY	REGION/STATE	STUDY PERIOD	COSTS	KEY DETAILS OF STORAGE INCLUDED IN RESOURCE PLANS
AEP	Arkansas, Louisiana, West Virginia, Virginia, Tennessee, Indiana, Michigan	2021–2041	$1,400 to $1,900/kW Decline to $700/kW by 2041	• 50 MW/200 MWh (4-hr) Li-ion battery candidates • 10 MW/40 MWh (4-hr) Li-ion battery candidates • High levels of energy storage are not selected unless installed costs are drastically reduced • Hybrid (4-hr) resources are preferred to standalone batteries • Standalone storage selected in near term to replace capacity retirement
Alliant	Illinois, Iowa, Minnesota, and Wisconsin	2020–2040	Wood Mackenzie, NREL ATB	• 28 MW of distributed storage, 94 MW of hybrid storage • Standalone 4-hr Li-ion, 25 MW, 250 MW max per year, 98% capacity credit, 30-yr lifetime candidates • Hybrid 40 MW solar, 10 MW battery, 1 GW maximum install per year • For distributed storage, avoided distribution costs accounted as capital cost savings and exogenously determined
Ameren	Missouri	2020–2040	Roland Berger and NREL costs data	• 800 MW storage by 2035 • Pumped hydro, 2-hr and 4-hr Li-ion battery candidates • 4-hr Li-ion batteries selected in portfolios
Consumers Energy	Michigan	2021–2040	$1000 to $1100/kW	• Co-owned 1172 MW of pumped hydro with DTE • Thermal storage, compressed air, flywheel screened out before CAPEX modeling • 4-hr Li-ion battery, 100 MW blocks modeled candidates • Value stack created using EPRI's StorageVET
Dominion	Virginia	2024–2038	Capital costs based on company history and NREL ATB Moderate Case	• Aiming to meet targets set by the Virginia Clean Energy Act • Battery Storage additions range from 3.9 GW to 10.3 GW over a 25-year horizon • Storage starting ELCC value is 82% for 4-hr systems, increasing after 2026 • 4-hr Li-ion, 30 MW, 20-yr lifetime battery candidates • Plans limited to 300 MW annual additions. For net zero cases, 900 MW additions after 2038 • Pursuing an LDES pilot

7 Acronym definition: EIA's Annual Energy Outlook (AEO); NREL Annual Technology Baseline (ATB); Compressed-air energy storage (CAES); Capital expenditure (CAPEX); Effective Load Carrying Capability (ELCC); Inflation Reduction Act (IRA); Integrated Resource Plan (IRP); Long Duration Energy Storage (LDES); round-trip efficiency (RTE); EPRI's Storage Value Estimation Tool (StorageVET); Upper Midwest (UM).

Table 1 (continued). *Energy storage in recent IRPs. Source: EQ Research IRP as a Data ServiceTM and official IRP filings [6]*

UTILITY	REGION/STATE	STUDY PERIOD	COSTS	KEY DETAILS OF STORAGE INCLUDED IN RESOURCE PLANS
DTE	Michigan	2024–2038	Cost data from NREL ATB Moderate Scenario cost assumptions	• Own 1.1 GW of pumped storage • Li-ion batteries selected after initial technology screening which included 4-hr, 8-hr, and 10-hr duration batteries • Battery capacity limits modeled for specific periods • Preferred portfolio has 1830 MW of storage by 2042 • Scenarios with large capital cost reductions and IRA incentives increase battery capacities • Ancillary services benefit and flexibility benefits estimated and included in expansion analysis
Duke Carolinas and Duke Progress	North Carolina, South Carolina	Through 2030	$2250-$4200 $/kW overnight capital cost	• Up to 2200 MW stand-alone batteries per year per utility available beginning 2027 • 1680 MW, 10-hr pumped storage considered for 2034 • Advanced reactor with integrated thermal storage (300 MW nuclear / 150 MW storage) available in 2038 • Solar paired with storage, 4-hr, 6-hr and 8-hr standalone batteries candidates, available after 2027/2028. 60% of new stand-alone batteries will be on retired coal sites • Preferred portfolio has over 6 GW of battery storage (standalone and hybrid) by 2038 and 1.7 GW of planned pumped hydro by 2034
Georgia Power	Georgia	2023–2037	N/A	• 4-hr, 8-hr Li-ion battery candidates • Piloting 2-hr Li-ion • Upcoming pilot 100-hr duration project • 2470 MW battery storage by 2040 • Goal of 1000 MW storage capacity by 2030
Great River Energy	Minnesota	2022–2042	$895/kW NREL ATB cost assumptions	• 4-hr Li-ion battery candidates • Preferred resource plan has 200 MW in 2030 • LDES pilot project of 1 MW/150 MWh aiming for 2024
Manitoba Hydro	Manitoba, Canada		$1563 (CAN)/ kW overnight cost	• 5-hr Li-ion battery candidates • System-wide maximum battery capacity set at 350 MW • Benefits from transmission/distribution deferral, congestion relief, time shifting, ancillary services, customer services not incorporated in analyses • Battery additions small overall and only after 2033

Table 1 (continued). *Energy storage in recent IRPs. Source: EQ Research IRP as a Data ServiceTM and official IRP filings [6]*

UTILITY	REGION/STATE	STUDY PERIOD	COSTS	KEY DETAILS OF STORAGE INCLUDED IN RESOURCE PLANS
Minnesota Power	Minnesota	2021–2035	NREL ATB, EIA AEO, and IHS Markit cost	• 4-hr, 8-hr Li-ion battery and 12-hr flow battery candidates. • Pre-screening included CAES and pumped hydro. • Portfolios did not select storage resources.
Omaha Public Power District	Nebraska	2022–2050	N/A	• 150 MW storage additions before 2030 is the ‘least regrets’ decision • Pumped hydro eliminated in the screening process • Hybrid and thermal storage resource not evaluated • Optimal net zero pathway adds 0.5 GW storage by 2030, and 2 GW by 2050 • 1–3 GW of storage are selected across all cases in 2050
PacificCorp	Utah, California, Idaho	2023–2042	$1460 to $4303/kW	• 7400 MW of storage by 2029, 8095 MW of storage by 2042. Most of new additions are Li-ion batteries (over 90%), pumped hydro (35 MW), and LDES (350 MW) • 4-hr Li-ion battery, Flow battery, gravity battery, pumped hydro (400 MW, 10 hours discharge, 14 hours charging, 78% RTE) candidates • IRP included a Natrium advanced reactor demonstration project with molten salt thermal energy storage (5.5-hr duration at max capacity of 500 MW) • Reliability assessment includes 8-hr li-ion battery options and 100-hr iron-air batteries, and flow batteries. Sizing options included 20 MW and 200 MW, and hybrid and standalone resources • Most new solar is paired with battery
Salt River Project	Arizona	2017–2037	EIA AEO, NREL ATB costs	• Study cases in upcoming Integrated System Plan (ISP) include at least 2000 MW of battery storage • 4-hr Li-ion battery candidates • 1 GW pumped hydro candidate for longer durations
TVA	Tennessee, Alabama, Mississippi, Kentucky, Georgia	2018–2038	$855 to $4050/kW	• Pumped hydro, utility-scale battery storage, CAES, fuel cells, advanced chemistry batteries candidates • Without incentives, storage is not selected in base case plan. • 50 MW storage contract was signed in 2019 • Recommended plan includes 2400 MW by 2028 and 5300 MW by 2038
Xcel Energy	Colorado, Upper Midwest (UM)	15–20 years	NREL ATB costs	• Existing 225 MW battery storage and 340 MW pumped hydro in Colorado • 1170 MW of storage additions (about 600 MW standalone) by 2030 in Colorado. 250 MW of storage by 2034 in UM • 4-hr Li-ion battery, 50 MW block, 250 or 365 round trip cycles per year candidates

2.2.1 Temporal and Spatial Resolution

Temporal simplifications typically include on-peak and off-peak days[8] with a limited number of hours or blocks per day[9], typical weeks, or one or two chronological weeks per month. Some companies may use a limited number of blocks of nonchronological hours each month, based on load net of wind and solar resources.

Companies reported that their preferred approach for resource planning studies often involves regional network aggregation, typically using a copper plate approach without an intraregional network representation. This method may incorporate an interregional link to external and neighboring markets to account for energy transfers between balancing authorities. In larger-scale models, multiple balancing authorities are typically consolidated into a single region in long-term studies, while some electric companies opt for a zonal capacity expansion representation[10].

Run times depend heavily on the type of problem being solved and the size of the systems under consideration. They can range from minutes to hours to days, subject to the problem horizon length and resolution, system temporal and regional details, and the inclusion of operational parameters and ancillary services for energy storage technologies. Typically, a study period of 20 or 30 years is employed, and companies either optimize for all years or adopt a segmentation approach for a limited number of years (e.g., a 30-year problem broken into 3 optimization periods of 10-years each) to speed up the simulations. The forward-looking nature of the first strategy allows perfect foresight, while the latter approach, while faster, may compromise the optimality of the solution and miss intertemporal dynamics. Some companies reported typical capacity expansion runs, including multiple storage alternatives, ranging in runtime from one to 20 hours. Meanwhile, others reported runtimes ranging from half a day to up to four days. The addition of ancillary markets roughly doubled the solving times for some.

2.2.2 Storage Capacity Accreditation

The capacity value or accreditation for storage is typically determined exogenously across various deployment levels[11] and through different assessment methods [8, 17]. Resource adequacy modeling is used to establish Effective Load Carrying Capability (ELCC) curves for each storage technology and capacity levels, which are subsequently incorporated into capacity expansion models as additional technology input.

In these analyses, various energy storage technologies with durations typically ranging from 2-hr to 8-hr are considered. Several incremental capacity segments are integrated into the models, with ELCC values decreasing as penetration increases. These values exhibit a wide range depending on the electric company and market location, starting at approximately 100%-70% in the base year and declining to around 70%-35% (or even lower) by the end of the study period. In simpler approaches, some companies employ a single capacity value in their long-term studies. For hybrid solar and storage resources, ELCC is typically represented as the sum of each individual resource's capacity credits (i.e., the "sum of parts")[12].

Some companies have expressed concerns that existing analytical tools cannot capture the interactions of different generation resources and their effects on ELCC, a feature that is relevant for storage resources. As a resource's ELCC level depends on the system's future resource mix [19], stand-alone valuations tend to ignore the interactions with other technologies within portfolios. For example, the ELCC of storage may increase with higher solar penetration because solar can modify the net peak in such a way that storage can effectively cover it. However, once storage

8 For instance, a day when demand is at its highest and a day when demand is at its lowest for each month.

9 These blocks may combine and average specific hourly data that has a specific feature such as off-peak demand hours.

10 Generally, a power system is typically represented by various regions, which may be based on specific Balancing Authorities (BAs). Depending on the spatial resolution chosen for planning studies, this representation may include regional, zonal, or nodal network aggregation. In a regional network aggregation, all resources within a region are connected to a single node, and only the links between regions are modeled. In a zonal representation, different nodes are clustered into zones, with resources inside those zones connected to a single node, and links established between these zones.

11 Resource Adequacy (RA) obligations vary by region and can be met through different mechanisms and various entities. Some regions meet RA through participation in capacity markets at an ISO/RTO with additional rules set by states and/or PUCs. Other regions meet RA through voluntary capacity markets or standards set by state entities. In non-market regions, utilities work with PUCs to achieve RA where each state and utility can set their own requirements. For additional details refer to [19].

12 Earlier research on resource accreditation [19] offers examples of storage ELCC curves in recent utility plans.

capacity reaches a certain threshold, the benefit of adding more storage to the system diminishes, leading to increased costs for maintaining reliability through the same resource under that scenario.

2.2.3 Storage Technologies, Features, and Services

Electric companies typically consider various energy storage technology candidates with different attributes, including battery technologies of 2-hr, 4-hr, 6-hr to 8-hr of duration, and generic sizes of typically 25, 30, 50 or 100 MW blocks. The most common technology is lithium-ion, while other candidates include pumped hydro storage, redox flow, compressed air energy storage, fuel cells, advanced chemistry batteries, gravity energy storage, and thermal storage. Preferred portfolios often prioritize Li-ion batteries and hybrid solar energy storage resources. In systems where pumped hydro is already in place, the addition of new storage competes with this technology, which makes it challenging for long-term capacity expansion optimization models to select them. Additionally, many companies limit the addition of new storage resources to a specified amount per year, reflecting their expectations regarding the deployment pace of this technology.

Battery degradation is normally not included because of the limited capabilities that commercial tools have in including this characteristic in long-term capacity expansion models. A proxy for including this feature is through the O&M costs which account for the cost of maintaining the resource at its original capacity level[13]. However, this cost is typically based on a predetermined number of cycles per year, which does not endogenously take into consideration potential variations due to more cyclical operation of the battery. Some companies are working on incorporating explicit degradation models for lithium-ion battery energy storage systems in their capacity planning models [14, 15].

The inclusion of storage for reserves in capacity expansion models varies per utility. Some include frequency (up, down) regulation, as well as spinning reserves which can increase computational complexity and run times. Others choose to not include ancillary services in their capacity expansion models. Still, other companies exogenously estimate the flexibility benefits that storage resources may contribute to offsetting renewable integration which are later used as inputs in the planning tools[14].

3 CONCLUSION

While valuing energy storage systems is more complex than evaluating many other technologies, electric companies and planning entities are increasingly incorporating this technology into their assessments and planning tools. They also have plans to continue improving the representation of energy storage systems in the future.

Electric companies consider a variety of storage options for their long-term assessments. In practice, 2-hour, 4-hour, 6-hour, and 8-hour Li-ion batteries are among the most evaluated due to their technological maturity and the availability of cost and technical specifications. Pumped hydro systems are also considered, which fall into the category of long-duration energy storage (LDES) resources. Some companies have even begun piloting advanced LDES systems capable of delivering electricity for 10 hours or more. These emerging technologies are expected to play a more important role in the future, depending on their relative costs, policy design and decarbonization strategies [18].

Modeling strategies can significantly impact the assessment of storage systems. When temporal and spatial simplifications are made, they can miss capturing realistic system variability and influence intertemporal dynamics, ultimately affecting the valuation of storage services. However, companies today use a variety of tools, including capacity models, production cost models, reliability assessments, and storage price-taker models, to address modeling challenges. Combining these tools enables a more practical and comprehensive assessment of energy storage across different timeframes, capturing reliability and operational impacts as well as interactions with the rest of the system.

In the end, planners and modelers must carefully weigh the tradeoffs between enhancing modeling strategies and increasing model complexity within the current

13 In this case, periodic augmentation to maintain energy storage operational conditions will be reflected in the costs covered in maintenance contracts between the project owner and the technology developer.

14 Typically, these benefits are estimated as the difference in cost to mitigate the additional flexibility events caused by increased renewables with and without storage.

suite of long-term modeling tools. Today's models need enhancements to address the existing challenges associated with storage to fully capture its range of potential services and capabilities, especially when energy storage is widely considered a key resource to support grid decarbonization efforts.

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